Essays on Financial Market Volatility

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ABSTRACT

Volatility is an important component of market risk analysis and it plays a key role in many financial activities, such as risk management, asset pricing, hedging, and diversification strategies. This thesis consists of four empirical essays that evaluate the utility of a wide range of econometric models as well as explore and propose the use of further novel methods to enhance the understanding of volatility mechanisms across emerging and developed financial markets of Asia. Specifically, the first empirical essay provides an in-depth analysis on the characteristics of volatility phenomenon by comparing various GARCH models using three different frequencies with 24 years of data. The findings reveal robust empirical evidence that asymmetric GARCH models outperform in daily and weekly return series, while symmetric GARCH models outperform in monthly return series, indicating that different frequencies have their own structure and characteristics. The second empirical chapter investigates the forecast ability of a number of representative econometric models belonging to two main model groups based on recursive and rolling window methods. The obtained results report that frequency of the data and choice of forecast method have strong effects on performance of the models. Furthermore, existence of strong volatility asymmetry has been found in the higher frequencies of data which is also systematically confirmed by the superiority of the asymmetric models in daily and weekly series. On the other hand, it is found that the monthly series of Asian stock markets are less sensitive to the leverage effects, thus the predictive capability of symmetric GARCH genre of models are more superior in lower frequencies. The third empirical chapter extended the volatility forecasting exercise by evaluating the utility of advanced Machine Learning models in comparison to traditional forecasting models. The findings indicate that the neural network prediction models exhibit improved forecasting accuracy across both statistical and economic based metrics, offering new insights for market participants, academics, and policymakers. The obtained results are further evaluated by the risk management settings of Value at Risk (VaR) and Expected Shortfall (ES). The final empirical essay introduced an Early Warning System (EWS) by integrating DCC correlations with state-of-the-art Deep Learning (DL) model. The novel results demonstrate that the bursts in volatility spillovers are successfully verified by the proposed model and EWS signals are generated with high accuracy before the 12-month period of crises, providing supplementary information that contributes to the decision-making process of practitioners, as well as offering indicative evidence that facilitate the assessment of market vulnerability to policymakers.

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CHAPTER 1

Introduction and Overview

1.1 Introduction

Stock market volatility of financial time series has been an attractive research area for market participants and academics over the last few decades. This interest emerges from the nature of volatility which is an important reference point to evaluate the ambiguity in price changes of assets. Therefore, volatility is considered in the centre of financial economics. Campbell et al. (1997) mention: "*... what distinguishes financial economics is the central role that uncertainty plays in both financial theory and its empirical implementation ... Indeed in the absence of uncertainty, the problems of financial economics reduce to exercises in basic microeconomics*" (p 3). More broadly, volatility is a crucial concept in investments, risk management, and asset allocation applications in financial markets. In simple words, the term volatility means fluctuations in a security's value within a short-term period. In economics, Andersen et al. (2006) describe volatility as *"the variability of the random (unforeseen) component of a time series. More precisely, or narrowly, in financial economics, volatility is often defined as the (instantaneous) standard deviation (or "sigma") of the random Wiener-driven component in a continuous-time diffusion model"* (p 780). A higher volatility indicates returns of assets can spread out widely from the mean of a given security's value while lower volatility indicates that the value of the asset does not move sharply within a short period of time. Thus, volatility is the lifeblood of trading activities and investors are willing to take that risk in order to operate with their capitals in financial markets and manage their portfolios.

The reason behind volatility in stock markets can be the consequence of external conditions such as macroeconomic events, politics, and natural disasters and/or the source of movements directly come from stock itself such as business performance of the firm or financial decisions. Therefore, the actions of brokers and the external or internal effects mentioned above are regulated by government agencies to ensure fairness and stock market efficiency. In some extreme occasions, a stock exchange is closed to trading by regulatory authorities for a while to protect markets from massive shocks. In previous financial crises, volatility created domino effects and spread worldwide. These crises revealed that volatility has different impacts in different markets depending on the geographical region, size of the market, and strength of the companies, but it might have undesirable consequences if it cannot be estimated and forecasted carefully.

The reasons above indicate understanding volatility is necessary because it is a key variable in pricing of financial instruments. Early applications of pricing securities started with Capital Asset Pricing Model (CAPM) which was developed independently by various academics between 1961 and 1966, building on the earlier work of Harry Markowitz on diversification and modern portfolio theory. However, the modern form of option pricing started with Black-Scholes model (1973) developed by Fischer Black, Myron Scholes, and Robert Merton to determine the fair price or theoretical value for a call and a put option. Although various parameters in the market are directly observed such as strike price, risk-free interest rate and the current price of the underlying asset, there is only one parameter in the Black-Scholes formula that cannot be directly observed from the market which is the volatility of the underlying asset. Therefore, volatility is extremely important for asset pricing, risk management, and investment strategies.

There is no doubt about the significance of the volatility for market participants and policymakers in the financial market and the world economy. Indeed, Engle and Patton (2001) explain "A *risk manager must know today the likelihood that his portfolio will decline in the future. An option trader will want to know the volatility that can be expected over the future life of the contract. To hedge this contract he will also want to know how volatile is this forecast volatility. A portfolio manager may want to sell a stock or a portfolio before it becomes too volatile. A market maker may want to set the bid–ask spread wider when the future is believed to be more volatile*" (p 2). Similarly, on importance of forecasting volatility, Brownlees et al. (2011) mention: "The *price of almost every derivative security is affected by swings in volatility. Risk management models used by financial institutions and required by regulators take time-varying volatility as a key input. Poor appraisal of the risks to come can leave investors excessively exposed to market fluctuations or institutions grounded on the edge of a precipice of inadequate capital*" (p 4).

Considering volatility's central role in financial markets, understanding of modelling and forecasting stock market volatility is crucially important for everyone involved in financial activities in terms of predicting the direction of the market and more broadly having a good idea what to expect from the economy. Moreover, in times of financial turbulence, estimating volatility becomes even more critical since increased uncertainty causes disruption in financial sector which then triggers turmoil in the region or global economy depending on the size and the spillover effect of the market. Since excessively volatile financial markets are one of the most prominent signals of these crises, understanding behaviour of volatility would be a key asset for existing in the market not only during financial prosperity but also in turmoil times for those involved in financial activities.

Empirical observations on stock market volatility, especially during the subprime crisis period, showed that there is a transmission of return and volatility among international financial markets. Ahlgren and Antell (2010) indicate, "One *of the salient features of globalisation and the rapid transmission of information across markets is the spread of financial crises from one country to another. The experience of recent financial crises has shown that dramatic movements in one market can have a powerful impact on other markets, even when the under-lying economic fundamentals are different*" (p 157). Although, liberalization and integration of different financial markets and economies offer great advantages such as more dynamic and profitable stock markets, as well as a broader range of retail and institutional investors, also leading to international shocks and causing exposure to more prominent crisis. Even though there is a rich literature on spillover effects and linkages among financial markets, recent developments in world stock markets regarding ongoing impacts of Covid-19 crisis and globalization encourage further investigation in this area. Thus, in addition to volatility forecasting the present thesis further examines the characteristics volatility transmission across developed and emerging Asian markets as well as the US market, aiming to contribute of spillovers, international asset allocation, and financial globalization literature. Moreover, the empirical analysis on co-movement and financial integration between the selected markets provides practical evidence, that makes the current study specifically related to econometricians, international investors, and economic policymakers.

Specifically, Chapter 2 evaluates a wide range of econometric models in the empirical literature, while Chapter 3 investigates the modelling performance of the well-known and most commonly applied time-series methodologies on Asian financial markets among the discussed literature in Chapter 2. Chapter 4 examines out-of-sample forecasting capabilities of the selected models in Chapter 3 by using daily, weekly, and monthly return data as well as recursive and rolling window methods. Chapter 5 extends the experimental analysis in Chapter 4 and provides an in-depth analysis on Machine Learning models, including Neural Network, Neuro-Fuzzy, and deep learning architectures, to address the theoretical and practical gap on optimal forecasting model in Asian financial markets. Chapter 6 assesses volatility transmission channels by adopting GARCH-BEKK, DCC, and Diebold-Yilmaz spillover index methodologies and further proposes a novel deep learning algorithm to investigate contagion risk across selected Asian markets and the US market. More detail on the main findings of each chapter will be given in Section 1.6.

1.2 Motivations

The present thesis has two main motivations.

First, the need for estimating and forecasting dynamics of volatility in Asian financial markets. Volatility has a significant role in financial sector and especially in stock markets since its nature is an important reference point to determine risk and ambiguity, the crucial concept in asset pricing, risk management, and investments. The violation of homoscedasticity, a methodological concept in conditional volatility, causes inaccurate evaluation of pricing financial instruments. Moreover, stock market returns usually show presence of volatility asymmetry and volatility clustering phenomenon. Thus, considering these prominent features of volatility and more specifically conditional variance, the present study focuses on three crucial facts consisting of the characteristics of volatility in Asian financial markets, estimation and comparison of the econometric models, and the optimal forecast evaluation for the selected markets.

Second, despite its size, Asian financial markets are under-studied. Ten Asian financial markets have been chosen for this study which represent 27.16% of the total world population as of November 2020 according to the United Nations projections. In 2020, the World Bank released the Gross Domestic Product (GDP) of the world and selected Asian markets counted for approximately one-third of the global GDP collectively, with 25.031 trillion US dollar. Among these countries, China comes into prominence as the greatest developing market and the major contributor to the global economy throughout the previous thirty years, with the average GDP growth rate of 9.2%. In addition to China, Asia also has a former engine of the world economy, Japan, progressively prosperous South Korea, and the rapidly developing Association of Southeast Asian Nations (ASEAN). Already representing such an important role in the global economy, Asia’s blossoming markets are still set to continue rocketing and providing strength to the world economy.

1.3 Contributions

The present study contributes to the financial literature of volatility in Asian markets. A lot of research has been undertaken about the US and European Markets, currencies, options, stocks, T-bills and futures as stated in Poon and Granger (2003). However, limited studies have been conducted on Asian financial markets. To the best of my knowledge, this work is the first to examine volatility in ten Asian markets covering modelling, forecasting, and spillover effects with a wide range of models, including the Machine Learning applications. The main contributions are:

1. To investigate behaviour of volatility and its characteristics on return series of emerging and developed stock markets of Asia:

    - to estimate volatility in emerging and developed stock markets by applying various GARCH family models, for the full sample period from 1994 to 2018;
    - to estimate volatility in emerging and developed stock markets by applying various GARCH family models, over the two different subsample period for the first 12 years from 1994 to 2006, and the second 12 years from 2006 to 2018;
    - to identify the presence of volatility persistence and asymmetric effects in return series of Asian markets for different frequencies;
    - to examine and compare the appropriateness of GARCH models considering stylized facts about volatility in return series; and
    - to analyse, discuss and compare the differences obtained for volatilities with earlier studies.

2. To analyse the predictive power of various econometric models and evaluate the optimal forecasting model:

    - to investigate and evaluate the relative out-of-sample forecasting ability of various GARCH models by comparing daily, weekly and monthly frequencies using recursive and rolling window methods;

- to investigate the forecasting capability of the Artificial Neural Network (ANN) models, including economic-based implications, against traditional benchmark econometric models;
- to investigate the forecasting performance of the ANN and GARCH family models by comparing the forecasts of the models based on MSE, RMSE, MAE, MAPE and QLIKE metrics; and
- to analyse, discuss and compare the differences with earlier studies.

3. To investigate the differences in patterns of volatility spillovers across emerging and developed stock market indices:

- to estimate volatility spillovers and contagion effects in emerging and developed stock markets of Asia as well as the US from 1997 to 2021;
- to estimate volatility spillovers between 11 emerging and developed stock markets over the five different subsample periods covering major crises, namely 1997-98 Asian Financial Crisis, GFC crisis of 2007-08, and COVID-19 crisis of 2020 as well as two tranquil periods with Pre-GFC and Pre-Covid episodes;
- to develop an Early Warning System (EWS) based on Deep Learning LSTM model through obtained correlation channels from Dynamic Conditional Correlation (DCC) model;
- to investigate the degree of contagion effects and reveal the role of benchmark index of the US, S&P 500 index, on selected emerging and developed Asian markets; and
- to evaluate the estimated differences for spillovers effects by applying three different correlation models and discuss the results in relation to previous studies.

1.4 Significance of the study

The significance of the present study is threefold:

1. to extend the literature by applying various econometric methods in ten emerging and developed stock markets of Asia which provide insights for the existing literature if the analysis is sensitive to the methods employed;

2. to capture properties of stock market volatility by using a set of symmetric and asymmetric GARCH family models under different window forecast procedures with three different frequencies, which has not been done before as of my knowledge;

3. to evaluate and compare a wide range of Machine Learning models, including standard NN, Neuro-Fuzzy, and Deep Learning techniques with improved learning rule and optimized hyperparameters; and

4. to provide evidence of the patterns, interdependencies, and predictive power of volatility spillover effects across stock market indices by applying GARCH-BEKK, DCC, and Diebold-Yilmaz spillover index methodologies with the integration of state-of-the-art LSTM model which distinguish this study from majority of the previous studies not only with its advanced deep learning algorithm but also covering a dataset reaching up to Q1 2021.

This study is expected to help financial market participants in Asian stock markets in three ways. First, the present study informs traders by providing key facts about volatility in daily frequency. Second, this study assists portfolio managers, macroeconomic forecasters, and investors by providing weekly and monthly information about volatility. Third, this work contributes to the empirical finance literature by assessing various GARCH family and ANN models which is expected to be a source for econometricians and academics.

1.5 Overview of Asian Markets

The Asian countries have stock markets for more than 100 years, yet their global and strategic significance sparkled with Japanese economic miracle after the post-World War II. The economy of Japan grew 9.2% per year from 1950 to 1970, before slowing down to 5% per year from 1950 to 1990 (Stewart and Andreychuk, 1998). Since the early 1990s property crash, Japan's demographics and workforce are no longer expanding as they did in earlier decades, but Japan is still the World's third largest economy after the United States and China.

The socialist market economy of the People's Republic of China has been rising expeditiously in the last four decades since introducing the Open-Door Policy in 1978 to foreign businesses that wanted to invest in China. Therefore, GDP per capita rose from US$828 to US$9,770 in the last 20 years, which has helped to obtain millions of Chinese people to live over the international poverty line of US$2 a day. According to the World Bank, the GDP of China grew at an annual rate of almost %10 from 1978 to 2018, which has ranked up China from lower-middle income group to upper-middle income group in the World Bank classification scheme. This rapid growth in economy is accompanied by the development of stock markets as it becomes appealing for foreign investors. In this regard, the Shanghai Stock Exchange (SSE) was re-established on November 1990, and the Shenzhen Stock Exchange (SZSE) on July 1991. As of 2021, Shanghai Stock Exchange is the World's 3rd and Asia's largest stock market by market capitalization based on the World Federation of Exchanges. Today, these markets continue to contribute the remarkable growth in Chinese economy by supplying the necessary funds.

In the meantime, neighbours of Japan and China followed their trend and the countries including Hong Kong, Singapore, Korea, and Taiwan, which have been called the Four Asian Tigers or the Four Asian Dragons by the Chinese, began rapid industrialization with the strong government development efforts and the injection of big amounts of foreign financial investments. Among these countries, Hong Kong and Singapore differentiated themselves by becoming world-leading international financial canters. In terms of population, they are quite small compared to China or Japan with the populations in ascending order Singapore (5.68 million), Hong Kong (7.49 million), Taiwan (23.57 million) and Korea (51.78 million) based on the United Nations estimates as of June 2020. When it comes to the ranking by GDP per capita, Singapore takes the leads with $59,797, followed by Hong Kong with $46,323, Korea with $31,631 and lastly Taiwan with $28,358 as of 2020. According to the World Bank classification scheme, the Four Asian Dragons belong to the high-income group based on Gross National Income per capita.

Association of Southeast Asian Nations (ASEAN) economies – Thailand, Malaysia, Philippines, and Indonesia identified the Four Asian Tigers countries as models for their achievements. In a descending order for GDP per capita as of 2020, Malaysia takes the lead with $10,412 followed by Thailand ($7,186), Indonesia ($3,869) and the Philippines ($3,298). The stand by population is almost adverse: Indonesia (273.52 million), Philippines (109.58 million), Thailand (69.80 million) and Malaysia (32.36 million) based on latest estimation by United Nations. According to the World Bank classifications by income level for 2020, Malaysia and Thailand belong to the upper middle-income group while Indonesia and the

Philippines belong to the lower middle-income group. Nevertheless, in the 21st century, all these economies are still booming with the rising gross domestic product and investment opportunities.

1.5.1 Characteristics of stock markets in Asia

Asian stock markets are significantly large and aggressively expanding. While the market capitalization of selected countries was US$3.5 trillion in 1991, they reached US$24.7 trillion U.S. dollar in 2017, which represents 31.2 % of World equity market and 86.7% of Asian equity market capitalization.

There are some distinctions between Asian stock markets in terms of size, turnover ratio and number of listed companies as shown in Table 1.1. Japanese stock market is the most developed and biggest market in terms of market capitalization and number of listed companies throughout the years. China and Hong Kong stock markets are the second biggest markets in terms of market capitalization and number of listed companies which also has seen the biggest expansion in the region in terms of market capitalization from 1991 to 2017 with 15,718.639% and 3,465.574% respectively. As of 2017, Korea and Taiwan are the other two markets which have market capitalization of over US$1 trillion followed by Singapore, Thailand, and Indonesia. Malaysia and the Philippines have relatively smallest stock markets compared to other countries.

Table 1.1: Equity market characteristics

	Japan	Hong Kong	Singapore	Thailand	Malaysia	Indonesia	China	Korea	Taiwan	Philippines
1991										
Market capitalization (in USD billions)	3,005.70	121.88	47.59	38.07	56.72	n/a	55.42	96.47	146.51	8.43
Market capitalization (in percent of GDP)	93.48	108.39	94.79	23.97	108.73	n/a	0.53	29.61	63.37	23.83
Stock market turnover ratio	34.30	31.61	38.00	50.96	18.84	n/a	0.67	85.57	n/a	n/a
Stock market return (percent)	-15.37	25.28	n/a	-11.83	1.49	-36.32	38.94	-11.80	n/a	16.95
Stock price volatility (percent)	24.83	19.45	n/a	40.30	23.52	21.07	n/a	24.9	n/a	36.27
Number of listed companies	1641	333	166	270	318	139	8	686	221	161
2004										
	Japan	Hong Kong	Singapore	Thailand	Malaysia	Indonesia	China	Korea	Taiwan	Philippines
Market capitalization (in USD billions)	3,557.67	861.46	217.50	115.39	181.62	73.25	447.72	428.33	401.54	28.6
Market capitalization (in percent of GDP)	73.89	509.44	190.47	66.74	145.59	28.52	22.90	56.00	120.08	31.30
Stock market turnover ratio	97.19	46.87	50.95	101.34	29.84	29.87	114.24	122.76	n/a	11.31
Stock market return (percent)	21.90	25.53	25.74	36.87	20.79	56.74	1.03	22.52	n/a	34.14
Stock price volatility (percent)	19.82	17.65	17.59	23.06	12.11	21.85	18.91	25.5	n/a	18.62
Number of listed companies	2276	1086	536	463	955	331	1373	1570	691	233
2017										
	Japan	Hong Kong	Singapore	Thailand	Malaysia	Indonesia	China	Korea	Taiwan	Philippines
Market capitalization (in USD billions)	6,222.27	4,350.51	787.26	548.80	455.77	520.69	8,711.27	1,771.76	1,073.79	290.40
Market capitalization (in percent of GDP)	128.04	1,273.39	232.64	120.54	144.82	51.28	71.74	115.75	181.88	92.60
Stock market turnover ratio	92.84	43.38	27.90	61.87	30.06	11.77	197.12	112.36	n/a	11.64
Stock market return (percent)	-12.76	-11.68	-12.18	-1.84	-3.78	2.50	-19.31	-1.20	n/a	-1.89
Stock price volatility (percent)	21.06	15.97	11.79	12.11	7.72	13.08	17.79	11.20	n/a	16.23
Number of listed companies	3604	2118	483	688	904	566	3485	2134	924	267

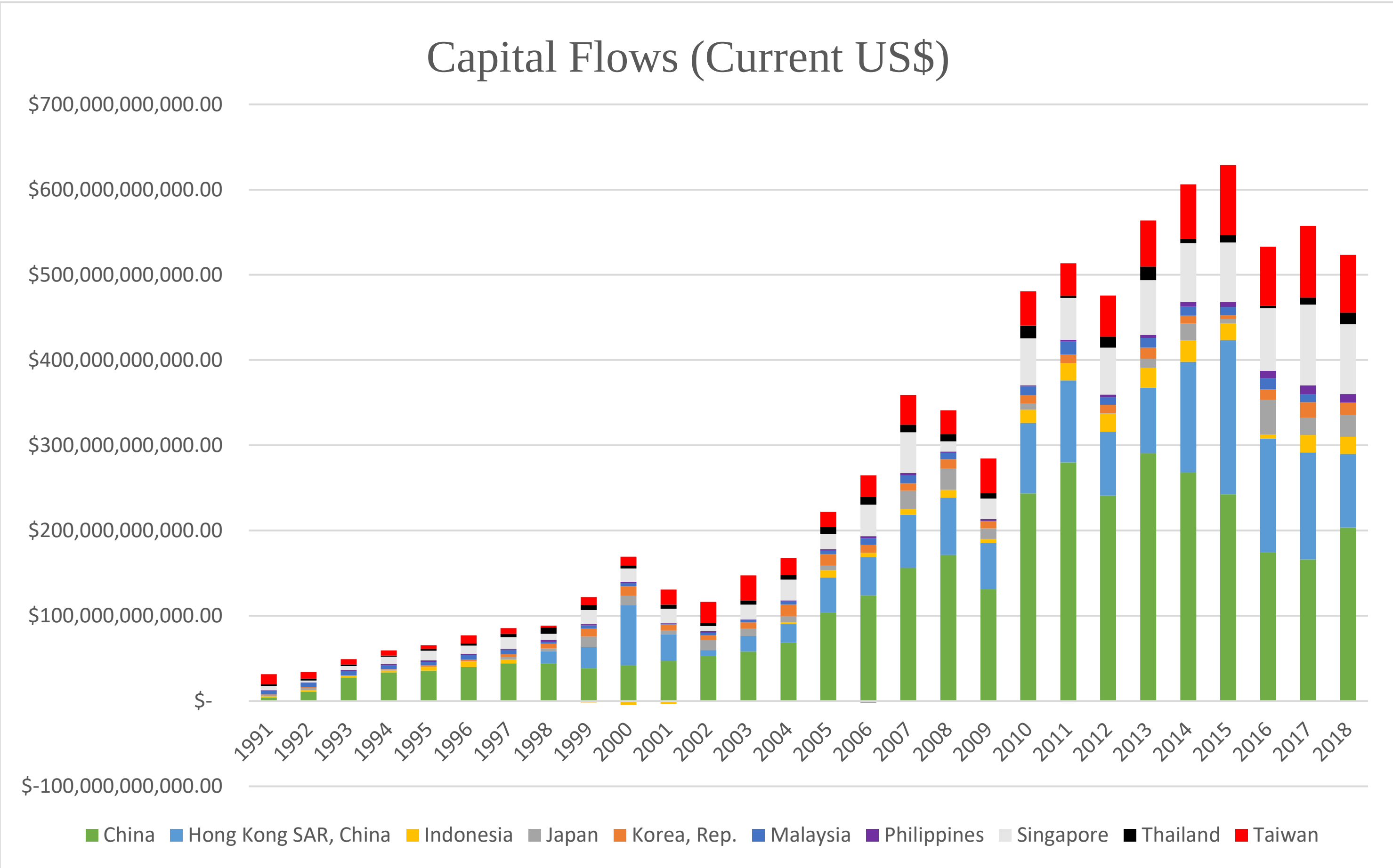
Source: The World Bank

Note: n/a = Not Available

1.5.2 Capital Flows

In the beginning of the 1990s, capital controls have been eased by local governments in Asian countries for both foreign individuals and institutional investors. Expanding foreign interests to Asian markets boomed after loosening controls on money flow. Lashaki and Ahmed (2017) report that between 1996 and 2012, international investments to emerging southeast markets totalled about $880 billion. Specifically, according to the World Bank data, capital inflow from foreign investors to financial markets of selected countries were measured $537.87 billion in total for the year of 2018, while China had the largest inflow with $203.49 billion and the Philippines experienced the smallest equity flow with $9.8 billion. Further details can be found in Table 1.2.

Table 1.2: Capital flows in Asian markets from 1991 to 2018



Source: The World Bank, Central Bank of the Republic of China (Taiwan)

1.5.3 Quality of Financial Infrastructure

One of the most fundamental roots behind the growth of financial markets is a well-functioning financial system and regulated institutions. Herring and Chatusripak (2000) suggest that well defined and enforceable legal and creditor rights is a must to attract potential investors. Porta et al. (1998) also include an efficient judicial system and commitment to the rule of law. Thus, the standards of financial markets infrastructure can be measured by some important elements: effective legal rights, the quality of regulations, efficient and reliable governance, and commitment to the rule of law. In Table 1.3, the quality of financial infrastructure is determined for selected countries in the mentioned framework. While legal rights are gauged from 0 (worst) to 12 (best), the other three factors ranked from -2.5 (weakest) to 2.5 (strongest). According to the World Bank data for 2017, the four emerging Asian markets are well below the developed Asian markets. While Singapore has the highest quality followed by respectively Hong Kong and Japan, Indonesia, China, and the Philippines have the lowest quality in all measured factors. Thailand market indicates weak rule of law and poor control of corruption, while Malaysia stands out with a relatively better quality of market infrastructure compared to its counterparts.

Table 1.3: Quality of financial market infrastructure

	Rule of Law	Regulatory Quality	Legal Rights	Control of Corruption
Japan	1.57	1.37	5	1.52
Hong Kong	1.72	2.16	8	1.61
Singapore	1.82	2.12	8	2.13
Thailand	0.04	0.14	7	-0.39
Malaysia	0.41	0.68	8	0.03
Indonesia	-0.35	-0.11	6	-0.25
China	-0.26	-0.15	4	-0.27
Korea	1.16	1.11	5	0.48
Taiwan	1.14	1.37	n/a	0.96
Philippines	-0.41	0.02	1	-0.48

Source: The World Bank

Note: n/a = Not Available

1.6 Structure of the Thesis

While Chapter 1 introduces the thesis and highlights the relevance, motivation and contribution of the present research, the remainder of the study is organized as follows:

Chapter 2 presents a review of the empirical literature on volatility models and explains the well-known and most commonly applied econometric methods that have been utilized by financial researchers examining financial market forecasting techniques.

Chapter 3 investigates the characteristics and differences in patterns of volatility across ten emerging and developed stock market indices of Asia by applying daily, weekly, and monthly data over a period of 24 years. Specifically, the comparison of stylized facts about volatility between daily, weekly, and monthly series; the predictability of variances and performance of alternative GARCH models; and the behaviour of volatility and its characteristics in two different sub-samples are examined. The empirical findings of the research report suggest that the normality hypothesis is not accepted due to strong kurtosis. Therefore, various specifications of the GARCH model are applied to explain excess kurtosis with the symmetric and asymmetric extensions. Further findings show that the conditional volatility of returns in all indices are persistent and depend on their previous lags. Increased presence of persistency was observed in daily return series compared to weekly and monthly data sets, indicating that the volatility models are sensitive to the frequencies of data series. Furthermore, the results indicate that asymmetric GARCH models outperform symmetric GARCH models in daily and weekly return series based on the SIC, AIC and HQIC criteria. Positive correlation has been found in daily return series, while weekly and monthly returns series report mixed results between conditional variance and expected asset returns. Asymmetry in stock returns has also been investigated by employing the asymmetric GARCH models and the results demonstrate the existence of leverage effect in the returns of the selected markets.

Chapter 4 enters the ongoing volatility forecasting debate by assessing and comparing the predictive capabilities of popular GARCH models. In this context, the chapter aims to examine the relative out-of-sample predictive ability of different GARCH models for ten Asian markets by using three different frequency and two different methods, considering the features of volatility clustering, leverage effect and volatility persistence phenomena, which the evidence of existence are found in the data. Five measures of comparison are employed in this research and a further dimension is investigated based on the classification of the selected models in order to identify the existence (or not) of any differences between the recursive and rolling window methods. The empirical results reveal that asymmetric models with the lead of EGARCH model provide better forecasts compared to symmetric models in higher frequencies. However, when it comes to lower frequencies symmetric GARCH models tend to outperform over their asymmetric counterparts. Furthermore, linear GARCH models are penalized more by the rolling window method, while recursive method places them amongst the best performers, highlighting the importance of choosing a proper approach. In addition, this study reveals an important controversy: that one error statistic may suggest a particular model is the best, while another suggests the same model to be the worst, indicating that the performance of the model heavily depends on which loss function is used. Finally, the chapter did not find any significant superiority between employed recursive and rolling window methods.

Chapter 5 extends the empirical finance literature by comparing Machine Learning models with traditional forecasting methods. Although finance practitioners and academics have advocated for the benefits of AI methods, there is relatively little understanding of the conditions in which neural networks provide accurate forecasts, the uncertainty bounds which can be put on such forecasts, and the most suitable network types and parameters for forecasting in the relatively small-sample settings encountered within finance. The chapter fits into a growing body of literature which aims to answer some of these questions. In this context, this chapter examines the utility of Machine Learning methods, specifically focusing on the application of Artificial Neural Network models for stock market prediction. The ANN models are estimated and assessed by comparing with traditional non-linear forecasting models in terms of prediction accuracy and robustness. Ten Asian markets have been studied using 24 years of daily data, while the first half is used for training and the second half is reserved for out-of-sample prediction. The empirical results of ANN models are promising. Out-of-sample forecast evaluation results show that ANN models are superior in each index compared to benchmark models of GARCH and EGARCH which indicates improved forecasting accuracy and strong performance, thus offering new exiting capabilities for market participants, academics, and policymakers. Furthermore, VaR and backtesting are performed by the average failure rate, the Kupiec LR test, the Christoffersen independence test, the expected shortfall, and the dynamic quantile test of Engle and Manganelli. The findings report that the VaR forecasts of the models accurately capture market risk exposure in selected markets with the desired confidence horizon supported by backtesting metrics, providing a reliable and satisfactory results for financial risk management.

Chapter 6 investigates in depth analysis on the volatility transmission channels of ten Asian markets as well as the US market. In order to do that, the chapter adopts GARCH-BEKK, DCC, and Diebold-Yilmaz spillover index methodologies for two pre-crisis periods and three major crisis episodes. Furthermore, an early warning system by integrating DCC correlations with state-of-the-art Deep Learning (DL) model is presented. The empirical findings of the study demonstrate that the climb in external shock transmissions has long lasting impacts in domestic markets due to contagion effect during the crisis periods. Moreover, it is revealed that the heavier magnitude of financial stress transmits among Asian countries via Hong Kong stock market, offering key information for investors and financial regulators in terms of diversification benefits and macroeconomic stability in the region. Additionally, it is revealed that the degree of volatility spillovers among advanced and emerging equity markets is less compared to the pure spillovers between advanced markets or emerging markets, offering window of opportunity for international market participants in terms of portfolio diversification and risk management applications. On the other hand, the experimental analysis of Long short-term memory (LSTM) network finds evidence of contagion risk. The proposed model successfully verified bursts in volatility spillovers and generate signals with high accuracy before the 12-month period of crisis, providing supplementary information that contributes the decision-making process of practitioners, as well as offering indicative evidence that facilitate the assessment of market vulnerability to policy-makers. Finally, the effectiveness and reliability of the LSTM model is confirmed with RMSE and MSE loss functions to avoid false signals.

Finally, Chapter 7 concludes the thesis with a summary of its findings and a brief discussion on what implications the analysis has for different entities, including policymakers, academics, and investors. In addition, it outlines the limitations of this thesis and provides direction and suggestions for further research.

CHAPTER 2

Empirical Literature

2.1 Introduction

A major concern in modern finance theory is ambiguity which has contributed to the developments for a set of econometric models to estimate time varying variance. Mandelbrot (1963 and 1967) reveals the fact that financial asset returns tend to exhibit fat tails and volatility clustering phenomenon. These early foundations lead the academics to apply some informal modelling methods such as recursive estimation, moving average etc… (see, Mandelbrot, 1963; James, 1968; Nelson, 1974; and Klein, 1977)

Engle (1982) developed the Autoregressive Conditional Heteroscedasticity Model (ARCH) to estimate the UK inflation which is seen as the first formal model that can distinguish time-varying volatility (Diebold, 1986). The generalized version of ARCH model was proposed by Bollerslev in 1986 to overcome the difficulty of large number of lags calculation in the ARCH model. Although empirical studies reveal that ARCH and GARCH models are efficient to model financial return series, there are also some deficiencies (Fan and Yao, 2003). One of the biggest inadequacies of these models is not taking account volatility asymmetries. Moreover, it has empirically proved that a negative shock has a greater impact on volatility than a same magnitude of positive information (Pagan and Schwert, 1990; Campbell and Hentschel, 1992; Bollerslev et al., 1992; and Sentana, 1992). Therefore, an extensive number of GARCH specifications have been proposed to cope with the asymmetry problem such as the EGARCH model of Nelson (1991), the PGARCH model of Ding et al. (1993), the TGARCH model of Zakoian (1994), and the QGARCH model of Sentana (1995). These models are able to take into account volatility asymmetries and fat tails in market return series (Alberg et al., 2008).

Following the success of above models, another property has been recognized in financial return series which is called "long memory". More precisely, Chkili et al. (2014) define "… *the low decay rates of long-lag autocorrelations and principally takes root in the problem of aggregation of multiple macroeconomic variables that may persist over time*" (p 3). To model this phenomenon several models have been proposed such as the FIGARCH model of Baillie et al. (1996), the FIEGARCH model of Bollerslev and Mikkelsen (1996), the CGARCH model of Engle and Lee (1999), and the HYGARCH model of Davidson (2004). Empirical applications of the long memory models on various financial datasets reveal that the models are sufficient to estimate volatility (see, Davidson and Teräsvirta, 2002; Doukhan et al., 2002; Disario et al., 2008; Wang et al., 2011; Lin and Fei, 2013; and Duppati et al., 2017).

The recent developments in the information technology allow accessing high-frequency data for financial instruments such as, shares, stock market indices, currencies, precious metals etc. This has drawn the attention of financial researchers to use of a proxy for a "true" volatility which is also called Realized Volatility (RV). Although majority of the empirical finance literature applies daily return series due to its accessibility and convenience to gauge the true volatility, Andersen and Bollerslev (1997) showed that this might be extremely noisy. Following year, Andersen and Bollerslev (1998) successfully measured the realized variance by using the sum of the intraday high frequency squared returns which is considered less noisy than traditional modelling approach. Since then, financial econometricians have made significant improvements to estimate realized volatility based on the high-frequency data (see, Andersen et al., 2001; Robinson, 2003; Deo et al., 2006; Wei, 2012; Patton and Sheppard, 2015).

This chapter covers an in-depth survey of the empirical volatility models as well as some definitions about volatility. In the following chapters, theoretical literature review will be discussed in the related parts of the thesis especially on Asian stock markets, but first it is important to comprehend the nature of volatility and the various traditional models of conditional variance.

2.2 Modeling Volatility

Almost in the last half-century where the early applications begin, measuring volatility is still a controversial topic in academia and the financial world. However, the difficulty of measuring and predicting volatility has shown the necessity of developing econometric models, and since the early 1970s, several models have been proposed and successfully implemented in the financial markets. The next chapter will cover these models starting from the earlier applications to the most recent ones, and some useful notation will be presented in related sections for further discussion.

2.2.1 Notions About Financial Market Volatility

There are several notable features for financial market volatility that needs to be mentioned before volatility models.

Fat Tails: A fat-tailed distribution is a probability distribution that refers to the excessive observations in a distribution. In finance, most of the time fat tails occur although it is considered undesirable because of the additional risk they imply. It is also called as large skewness and excess kurtosis. The pioneering studies about this feature started with Mandelbrot (1963) and Fama (1963, 1965).

Volatility Clustering: Mandelbrot (1963) definition for volatility clustering is "*large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes*" (p. 418). The mathematical expression of this fact is that, despite the uncorrelated returns, absolute returns show a positive, significant and gradually decaying autocorrelation function. It is also the signal of persistence of volatility shocks.

Leverage Effect: The basic definition of leverage effect is 'the price movements are accompanied by negatively correlated volatility which means when volatility rises asset prices decline, and vice versa. This feature is also called as volatility asymmetry. The term 'leverage' developed by Black (1976) for asset returns. The phenomenon of leverage effect is highly noticed during financial crises. The further empirical documentation of volatility asymmetry can be found in Nelson (1991), Gallant, Rossi, and Tauchen (1992, 1993) and Engle and Ng (1993).

Long Memory: Long memory is an important feature for stock market volatility, and it refers to strong volatility persistence. In financial markets, it occurs often since past values have significant effect on future values. In other words, high autocorrelation shows long memory. Further studies for this feature can be found in Taylor (1986), Ding et al. (1993), Davidson (2004), Harvey (2007) and Bentes et al. (2008).

Co-movements in Volatility: Joint movements in volatility and returns is a common phenomenon between different securities but especially in stock markets. Recent studies about co-movement show that correlation between volatility in different markets is higher than between returns, and during financial turmoil both tend to rise.

2.3 Simple Volatility Models

The following models are first introduced before the ARCH and GARCH models, including random walk, moving average (MA), and exponentially weighted moving average (EWMA). The literature is wide in this section, therefore only the most traditional and broadly used models will be presented.

The Random Walk Model (RW)

One of the most primitive and yet well-known models in financial modelling is the random walk model. This model presumes that “the best forecast of next period’s volatility is the current period’s volatility” (Meng and Rafikova, 2006).

$$\sqrt{h_{t+1}^2} = \sqrt{\sigma_t^2} \tag{2.1}$$

where σ^2 is the current conditional variance and h_{t+1}^2 is the next period’s forecasted conditional volatility. A random walk model predicts that there will be no change in future values than the last observed one. However, it does not mean that the forecasted volatility will be exactly the same, but it will more likely be close to the last observed value.

Moving Average (MA)

Another classic model is simple moving average where it suggests that the best forecasts are obtained from the most recent data.

$$h_{t+1}^2 = \frac{1}{n}\sum_{k=1}^{n} \sigma_{t+1-k}^2 \tag{2.2}$$

where *n* determines the averaging window width. The big issue in simple moving average for researchers is the size of the data. The problem with the data is, excessive data amount includes periods that do not have influence on current volatility, and it loses predictive power whereas inadequate data does not include periods that have an effect on current volatility and again it loses its predictive power.

Exponentially Weighted Moving Average (EWMA)

Exponentially Weighted Moving Average (EWMA) is a more advanced version of Moving Average (MA), yet it is in the same category with MA that uses historical volatility for forecasting. The difference of the EWMA model from MA comes from relying less on older data and putting more weight on recent data, which enables recent observations to have more influence on forecasting volatility than the older observations.

$$h_{t+1}^2 = (1-\gamma)h_t^2 + \gamma \frac{1}{n}\sum_{k=1}^{n} \sigma_{t+1-k}^2 \tag{2.3}$$

The decay parameter, γ, has a value between zero and one. However, if the decay parameter is 0 then it turns to random walk whereas a higher γ puts more weight on past forecast. The optimal decay parameter can be determined by the root mean squared criteria.

2.4 ARCH and GARCH Models

Although the historical-based models mentioned above are suitable to capture volatility, they have issues about window size. Autoregressive Conditional Heteroskedasticity (ARCH) and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models are more efficient and advanced than former ones since they are time series models and are able to capture variance of the current error term from the previous time periods residuals. This section will present the selection of models in this category.

2.4.1 ARCH Model

Autoregressive Conditional Heteroscedasticity (ARCH) model is a financial time series model and was introduced by Nobel winner Robert Engle in 1982. ARCH is the first model that can distinguish time-varying volatility. More broadly, as the term "heteroscedasticity" stands for changing variance in the ARCH model; conditional variance alters with time, yet the unconditional variance stays constant. Engle (1982) describes the advantage of the model as "*improving the performance of a least squares model and obtaining more realistic forecast variances*" (p. 1004). Thus, ARCH is a very useful method for modelling and forecasting financial market volatility.

To continue the context of ARCH process, time-varying error term, ε_t, is necessary. Let h_t^2 denote the conditional variance of the error term and it is defined as follow:

$$h_t^2 = var\left(\varepsilon_t \mid \varepsilon_{t-1,}\varepsilon_{t-2,}\varepsilon_{t-3,}\ldots\right) = E\left[(\varepsilon_t - E(\varepsilon_t))^2 \middle| \varepsilon_{t-1,}\varepsilon_{t-2,}\varepsilon_{t-3,}\ldots\right] \tag{2.4}$$

Under the assumption of E (ε_t) = 0,

$$h_t^2 = var\left(\varepsilon_t \mid \varepsilon_{t-1,}\varepsilon_{t-2,}\varepsilon_{t-3,}\ldots\right) = E\left[{\varepsilon_t}^2 \middle| \varepsilon_{t-1,}\varepsilon_{t-2,}\varepsilon_{t-3,}\ldots\right] \tag{2.5}$$

As it is shown in the equation above, conditional variance of the error term is equal to the expected value of the squared series $\{{\varepsilon_t}^2\}$, which enables to model autocorrelation in volatility. In other words, the value of the squared error in previous period $(t-1)$ will determine the conditional variance of the error term in current period (t). The following formula shows the ARCH (1,1) process where conditional volatility h_t^2 relies on one lagged squared error.

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 \tag{2.6}$$

Although the above formula reflects the basic form of the model, the full model which is known as ARCH (p) process is as follows:

$$h_t^2 = \alpha_0 + \sum_{k=1}^{p} \alpha_k \varepsilon_{t-k}^2 \tag{2.7}$$

where $\alpha_0 > 0$, $\alpha_k \geq 0$ and $k = 1, \ldots, p$. These two assumptions ($\alpha_0 > 0$, $\alpha_k \geq 0$) confirm that the conditional variance h_t^2 will have a non-negative value.

2.4.2 Symmetric GARCH Models

GARCH Model

Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model was developed by the student of Robert Engle, Tim Bollerslev in 1986. ARCH family models are a milestone in regression analysis in terms of estimating variance by a nonlinear estimation model. ARCH model theorizes the variance of subsequent returns as putting equal weight on average of the previous squared residuals which makes the model weaker since recent observations might be more related and have more effect on following returns. GARCH model is another time series model based on weighted average of past squared residuals with a few improvements. First, GARCH has decaying weights on past squared residuals that stay above from the zero no matter how much it falls. Second, it puts greater weight on more recent events. Third, it is more superior to handle with different sets of data in different frequencies. Therefore, GARCH is an avant-garde model with wide selection of extensions in predicting conditional volatility.

This model can be expressed with a mean specification and a variance specification. The standard form of the model is GARCH (1,1) and it can be represented as:

Mean specification $$r_t = \mu + \varepsilon_t \tag{2.8}$$

Variance specification $$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \, \mathrm{h}_{t-1}^2 \tag{2.9}$$

where $\alpha_0 > 0$, $\alpha_1 \geq 0$ and $\beta \geq 0$, and:

r_t = asset return,

μ = average return,

ε_t = returns of residual.

Returns of residual can also be expressed as:

$$\varepsilon_t = h_t z_t \tag{2.10}$$

where z_t is a random variable with zero mean and 1 variance (*i.i.d.*), and h_t is the time-dependent standard deviation. For GARCH (1,1) model, these two assumptions ($\alpha_1 \geq 0$, $\beta \geq 0$) again is needed to confirm that the conditional variance h_t^2 will have a non-negative value. To make sure that the model is covariance stationarity $\alpha_1 + \beta < 1$ is required.

The mean specification is formed of by the aggregate of average term and error term. This process generates a one-period ahead estimate for the conditional variance h_t^2 which is a function of:

- Hypothetical long-run average variance: α_0 (known as the constant term)
- First independent variable which reflects "news" about previous period volatility: ε_{t-1}^2 (known as ARCH term)
- Second independent variable which reflects forecast variance from previous period: h_{t-1}^2 (known as GARCH term)

The general representation of the GARCH specification is GARCH (p, q) and it can be shown as follows:

$$h_t^2 = \alpha_0 + \sum_{k=1}^{q} \alpha_k \varepsilon_{t-1}^2 + \sum_{l=1}^{p} \beta_l \mathrm{h}_{t-1}^2 \tag{2.11}$$

where q shows the order of ε^2 term (ARCH term) and p shows the order of h^2 term (GARCH term).

GARCH-M Model

Most models used in finance suppose that investors should be rewarded for taking additional risk by obtaining a higher return (Brooks, 2008). Engle et al. (1987) proposed a new model to fit this theory that is called GARCH in Mean (GARCH – M). This model is another variant of GARCH class models with some extensions which considers the conditional mean as a function of the conditional variance. The basic form of GARCH-M (1,1) model can be expressed by the two specifications as:

Mean specification $$r_t = \mu + \gamma h_t^2 + \varepsilon_t \tag{2.11}$$

Variance specification $$h_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{2.12}$$

The γ parameter in the mean specification indicates risk premium coefficient. A positive γ indicates that the conditional variance is positively correlated with the return and vice versa.

Engle, Lilien, and Robins applied the model both with h_t and $\log(h_t)$ and they revealed that the model with the logarithm is superior to predict time-varying risk premium. The logarithmic model of risk premia in the literature can be written as:

$$r_t = a_0 + \gamma ln h_t^2 + \varepsilon_t \qquad (2.13)$$

2.4.3 Asymmetric GARCH Models

Engle and Ng (1993) introduced an interesting feature which they called as "news impact curve" that measures effect of news on current conditional variance. In financial markets, there is usually a negative correlation between the current stock return and the future volatility. The main advantage of asymmetric GARCH models is, asymmetrically responding to increases and decreases in conditional variance and providing information about the behaviour of the returns. In equity returns, these asymmetries are named as "leverage effects" and symmetric GARCH models are unable to take account the leverage effect in the market returns. Therefore, EGARCH, TGARCH, and PGARCH models are introduced to the literature to deal with this issue.

EGARCH Model

The Exponential GARCH model was proposed by Nelson (1991) based on the logarithmic version of conditional volatility. The benefit of the EGARCH model is no restrictions on parameters which allows negative coefficients in the model. Therefore, even negative parameters exist in the equation, the conditional variance will remain positive. The EGARCH (1,1) equation is implied as follows:

$$\ln(h_t^2) = a_0 + \beta_1 \ln(h_{t-1}^2) + a_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} \qquad (2.14)$$

where the parameter γ indicates the leverage effect which captures the impact of asymmetric news. If the leverage parameter γ is positive, it demonstrates that the good news (positive shock) will reduce the future volatility. However, when bad news (negative shock) increases the future volatility the leverage effect γ will be negative and the term a_1 will be capturing volatility clustering effect. Finally, since the above model indicates the EGARCH (1,1) model, the general specification of EGARCH (p,q) can be shown as follows:

$$\ln(h_t^2) = a_0 + \sum_{k=1}^{p} \beta_k \ln(h_{t-k}^2) \sum_{l=1}^{q} a_l \left\{ \left| \frac{\varepsilon_{t-l}}{h_{t-l}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma_j \frac{\varepsilon_{t-j}}{h_{t-j}} \qquad (2.15)$$

TGARCH Model

The Threshold GARCH model (also called as GJR model) is one of the most known and commonly used asymmetric models to measure and handle with possible asymmetries such as leverage effects. This model was developed by Zakoian (1994), but also studied by Glosten, Jagannathan and Runkle (1993) as the Gloster-Jagannathan-Runkle GARCH (GJR-GARCH). In the TGARCH (1,1) model the variance equation is defined as follow:

$$h_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \gamma D_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \qquad (2.16)$$

where D_{t-1} is a dummy variable to capture leverage effect and:

$$D_{t-1} = \begin{cases} 1 & \varepsilon_{t-1} < 0 \quad bad\ news \\ 0 & \varepsilon_{t-1} \geq 0 \quad good\ news \end{cases} \qquad (2.17)$$

the term γ is the leverage effect parameter. If $\gamma = 0$, the specification above turns into the general GARCH (p, q) form. Apart from that, the impact of good news on volatility is a_1, and the impact of bad news on volatility is $a_1 + \gamma$. Thus, with positive and significant leverage parameter (γ), bad news has greater effect than good news on conditional volatility (h_t^2).

The general specification of TGARCH (p, q) model can be shown as follow:

$$h_t^2 = a_0 + \sum_{k=1}^{p} \beta_k h_{t-k}^2 + \sum_{l=1}^{q} (a_l + \gamma_l D_{t-l}) \varepsilon_{t-1}^2 \qquad (2.18)$$

where conditions for parameters are $a_l > 0,\ \gamma_l \geq 0,$ and $\beta_l \geq 0$ as in the GARCH model.

PGARCH Model

The Power GARCH (PGARCH) model was developed by Ding, Granger, and Engle in 1993. The PGARCH model differentiates itself from the other asymmetric models by using conditional standard deviation instead of the conditional variance. Power parameter is defined as θ and h_t^θ is used instead of h_t^2. The model is defined as follow:

$$h_t^{\theta} = a_0 + \sum_{k=1}^{p} \beta_k h_{t-1}^{\theta} + \sum_{l=1}^{q} a_l (|\varepsilon_{t-l}| - \gamma_l \varepsilon_{t-1})^{\theta} \quad (2.9)$$

where

a_l = standard ARCH parameter

β_k = standard GARCH parameter

γ_l = leverage parameter

The leverage parameter γ_l captures asymmetric effects of previous shocks. When the power parameter $\theta = 2$, the equation turns into a classic GARCH model, and for $\theta = 1$, the model estimates conditional standard deviation instead of conditional variance.

QGARCH Model

Quadratic GARCH model (QGARCH) introduced by Engle (1990) and further separately developed by Campbell et al. (1992) and Sentana (1995). By coping with skewed returns and using second-order Taylor expansion, it can capture fat tails and asymmetries in financial data. The simple QGARCH (1,1) is given by:

$$h_t^2 = \omega + \alpha\varepsilon_{t-1}^2 + \beta h_{t-1}^2 + \varphi\varepsilon_{t-1} \quad (2.21)$$

where $\varphi\varepsilon_{t-1}$ is added as an asymmetry parameter which is the main difference with standard variance equation of GARCH (1,1) process as Sentana (1995) stated in his study.

2.4.4 Long Memory Models

The empirical applications of the GARCH family models proved their success in financial markets during the past few decades and it encouraged academics and researchers to develop more advanced GARCH models. Apart from the most common symmetric and asymmetric GARCH models that have been mentioned above, there are four more GARCH family models that are broadly known which is briefly worth to mentioned here: FIGARCH, FIEGARCH, CGARCH, and HYGARCH models.

FIGARCH Model

Fractionally Integrated GARCH or the FIGARCH model was developed by Baillie et al. (1996) to obtain stronger persistence on conditional variance, therefore it has a better ability than GARCH model to forecast long memory characteristic of financial volatility. The FIGARCH model is given as follows:

$$h_t^2 = \omega + [1 - \beta L - (1 - \varphi L)(1 - L)^d]\varepsilon_t^2 + \beta h_{t-1}^2 \qquad (2.22)$$

where d is fractional difference operator and L is the lag operator. If $d = 0$, the FIGARCH model converts to the GARCH model and if $d = 1$ the process becomes Integrated GARCH (IGARCH) process. Baillie et al. (1996) exhibit that for $0 < d < 1$, the FIGARCH model has strong stationarity with long memory process for conditional variance.

FIEGARCH Model

By combining EGARCH and FIGARCH model, Bollerslev and Mikkelsen (1996) developed fractionally integrated exponential GARCH (FIEGARCH) model to overcome of the drawbacks in the FIGARCH model. The drawback is when $0 < d$, the error term becomes no longer second-order stationary and autocorrelation cannot be determined. In FIEGARCH model, Bollerslev and Mikkelsen (1996) fixed this issue and indicate that if $0 < d < 1$ the model becomes stationary which provides more reliable and consisted results (see, e.g., McMillan and Thupayagale, 2010; Goudarzi, 2010; Ogega, 2014; Beyer et al., 2015). The model is defined as follow:

$$\ln(h_t^2) = \omega + \varphi(L)^{-1}(1 - L)^{-d}[1 + \beta(L)]g(z_{t-1}) \qquad (2.23)$$

where $g(z_t) = \gamma_1 z_t + \gamma_1[|z_t| - E|z_t|]$,

the term $\gamma_1 z_t$ indicates the sign effect and $\gamma_1[|z_t| - E|z_t|]$ shows the magnitude effect. As a combination of both, $g(z_t)$ refers the news impact function and satisfies $E_{t-1}[g(z_t)] = 0$. When $d = 0$, the process becomes the EGARCH, and for the case $d = 1$ the model converts to the integrated EGARCH (IEGARCH).

CGARCH Model

Component GARCH model (CGARCH) was proposed by Engle and Lee (1999). By distinguishing short-run and long-run components of conditional variance, it allows to capture long memory dependence of financial time series and reflects volatility dynamics better (see, for example, McMillan and Speight, 2001; Christoffersen et al., 2008; Guo and Neely, 2008).

The simple CGARCH (1,1) model can be empirically described as the following:

$$h_t^2 = q_t + \alpha(\varepsilon_{t-1}^2 - q_{t-1}) + \beta(h_{t-1}^2 - q_{t-1}) \tag{2.24}$$

$$q_t = \omega + \rho q_{t-1} + \varphi(\varepsilon_{t-1}^2 - h_{t-1}^2) \tag{2.25}$$

where q_t refers to the long-run volatility which can also be considered as the expected value of conditional variance.

HYGARCH Model

Hyperbolic GARCH model was developed by Davidson (2004) to cope with the defects of the FIGARCH model. By removing the infinite variance problem in the FIGARCH process, Davidson aimed to fully capture stock markets phenomena, such as volatility clustering and fat tails. Although the HYGARCH model is comparatively newer than other GARCH models, it has been applied various financial data series and the results showed outstanding modelling performance in the long memory feature of the conditional variance (Davidson, 2004; Tang and Shieh, 2006; Li et al., 2015; Nguyen et al., 2019). The general form of the model is given formally by:

$$h_t^2 = \omega + \left\{1 - \left(1 - \beta(L)\right)^{-1} \varphi(L)[1 + \psi((1 - L)^d - 1)]\right\} \varepsilon_t^2 \tag{2.26}$$

where $0 \leq d \leq 1,\ \omega > 0,\ \psi \geq 0, \varphi, \beta < 1$. When $d = 0$ (or $\psi = 0$) the process becomes the GARCH process, and for the case $\psi = 1$ the model converts to the fractionally integrated GARCH (FIGARCH) process. As Davidson (2004) mentioned, testing $d = 1$ helps to differentiate whether the model follows geometric memory or hyperbolic memory process and if $d = 1$, the ψ coefficient serves as an autoregressive root which makes the HYGARCH process GARCH specification for $\psi < 1$, and Integrated GARCH for $\psi = 1$.

2.5 Realized Volatility

Realized volatility is firstly introduced by Merton (1980), but due to the lack of intra-day data, his findings have not considerably noticed in finance literature until the late 1990s. Since the early 2000s, high frequency and intra-day data have become more accessible for academics and financial researchers to conduct broader empirical studies by applying Merton's theory. Andersen and Bollerslev (1998) obtained realized volatility by using the sum of intraday squared returns and they initially applied the high-frequency data to estimate intraday volatility. After Anderson and Bollerslev's (1998) outstanding work, Barndorff-Nielsen and Shephard (2002), Meddahi (2002), and Andersen et al. (2006) extended the literature by estimating properties of realized volatility for different asset classes. Furthermore, Andersen, Bollerslev, Diebold and Labys (2001) investigated realized volatility for different currencies, and Areal and Taylor (2002) extensively examined for the futures market. All the works mentioned above indicate that the ‘true' volatility can be achieved by applying intra-day observations which gives more accurate results for spot volatility than the squared returns.

The realized variance is given by:

$$RV_t = \sum_{j=1}^{N} r_{t,j}^2 \tag{2.27}$$

where $r_{t,j}$ is the *j*th intraday return on day t, and N is the number of returns applied. Since realized variance is total of squared high-frequency intraday returns, realized volatility can be found by taking the squared root of realized variance, which is:

$$RV_t = \sum_{j=1}^{N} r_{t,j}^2 \, , RVol_t = \sqrt{RV_t} \tag{2.28}$$

Since Andersen and Bollerslev (1998) discovered the realized volatility outperforms GARCH model in terms of the gauging true volatility, Andersen, Bollerslev, Diebold and Labys (2001) also proved that the realized volatility is unbiased and observable process, therefore, it is highly successful for estimating return volatility. For further information about the theoretical framework of realized volatility, see Andersen and Bollerslev (1998), and Barndorff-Nielsen et al. (2002).

Although Andersen, Bollerslev, Diebold and Labys (2003) and Pong et al. (2004) found the superiority of realized volatility on GARCH and other stochastic volatility models, one of the biggest limitations was long memory as recently discussed by Hwang and Shin (2018), Shin (2018) and Baillie et al. (2019). In order to deal with long memory and any remaining short-term effects, Autoregressive Fractionally Integrated Moving Average (ARFIMA) model fitted to the realized volatility which its superiority later proved by Hol and Koopman (2002). ARFIMA model is given by using logarithmic realized volatility:

$$\varphi(L)(1-L)^d(\log(RV)-\mu_t = \emptyset(L)\varepsilon_t \tag{2.29}$$

where $\varphi(L) = 1-\varphi_1(L)-\cdots-\varphi_i L^i$ and $\emptyset(L) = 1-\emptyset_1(L)-\cdots-\emptyset_j L^j$ are the autoregressive and moving average lag operators for the short memory, while *d* is the fractional difference operator which is capable of capturing long memory, and ε_t is a white noise process with zero mean and σ_t^2 variance as symbolized $N(0,\sigma_t^2)$. For further studies about the forecasting superiority of the ARFIMA model over other models, see Koopman et al. (2005), Deo et al. (2006), and Martens et al. (2009).

As an alternative model to ARFIMA, another approach has been suggested to model financial data. Corsi (2009) proposed Heterogeneous Autoregressive model (HAR) which is inspired by the HARCH model of Dacorogna et al. (1997). Corsi successfully achieved to model long memory behaviour of volatility in three different time horizons (daily, weekly, and monthly) by applying HAR model while formally not regarded as a long-memory model. Furthermore, Corsi stated that forecasting performance of HAR model outperforms short memory models in all three series which are USD/CHF, S&P500 Futures, and 30-year US Treasury Bond Futures. The HAR model is given by:

$$RV_t = \beta_0 + \beta_1 RV_t^{(D)} + \beta_2 RV_t^{(W)} + \beta_3 RV_t^{(M)} + \varepsilon_t \tag{2.30}$$

where

$$RV_t^{(W)} = \frac{1}{5}(RV_{t-1}^{(D)} + RV_{t-2}^{(D)} + RV_{t-3}^{(D)} + RV_{t-4}^{(D)} + RV_{t-5}^{(D)}) \tag{2.31}$$

$$RV_t^{(M)} = \frac{1}{22}(RV_{t-1}^{(D)} + RV_{t-2}^{(D)} + \cdots + RV_{t-21}^{(D)} + RV_{t-22}^{(D)}) \tag{2.32}$$

and ε_t is the regression error which distributed as $N(0, \sigma_t^2)$. Various extensions of HAR model have been developed after the initial work of Corsi where some of them cover leverage effects, jump components, and negative returns, while others assess the forecasting performance of the HAR process. For further information, see Corsi and Reno (2009), Hwang and Shin (2014), Cho and Shin (2016), Audrino and Kanus (2016), Bollerslev et al. (2016), Song et al. (2018).

2.6 Conclusion

Conditional volatility models and realized volatility have been broadly introduced in this chapter from the very early applications to the most recent ones. Apart from the symmetric and asymmetric models, long memory GARCH family models are also discussed. Conditional volatility is essential for studying and analysing stock market volatility since it has a deep background and significant place in the present financial world. A summary of the GARCH family models is provided and shown in Table 2.1.

Table 2.1: Summary of the GARCH family models

Models	Pros and Cons
ARCH Engle (1982)	Engle's ARCH model is a basic yet powerful model to describe time-varying variances in financial time series data, and able to provide satisfactory estimation on return series, however it requires high order of lags which causes a rise on estimated parameters and induces high correlations among independent variables.
GARCH Bollerslev (1986)	A widely used method in financial econometrics due to its effectiveness on modelling time series data when the data exhibits heteroscedasticity and volatility clustering. GARCH requires less parameters and comparatively performs better than ARCH, but two conditions must be met for its application, and it fails in capturing leverage effects which are observed in financial time series.
GARCH-M Engle, Lilien, and Robins (1987)	Can describe the degree of effects on return by its own variance and use risk premium as a function of conditional standard deviation to determine expected risk.

EGARCH Nelson (1991)	A method based on the logarithmic version of conditional volatility which allows h_t^2 and ε_t more flexibility than GARCH model in terms of residual term distribution. Removing restrictions on parameters enables negative coefficients in the model and impact of asymmetric news can be captured by leverage effect parameter which makes the estimation of series more precise.
PGARCH Ding, Granger, and Engle (1993)	By adding two more coefficients in the classic GARCH equation, not only captures the leverage effect, but also provides an alternative way to estimate the long memory feature in volatility.
TGARCH Zakoian (1994)	By integrating a threshold (dummy) parameter into the GARCH structure, it considers the asymmetric impact of good and bad news on market volatility and makes the estimation of series more accurate.
QGARCH Sentana (1995)	Based on the earlier work of Engle (1990), Sentana developed the model further. By coping with skewed returns and using second-order Taylor expansion, it provides a better approximation in the estimation of volatility.
FIGARCH Baillie, Bollerslev, and Mikkelsen (1996)	By using fractional difference operator $(1 - L)^d$ $(0 < d < 1)$, it obtains stronger persistence on conditional variance and provides a better ability to capture long memory characteristic which may have influence on subsequent returns.
FIEGARCH Bollerslev and Mikkelsen (1996)	As a combination of EGARCH and FIGARCH models, not only good at capturing asymmetric effect, but also able to catch long memory feature. The drawback is when $0 < d$, the error term becomes no longer second-order stationary and autocorrelation cannot be determined.
CGARCH Engle and Lee (1999)	By distinguishing short-run and long-run components of conditional variance, it allows to capture long memory dependence of financial time series and reflects volatility dynamics better.
HYGARCH Davidson (2004)	Removing the infinite variance problem in the FIGARCH process, Davidson aimed to fully capture stock markets phenomena, such as volatility clustering and fat tails.

CHAPTER 3

Modeling Stock Market Volatility Using GARCH Models: Evidence From Asia

3.1 Introduction

Volatility is an important phenomenon for financial markets. With the growing number of market participants and globalization, stock market volatility has been increased, and this has encouraged financial researchers, econometricians, and asset managers to obtain the most accurate estimation of volatility since it is considered an early sign of market disruptions. Volatility is a part of the stock prices, however due to its nature it is not directly observable. Therefore, a number of conditional heteroscedastic models have been proposed to obtain the most accurate estimation of volatility and these models have been applied various countries over the years. For example, French et al. (1987), Chan et al. (1992), and Blair et al. (2001) studied the stock market volatility in the US indices and revealed that unanticipated returns in the stock prices have negative correlation with the unanticipated change in the conditional volatility of the stock prices. Various studies have been undertaken to estimate the stock market volatility in some key markets of Europe, such as Poon and Taylor (1992), Corhay and Rad (1994), McMillan et al. (2000), Bluhm and Yu (2001), Siourounis (2002), Bologna and Cavallo (2002), Eizaguirre et al. (2004).

Although there are a vast number of studies and empirical findings about volatility on the mature financial markets, such as US and Europe, only limited research has been undertaken about modelling stock markets volatility in Asia. Among them, to the best of my knowledge, none of them analyse and discuss the key features about volatility in three different frequencies over the 24 years period in ten different markets. Thus, the present study examines the emerging and developed stock markets in Asia and probably it is one of the most updated works in terms of assessing the characteristics of volatility in Asian financial markets covering the periods of 1997-98 and 2007-08 financial crises.

The main aim of this chapter is to evaluate and discuss the nature of risk in Asian financial markets as well as investigate and compare the predictability power of selected GARCH family models on return series by analysing the conditional variance. The remainder of this chapter is structured as follow. The second section briefly surveys the related works about volatility modelling in related countries. The third and the fourth chapters discuss methodology, data and empirical framework used in this chapter. Empirical results are broadly presented in Section 5. The final section provides the summary of the findings and conclusion.

3.2 Background and Related Work

3.2.1 Introduction

The question of modelling stock market volatility has been a controversial topic over the years in empirical finance. Although, there are a lot of work in the financial literature regarding the concept of volatility, there is no single outperforming model or certain result for the most precise model (e.g., Granger and Poon, 2001). The present literature survey will discuss both theoretical and empirical studies on modelling stock market volatility beginning from the earlier studies to cover the most recent ones especially in selected Asian countries. Although it is not possible to survey every study published on the subject, this chapter aims to provide an overview of the most related works and the main theoretical concepts on modelling stock market volatility.

3.2.2 Literature Review

Stock market is a place where shares of public listed companies are traded. A stock market index is a statistical measurement of the movements in the stock market or industry to help investors and traders determine a market's return on investment. Kleidon (1995) defines and mentions about stock market crashes as "p*recipitous declines in value for securities that represent a large proportion of wealth, are rare, difficult to explain, and potentially catastrophic*"(p 465). Since the stock market incidents in early 1990's triggered by Japanese asset price bubble and Hong Kong's stock market collapse in 1992, a significant amount of study has been undertaken to examine the uncertainty of stock markets in Asia. As Franses and Mcaleer (2002) states, researchers are committed to seek how to model stock market volatility better to forecast stock markets movements more accurate and possibly foresee these shocks. Regarding in the light of prominent studies by Engle (1982), French et al. (1987), and Bollerslev (1987), the accumulated literature of financial econometrics indicates that, as well as the set of economic variables suggested by Chen et al. (1986), stock market volatility has been mainly examined and estimated by time series volatility models.

Mandelbrot (1963b) and Fama (1965) revealed that stock market volatility shows volatility clustering property. This market phenomenon has been modelled by ARCH model of Engle (1982) and its extension GARCH model of Bollerslev (1986). For example, Bera and Higgins (1993) highlighted that the main contribution of ARCH family models would be the finding on unconditional variance changes with time in the volatility of financial time series might be anticipated. On the other hand, Engle and Patton (2001) argued that "*despite the success of GARCH models in capturing the salient features of conditional volatility, they have some undesirable characteristics* "*(*p 244). The drawback of these models triggered the development of alternative specifications. Ones that consider asymmetric effects such as EGARCH (Nelson, 1991), PGARCH (Ding et al., 1993), and TGARCH (Zakoian, 1994) have been introduced by researchers over the years. Furthermore, models that consider the long memory phenomenon have been developed such as FIGARCH (Baillie et al., 1996), FIEGARCH (Bollerslev and Mikkelsen, 1996), CGARCH (Engle and Lee, 1999), and HYGARCH (Davidson, 2004). Although, success of the above models changes depending on the selected markets and frequencies, it can be concluded that GARCH family models are powerful in estimating stock market volatility, confirming the studies of Chiang et al. (2000), Hung (2009), and Ahmed and Suliman (2011).

Pindyck (1984) examined escalating volatility on stock returns are related with decrease in stock prices. Furthermore, positive correlation between lagged volatility and estimated returns have been empirically proved by Whitelaw (1994). Koutmos (1999) demonstrated the conditional variance and conditional mean are the asymmetric function of previous returns in Asian stock markets. More specifically, Thomas (1995) examined Bombay stock exchange from April 1979 to March 1995 by using symmetric GARCH models on daily, weekly, and monthly return series. The findings revealed that strong evidence of regime shift and seasonality exists on the return series accompanied by high degree of persistence on volatility in all frequencies. They concluded that ARCH family models are best fit to address these empirical irregularities. Caiado (2004) investigated the persistence and asymmetries on volatility in Portuguese stock market by applying symmetric and asymmetric GARCH models. Although mixed results are found on different sub-periods for volatility persistence, they conclude that asymmetric GARCH models are better in higher frequencies due to the asymmetry phenomenon. Rafique (2011) also found that presence of ARCH effects is more visible in higher frequency data, confirming the study of Thomas (1995). In another study for major Chinese stock exchanges, Lee et al. (2001) proved time-varying volatility is persistent and predictable with evidence of fat-tailed conditional distribution of returns. Balaban et al. (2003) extended stock market volatility for fourteen stock markets by applying both symmetric and asymmetric regression models and found positive volatility effect on weekly and monthly stock returns of the Philippines SE Composite Price Index and Thailand SET Price Index.

Shamiri and Isa (2009) studied the comparison of symmetric (GARCH) and asymmetric (EGARCH and NAGARCH) models on Kuala Lumpur Composite Index from Malaysia using daily data between 1 January 1998 and 31 December 2008. Their results indicated that KLCI index exhibits leverage effect with a negative sign, and since EGARCH model is successful to capture this phenomenon, EGARCH model outperforms GARCH model on KLCI index. On the other hand, Lim and Sek (2013) studied stock market volatility in Malaysia comparing the performance of GARCH, TGARCH and EGARCH models for the periods of January 1990 to December 2010. They divided the data into three sub-periods to examine the impact of Asian financial crisis. The findings of the study revealed that GARCH model performs well during the crisis period, while TGARCH model outperforms pre-crisis and post-crisis periods.

Guidi and Gupta (2012) studied stock markets of five ASEAN countries by using asymmetric PARCH model. The results showed that existence of asymmetric effect in all selected markets, while Indonesian stock market has the largest leverage effect and Philippines has the lowest. They concluded with asymmetric PARCH model performs well to estimate characteristics of stock market volatility among ASEAN countries. Meanwhile, Islam and Mahkota (2013) studied financial asset returns of three ASEAN countries, namely Malaysia, Indonesia, and Singapore, over the period of 02/01/2007 to 31/12/2012 using daily return series. They applied two symmetric GARCH models to estimate the characteristic of volatility and the presence of risk-return trade-off. The study found that both models are capable of capturing volatility clustering and leptokurtosis phenomena. Positive risk-return trade-off have been found on selected indices, while Indonesia's JSE index indicated highest volatility compared to Malaysia and Singapore and offered higher potential returns.

Islam (2013) investigated the performance of symmetric and asymmetric GARCH models in four Asian stock markets over the period from January 2007 to December 2012. Singapore, Japan, and Hong Kong are chosen as a developed markets and, Malaysia is chosen as an emerging market. The results of the research demonstrated that all selected GARCH models are capable of capturing characteristics of volatility. Positive risk premium effect found in all return series, but due to the insignificant parameter, market participants are not rewarded with higher return for taking additional risk. Highest leverage effect found in Nikkei of Japan, while lowest in KLCI of Malaysia. They concluded with Malaysia has a lower volatility as an emerging market compared to three developed markets of Asia. Lee et al. (2017) selected stock markets of Japan, Hong Kong, Malaysia, and Indonesia over the period of 1998 to 2015. The output of the study showed that Hong Kong has higher volatility than Malaysia indicating that emerging markets can have smaller volatility than developed markets which is contradicting with the study of Islam (2013).

Lee et al. (2001) studied four of China's stock markets and favoured GARCH and EGARCH models while, Fabozzi et al. (2004) examined the dynamics of volatility in the Shanghai and Shenzhen stock exchanges by using GARCH framework. The findings of the study revealed that the daily volatility on the Shenzhen stock exchange is well estimated by GARCH model while, the Shanghai stock exchange is well defined by TAGARCH model. More recently, Su (2010) investigated Hong Kong, Shanghai and Shenzhen stock exchanges covering the period from 1999 to 2010 by using GARCH and EGARCH models. The empirical results of the study showed that the EGARCH model is superior than GARCH model in terms of describing characteristics of volatility for the selected indices. Kang et al. (2009) argued the long memory property in the volatility on Chinese markets by using GARCH family models. They concluded that indices of Shanghai and Shenzhen stock exchanges exhibit long memory features and FIGARCH model provides better description and more parsimonious prediction than GARCH and IGARCH models. On the other hand, Lin and Fei (2013) suggest that APGARCH model is better than GARCH, EGARCH and TGARCH models for predicting volatility in Chinese stock markets. For further discussion see; Cajueiro and Tabak (2004), Lu and Wang (2008), Joshi (2010), and Cheteni (2016).

3.2.3 Conclusion

This section of the chapter argued a review of the theoretical literature in terms of modelling and predicting volatility, with the emphasis on Asian stock markets. Since the influential studies of Engle (1982) and Bollerslev (1986), it is common to model the conditional variance of financial time series by following a GARCH process. Although the reviewed literature has considerably enhanced our understanding of the modelling performance of a variety of models and volatility behaviors in emerging and developed markets, the findings from the previous studies are quite unclear, given that they were highly dependent on the selection of countries and the range of data period. Throughout the literature reviewed, some found that symmetric GARCH models outperforms, while others found asymmetric GARCH models are more accurate. Moreover, the true nature of financial market volatility in countries such as, the Philippines, Thailand, and Taiwan tend to be ignored. In this regard, Chapter 3 devoted to extending the literature of volatility modelling by selecting ten Asian markets with up-to-date data and covering periods of both financial crisis and recent developments as well as investigating whether linear or non-linear GARCH models are better suited to modelling the Asian stock market data used.

3.3 Methodology

The mean equation has been determined by trying various models, such as AR (1), MA (1), ARMA (1, 1) and more combinations with parameter p and q which are the orders of AR and MA parts respectively. Appropriate values of p and q can be decided by autocorrelation and partial autocorrelation for each market and model. For instance, the conditional mean equation for the standard ARMA (1,1) process can be specified as follows:

$$r_t = \phi r_{t-1} + \varepsilon_t + \psi \varepsilon_{t-1} \quad (3.1)$$

where $\phi \neq 0, \psi \neq 0$ and r_t is the return series. ε_t is a weak white noise process with expectation zero and variance $\sigma_\varepsilon^2 \left(\varepsilon_t \sim WN(0, \sigma_\varepsilon^2)\right)$. Once the residuals are obtained, the following equation can be applied to regress the squared residuals:

$$e_t^2 = a_0 + a_1 e_{t-1}^2 + a_2 e_{t-2}^2 + \cdots + a_q e_{t-q}^2 + v_t \quad (3.2)$$

Where q is the number of lags, e_t^2 is the squared residuals and a_0 is the constant. The null hypothesis that there is no autoregressive conditional heteroscedasticity (ARCH) up to order q can be formulated as:

$$H_0 = a_1 = a_2 = \cdots = a_q = 0 \quad (3.3)$$

against the alternative:

$$H_1: a_i > 0, \qquad for\ at\ least\ one\ \ i = 1, 2, \ldots, q \qquad (3.4)$$

It is important to note that ARMA (p,q) model can only be used with a data that follow stationary process, yet in practice time series data follows a non-stationary process. Therefore, after plotting the colerogram of the series, no ACF and PACF value have been found out of the band and all variables are regressed based on the constant term. Before proceeding to GARCH family models, ARCH-LM test was applied and as the results in Table 3.5 show, all return series have remaining ARCH effects in the residuals. In the existence of heteroscedasticity, Ordinary Least Squares (OLS) method cannot be used to estimate the parameters of the model. The estimation will no longer be efficient since the best linear unbiased estimator (BLUE) condition is violated. To overcome the problem of heteroscedasticity, the GARCH family models have been used in the Maximum Likelihood framework to estimate time series data. Each of the selected models has their own features to deal with prominent characteristics of volatility like the leverage effect, volatility clustering, fat tails and mean reversion. The selected models for this study as follow:

i. GARCH (1,1)
ii. GARCH in Mean or GARCH-M
iii. Exponential GARCH or E-GARCH
iv. Threshold GARCH or T-GARCH
v. Power GARCH or P-GARCH

In this study, all the mentioned models above were determined depending on the correct lag length by the VaR estimation. The symmetric GARCH models (GARCH and GARCH-M) estimated using the proper lag length for each return series, and the conditional variance equation for these models can be written as follow:

$$h_t^2 = \alpha_0 + \alpha_1 \varepsilon_t^2 + \beta h_t^2 \qquad (3.5)$$

where α_0, α_1 and β are the parameters to be estimated. α_0, α_1 and β denote the constant term, ARCH term, and GARCH term respectively. GARCH-M model also takes advantage of the power parameter which indicates the risk premium coefficient. A positive risk premium shows that the conditional variance is positively correlated with the return and vice versa.

The conditional variance of asymmetric GARCH models (EGARCH, TGARCH, and PGARCH) are estimated respectively as follow:

$$\ln(h_t^2) = a_0 + \beta_1 \ln(h_{t-1}^2) + a_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} \tag{3.6}$$

$$h_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \gamma D_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{3.7}$$

$$h_t^\theta = a_0 + a_1 (|\varepsilon_{t-1}| - \gamma \varepsilon_{t-1})^\theta + \beta_1 h_{t-1}^\theta \tag{3.8}$$

where γ is the leverage parameter, θ is the power parameter and D_{t-1} is the dummy variable. The parameter γ indicates the leverage effect which captures the impact of asymmetric news. The positive leverage parameter γ demonstrates that positive shocks will reduce the future volatility. However, when negative shocks increase future volatility, the leverage effect γ will be negative and the term a_1 will capture the volatility clustering effect.

It is broadly acknowledged by the financial literature that an increase in data frequency is accompanied by excess kurtosis, which challenges the capabilities of forecasting models due to the fat-tailed distribution on return series (Mandelbrot, 1963). Under assumption of normality for errors, the results of the models would be biased. Therefore, student-t distribution has been applied since normal distribution cannot capture fat tails in the error term. Although, there are different alternative distributions to deal with this issue such as Gaussian, student-t, and Generalized error distributions, student-t is usually preferred in GARCH family models as revealed by Hamilton and Susmel (1994) and Wilhelmsson (2006). The density function of student-t distribution is given by:

$$Z_t = \frac{\Gamma\left(\frac{v+1}{2}\right)}{\Gamma\left(\frac{v}{2}\right)\sqrt{(v-2)\pi}}\left(1+\frac{Z_t^2}{v-2}\right)^{-\frac{1}{2}(v+1)} \quad (3.9)$$

where $Z_t = {}^{\varepsilon_t}/_{h_t}$, Γ is gamma function, and v is the degree of freedom, $2 < v < \infty$. With the lower v the tails tend to be fatter.

All selected GARCH models are estimated by the given observations applying an iterative computer algorithm (Marquardt algorithm) which is the built-in algorithm from the Eviews package. The paper aims to enrich the depth of the study by using two different symmetric and three different asymmetric models with providing different values for the conditional variance of the estimated stock market series.

3.4 Data and Empirical Framework

3.4.1 Introduction

Before proceeding to the empirical results, it is important to understand the collection of time series data and the preliminary analysis which will be introduced in this section. This section focuses on data collection and explains the difficulties of the data filtering process. The overall sample period is divided into two sub-sample in order to observe the effects of two major crisis where Asian stock markets severely got affected; the first sub-period covers the first twelve years from 1993 to 2005 including the 1997-98 Asian financial crisis, while the second sub-period analyses the second twelve years from 2005 to 2018 by covering the 2007-08 global financial crisis.

Descriptive statistics for return series for the full sample and the sub-sample periods are presented in this section to discuss the values of skewness, kurtosis, normality, and the analysis of heteroscedasticity. Furthermore, this section provides stationarity analysis on series based on Augmented Dickey-Fuller (ADF) unit root test.

3.4.2 Data

Asia is divided into two regions which are developed and emerging economies. The highly developed countries include Japan and the four Asian Tigers – Hong Kong, South Korea, Taiwan, and Singapore. China and Malaysia are other major economic forces which are considered an important powerhouse in the region; however, academics often classify these countries as “developing”, see Johansson and Ljungwall (2009), Luo et al. (2010), Jayasuriya (2011), Zhang et al. (2013), and Li and Giles (2015). Besides, the Shanghai Stock Exchange is founded in 1990 which is 99 years later compared to the Hong Kong Stock Exchange as it formerly founded in 1891. Even today, most of mainland Chinese companies are listed in Hong Kong. Therefore, the Chinese stock market will be evaluated in emerging markets category.

In this study, ten Asian countries have been selected for investigation and their widely accepted indices have been chosen. The five developed market indices that have been added are as follows: Nikkei 225 Index (NIKKEI) from Japan, Hang Seng Index (HSI) from Hong Kong, Korea Composite Stock Market Index (KOSPI) from South Korea, Taiwan Capitalization Weighted Stock Index (TAIEX) from Taiwan, and the Straits Times Index (STI) from Singapore. The remaining five Asian countries are chosen as emerging markets and their broadly accepted stock market indices are considered as follow: SSE Composite Index (SSE) from China, PSE Composite Index (PSE) from the Philippines, The Stock Exchange of Thailand Index (SET) from Thailand, Kuala Lumpur Composite Index (KLCI) from Malaysia, and Jakarta Stock Exchange Composite Index (JCI) from Indonesia.

Daily, weekly, and monthly time series data is obtained from Bloomberg database. The overall sample period covers 25 years in total, starting from November 1993 to May 2018. However, one problem was the limitation of accessing older data in higher frequencies of data, thus daily and weekly data start from 1994 instead of 1993. Another challenge was non-synchronous holidays in different markets which may cause computation difficulties and negatively effect the output of the models. Therefore, the data range has been chosen separately for each market to not get exposed to data loss.

The main advantage of daily data is providing more information in terms of estimating volatility for applied econometric models since they are more data-intensive than simple regression models. Weekly and monthly frequencies are also estimated since they provide broader framework regarding volatility, and it is crucial to understand comparison between different frequencies. In order to satisfy stationarity, closing price series are transformed to return series in all daily, weekly and monthly time periods for each index. The Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) has been applied to investigate stationarity on series. The test result clearly showed that the stock returns are stationary.

Return series have been obtained as shown in the following formula:

$$R_t = \log{(P_t/P_{t-1})} * 100 \tag{3.10}$$

where R_t denotes the logarithmic return at time t. P_t and $P_{t-1}$are the closing price of the index at time t and $t - 1$ respectively.

The descriptive statistics of the index returns are presented in Table 3.1, 3.2 and 3.3 for daily, weekly, and monthly return series respectively. The mean fluctuates between 0.004651 and 0.044841 for daily returns. Indonesia outperforms other markets, while Thailand stock market performs worst. Furthermore, Indonesia also outperforms other markets in weekly and monthly mean return series, while Japanese stock market produces the smallest mean returns. Mean returns increase from higher to lower frequency in all markets, as expected, with the only exception of Japanese NIKKEI from daily to weekly frequency which declines.

Based on the result of Jarque-Bera test statistic, the normality assumption of null hypotheses is rejected in all selected markets for each frequency, confirming the non-normal distribution in all series. Thus, return distribution is not symmetrical and the series have either positive or negative skewness. Positive skewness appears when the median has smaller value than the mean, while negative skewness occurs when the median has greater value than the mean. Eastman and Lucey (2008) suggest that in the event of negative skewness, most returns will be higher than average return, therefore market participants would prefer to invest in negatively skewed equities. According to the tables from 3.1 to 3.3, majority of the markets present negative skewness, with the only exception of Malaysia and China which indicate positive skewness in all frequencies. Although Hong Kong, Thailand, and the Philippines stock markets positively skewed in daily frequency, they all negatively skewed in weekly and monthly return series. In a similar way to the concept of skewness, kurtosis indicates sharp events and can be interpreted as a gauge of greatest point in both ways. The kurtosis in a normal distribution is three. A positive kurtosis with the value of greater than three refers to leptokurtosis. Emenike and Aleke (2012) suggest that high kurtosis values indicate big shocks in the time series with either type of sign. As is clear from the tables, the values of kurtosis are positive and greater than three in all selected return series which demonstrate leptokurtosis.

China has the highest maximum values in all frequencies, while Singapore and Taiwan have the lowest maximum values in daily return series and Japan has the smallest maximum values for weekly and monthly series. The greatest single-day hike has been viewed in China's SSE with 26.99277% and the biggest drop has been occurred in Malaysia's KLCI with -24.15339%. Singapore has the smallest single-day gain with 7.531083%, while Japan has the lowest weekly and monthly gain with 11.44965% and 14.96626% respectively. China's SSE Index has the greatest gap between maximum and minimum values with 85.52026%, and -34.03195% respectively. This result is also justified by the standard deviation, which measures the average volatility. The value of standard deviation is 9.909528% in China's SSE Index for monthly returns which is the highest all among others. Singapore's STI and Taiwan's TAIEX Indices have the smallest gap between minimum and maximum values in daily frequency with -8.695982% & 7.531083% and, -6.975741% & 6.52462% respectively. This is also supported by the standard deviation which is 1.141326% for STI and 1.36745% for TAIEX. This result indicates lowest volatility compared to others. To sum up, Asian stock markets are likely to show high volatility in the return series, especially countries like China and Thailand.

The line graphs in appendix from Figure A.1 to Figure A.6 indicate the closing prices and returns in all frequencies for each selected market. As reported by the closing prices graphs, there are slumps in all markets during the crisis times of 1997-98 and 2007-08. Although the stock market downturn of 2002 (also called as dot-com crash) hit some markets, there is no sharp declines in the mentioned crisis above. However, it is clear that a financial crisis in the US directly or indirectly influences the Asian stock markets, and the contagion differs for each market depending on integration with the US market. The return series also reflects high volatility during the crisis, especially in the period of 2007-08. Although the fluctuations are around zero, the sign of volatility clustering is clear in all return series.

Table 3.1: Summary of descriptive statistics for daily return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	0.0294	0.0105	0.024194	0.012354	0.044841	0.004651	0.028739	0.015257	0.015445	0.015835
Median	0.030928	0.02846	0.0511	0.025455	0.090305	0.015914	0.065357	0.043451	0.050211	0.021669
Maximum	13.23458	7.531083	17.2471	20.81737	13.12768	11.34953	26.99277	6.52462	11.28435	16.1776
Minimum	-12.11103	-8.695982	-14.73468	-24.15339	-12.73214	-16.06325	-17.90509	-6.975741	-12.8047	-13.08869
Std. Dev.	1.504108	1.141326	1.60473	1.267938	1.52564	1.526721	1.761533	1.36745	1.66492	1.393054
Skewness	-0.300663	-0.266133	0.064089	0.502157	-0.19832	0.049086	0.195354	-0.182956	-0.291322	0.162169
Kurtosis	8.540723	8.37642	13.32528	65.37193	11.58383	10.95738	18.86232	5.815682	8.152126	14.21301
Jarque-Bera	7439.159	5702.84	25546.27	930661.1	17499.95	15048.69	59332.79	1979.211	6656	30033.07
Probability	0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	5748	4689	5750	5740	5688	5703	5656	5892	5942	5728
Sample	12/09/1994 5/03/2018	8/31/1999 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/11/1995 5/03/2018	1/11/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018

Table 3.2: Summary of descriptive statistics for weekly return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	0.01014	0.051732	0.095882	0.041387	0.199801	0.013218	0.125445	0.036399	0.066467	0.075039
Median	0.190374	0.165185	0.273139	0.135188	0.324307	0.289045	0.21362	0.26156	0.274783	0.178181
Maximum	11.44965	15.32099	13.9169	24.57857	18.80297	21.83839	38.07101	18.31817	17.03191	16.18463
Minimum	-27.8844	-16.46836	-19.92123	-19.02678	-23.2971	-26.66136	-22.6293	-16.40812	-22.92881	-21.98549
Std. Dev.	3.011319	2.565851	3.300553	2.713824	3.587437	3.4868	3.777609	3.12067	3.731726	3.196981
Skewness	-0.855294	-0.379963	-0.430761	0.125259	-0.427649	-0.292138	0.566883	-0.318568	-0.41684	-0.525817

Kurtosis	9.680724	8.8305	6.440567	15.12496	8.7454	8.73938	13.83485	6.091364	6.902207	8.792161
Jarque-Bera	2441.32	1403.056	643.6624	7519.331	1710.958	1702.922	5874.626	503.5199	814.0247	1773.184
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	1232	974	1228	1227	1217	1228	1188	1213	1227	1228
Sample	9/23/1994 5/04/2018	9/03/1999 5/04/2018	10/21/1994 5/11/2018	10/21/1994 4/27/2018	10/21/1994 2/16/2018	10/21/1994 5/04/2018	10/21/1994 5/11/2018	10/22/1994 5/05/2018	10/23/1994 5/06/2018	10/21/1994 5/11/2018

Table 3.3: Summary of descriptive statistics for monthly return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	0.044588	0.218815	0.399475	0.218498	0.85803	0.116933	0.452484	0.328061	0.397198	0.385517
Median	0.418832	0.901965	0.954036	0.617426	1.42568	0.839904	0.445941	0.716868	0.522226	0.872722
Maximum	14.96626	19.30023	26.45214	29.44212	25.01933	28.42753	85.52026	33.23789	41.0616	33.16657
Minimum	-27.21623	-27.36404	-34.82366	-28.4632	-37.8555	-35.91878	-34.03195	-21.50303	-31.81042	-29.89063
Std. Dev.	5.7749	5.406544	7.172065	6.544275	7.723204	8.223748	9.909528	6.98501	7.71871	7.107765
Skewness	-0.615536	-0.955586	-0.324166	0.031696	-1.100217	-0.309982	1.881884	0.170202	0.230609	-0.137723
Kurtosis	4.223177	7.07059	5.840673	7.686821	8.079187	5.721916	21.15162	5.187998	6.941817	7.101083
Jarque-Bera	37.01882	189.5839	104.3532	270.0518	376.6173	95.79117	4223.999	60.26863	193.6016	207.6647
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	295	225	295	295	295	295	295	295	295	295
Sample	10/1993 5/2018	8/1998 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018	10/1993 5/2018

Notes: Jarque-Bera is a test statistic for normality.

3.4.3 Testing for Stationarity

In order to test stationarity of the return series, the Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) has been conducted. The following equation shows the testing procedure for the ADF test regression:

$$\Delta Y_t = a_0 + \beta Y_{t-1} + a_1 \Delta Y_{t-1} + a_2 \Delta Y_{t-2} + \cdots + a_p \Delta Y_{t-p} + \varepsilon_t \qquad (3.11)$$

where Y is the dependent variable, a_0 is the constant and p is the lag order of the autoregressive process. Lag length is determined based on the Schwarz information criterion (SIC). The null hypothesis refers Y_t series have unit root, which signifies the data is nonstationary if it is accepted. Table 3.4 reports the results of index returns for daily, weekly, and monthly frequencies. According to the results on the table, the test statistic is smaller than critical values which allows rejecting null hypothesis of unit root (nonstationary) at all levels of significance for each series in all frequencies.

Table 3.4: ADF Unit Root test results for the return series

	Daily				Weekly				Monthly			
	ADF statistic	**Critical Values**			**ADF statistic**	**Critical Values**			**ADF statistic**	**Critical Values**		
		1%	5%	10%		1%	5%	10%		1%	5%	10%
NIKKEI	-78.95141(0)*	-3.43131	-2.86185	-2.56698	-36.37048(0)*	-3.43545	-2.86368	-2.56796	-15.72592(0)*	-3.45244	-2.87116	-2.57197
STRAITS TIMES INDEX	-66.62699(0)*	-3.43156	-2.86196	-2.56704	-30.03412(0)*	-3.43685	-2.8643	-2.56829	-13.32026(0)*	-3.45949	-2.87426	-2.57363
HANG SENG INDEX	-75.51626(0)*	-3.43131	-2.86185	-2.56698	-34.36991(0)*	-3.43547	-2.86369	-2.56796	-16.34133(0)*	-3.45244	-2.87116	-2.57197
KUALA LUMPUR COMPOSITE INDEX	-33.57448(4)*	-3.43131	-2.86185	-2.56698	-17.78102(2)*	-3.43548	-2.86369	-2.56797	-15.35530(0)*	-3.45244	-2.87116	-2.57197
JAKARTA COMPOSITE INDEX	-65.00642(0)*	-3.43132	-2.86185	-2.56698	-12.28821(4)*	-3.43553	-2.86372	-2.56798	-14.49578(0)*	-3.45244	-2.87116	-2.57197
SET INDEX	-48.82781(1)*	-3.43132	-2.86185	-2.56698	-21.07273(1)*	-3.43547	-2.86369	-2.56796	-16.38432(0)*	-3.45244	-2.87116	-2.57197
SSE INDEX	-72.96887(0)*	-3.431326	-2.861856	-2.566981	-33.41706(0)*	-3.435645	-2.863766	-2.568005	-17.7813(0)*	-3.452442	-2.871161	-2.571968
TAIEX	-72.66075(0)*	-3.43129	-2.86184	-2.566972	-35.87423(0)*	-3.435532	-2.863716	-2.567979	-11.23337(0)*	-3.452519	-2.871195	-2.571986
KOSPI	-71.69293(0)*	-3.431271	-2.861832	-2.566968	-37.51071(0)*	-3.435471	-2.863689	-2.567964	-14.84137(0)*	-3.452442	-2.871161	-2.571968
PSE INDEX	-65.17989(0)*	-3.431314	-2.861851	-2.566978	-21.85793(0)*	-3.435471	-2.863689	-2.567964	-15.85243(0)*	-3.452442	-2.871161	-2.571968

Notes: 1- Figures in parentheses show the optimal lag lengths, which were automatically determined based on Schwarz Information Criterion (SIC).

2-Test critical values are based on MacKinnon (1996).

3- * implies statistical significance at 1% level.

4- ADF test has an intercept term in it but no trend in line with the test equation.

3.4.4 Testing for Heteroscedasticity

Financial time series data tend to exhibit non-constant variance which means heteroscedasticity. If the residuals of the series indicate heteroscedasticity, ARCH, and GARCH models can be examined since they are developed to account non-constant variance. Thus, the Lagrange Multiplier (LM) test proposed by Engle (1982) conducted to detect the presence of ARCH effects in the residuals of the return series. The residuals of the series ε_t is captured from the OLS regression of the conditional mean to conduct test procedure. The conditional mean equation process is as follows:

$$Y_t = \mu + \varepsilon_t \quad (3.12)$$

the acquired residuals of the series from the equation above have been carried to the following equation as a dependent variable:

$$\varepsilon_t^2 = a_0 + a_1\varepsilon_{t-1}^2 + a_2\varepsilon_{t-2}^2 + \cdots + a_q\varepsilon_{t-q}^2 + v_t \quad (3.13)$$

where a_0 is the constant term and q is the lag length. The null hypothesis of coefficient values is not different from zero up to q lags which means there is no ARCH effects can be shown as follow:

$$H_0: a_1 = a_2 = \cdots = a_q = 0 \quad (3.14)$$

where the alternative hypothesis is:

$$H_1: a_i > 0 \; for \; at \; least \; one \;\; i = 1, 2, \ldots, q \quad (3.15)$$

The procedure above has been applied in this study and the results of the ARCH-LM tests are presented in the Table 3.5 for all return series. The ARCH-LM test results report that residual series contain existence of ARCH effects, thus the null hypothesis in all indices can be rejected. Although daily and weekly frequencies show strong ARCH effects at the 1% level, monthly series are rejected in 5% level except for Malaysia which is rejected in 1% level. The p-values either zero or very close to zero which refer departure from the $i.i.d.$ condition, meaning the variance of the return series is not constant over time. The ARCH-LM test was operated up to 5 lags in the residual series.

Table 3.5: ARCH-LM test for residual of the return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
					Daily					
F-statistic	261.8293(0.000)	106.2249(0.000)	464.4779(0.0000)	412.3136(0.000)	96.8613(0.000)	342.7864(0.000)	174.5167(0.0000)	146.7598(0.0000)	239.6838(0.0000)	72.89534(0.0000)
LM	1067.027(0.000)	936.8661(0.000)	1122.138(0.0000)	1517.616(0.000)	527.8304(0.000)	612.2669(0.000)	169.3503(0.0000)	143.2099(0.0000)	230.4636(0.0000)	72.00215(0.0000)
					Weekly					
F-statistic	18.19877(0.0000)	73.11952(0.0000)	16.06701(0.0000)	18.38844(0.0000)	51.44115(0.0000)	27.53412(0.0000)	35.12662(0.0000)	12.73312(0.0000)	86.03043(0.0000)	12.37259(0.0000)
LM	35.43538(0.0000)	127.4227(0.0000)	31.38814(0.0000)	35.79004(0.0000)	95.06706(0.0000)	52.82478(0.0000)	34.17293(0.0000)	25.00241(0.0000)	151.1947(0.0000)	24.31393(0.0000)
					Monthly					
F-statistic	4.694110(0.0311)	3.595044(0.0291)	3.377458(0.0188)	21.79194(0.0000)	5.372956(0.0211)	5.466529(0.0201)	5.456579(0.0202)	6.299024(0.0004)	21.35984(0.0000)	6.75895(0.0002)
LM	4.651486(0.0310)	7.057480(0.0293)	9.923958(0.0192)	20.41745(0.0000)	5.312013(0.0212)	5.402825(0.0201)	5.393171(0.0202)	17.97979(0.0004)	53.14486(0.0000)	19.20624(0.0002)

Note: Null hypothesis indicates there are no ARCH effects in the residual of the series.

3.5 Empirical Results

3.5.1 Estimation Results and Their Economic Meaning for Daily Return Series

The detail estimation output of GARCH, EGARCH, TGARCH, GARCH-M, and PGARCH models are reported in Appendix A for daily return series from Table A.1 to Table A.10. p-values are presented in the parentheses while Student-t statistics in square brackets. Log-likelihood numbers represent the maximized log likelihood value. Residual diagnostics test results are also attached in the tables to look whether there are any remaining ARCH effects in the estimated GARCH models. Durbin-Watson test statistic is added to see autocorrelation.

The first three coefficient constant (ω), ARCH term (α) and GARCH term (β) have high statistical significance at 1% level for all estimated models which indicate that lagged conditional variance (GARCH term) and ARCH term has an influence on current volatility, in other words, the news from previous periods have an impact on current volatility. The degree of persistence is measured by the sum of ARCH term (α) and GARCH term (β) for GARCH, GARCH-M, and PGARCH models. β (GARCH term) is considered as a degree of persistence for the EGARCH model while $\alpha + \beta + \frac{1}{2}\gamma$ for TGARCH model.

One of the well-known models of volatility introduced in this work is the GARCH (1,1) model. The sum of ARCH and GARCH coefficients close to unity in this model for all estimated index returns which indicate that there is a high degree of persistence in the shocks to the conditional variance. The variance intercept term (ω) has minimum and maximum values in Korea's KOSPI index with 0.007022 and the Philippines's PSE index with 0.086337 which are relatively very small compared to GARCH terms as expected. For Hang Seng index, a unit shock to the model will initially increase the conditional variance around 0.057690 of the shock. The initial shock will die away day by day with 1/ (1-0.938032) = 16.13 days. The conditional variance will subsequently approach on its unconditional value of 0.11582/ (1-0.057690-0.938032) = 27.0733 (s.d. = 1.67% a day). In PSE index, a smaller stock market compared to Hong Kong, the initial shock dies away with 1/ (1-0.796884) = 4.92 days. The variance converges of its unconditional variance with the value of 0.086337/ (1-0.160264-0.796884) = 23.3361 (s.d = 4.74% a day). This small comparison between an emerging and a developed stock market indicates that shocks have different magnitude on different markets. The ARCH-

LM heteroscedasticity test indicates that there are no remaining ARCH effects in the residuals of the model. Thus, variance equations are well specified in all selected indices.

In finance, the return of a security may depend on its risk. To model this phenomenon, the GARCH-M model has been applied. It allows estimating mean equation by using risk premium feature as an exogenous variable which is denoted by λ on the function of the conditional variance. If the risk premium has a positive value and statistical significance, it indicates that the return series is positively correlated with its volatility. This tells people who are involving in financial markets that they have greater returns for the higher risk taken.

The estimation of risk premium parameter (λ) is positive and insignificant for all estimated indices. The economic interpretation of this result is; the conditional variance which has been used as a proxy for risk of return is not related to the level of return. Although the results confirm the well-known risk-return spectrum of higher risk is associated with greater probability of higher return and lower risk with a greater probability of smaller return, the insignificant risk premium indicates that investors are not compensated for bearing higher risk for the selected indices. The ARCH (α) and GARCH (β) coefficients are statistically significant and the sum of the two coefficients are close to unity which is similar to GARCH estimation. The null hypothesis of ARCH LM test that says series has ARCH effect is rejected.

To investigate the presence of leverage effects three asymmetrical models EGARCH (1,1), TGARCH (1,1) and PGARCH (1,1) have been applied on selected return series. The first estimated model EGARCH (1,1) shows statistically significant parameters at 1% confidence level including the asymmetry parameter (γ). A negative and significant leverage parameter, as estimated in all series, implies that negative news has a greater effect on conditional variance than the positive news with the same magnitude. The value of the asymmetry parameter is measured maximum with -0.023318 for China’s SSE index and minimum with -0.098558 for Japan’s NIKKEI index. The null hypothesis of no heteroscedasticity is accepted in all selected return series, but not for Malaysia’s KLCI index.

The other asymmetric model to test leverage effect is the TGARCH (1,1) model. The results indicate that ARCH term, GARCH term, and the asymmetry term are positive and statistically significant at 1% confidence level for all selected markets. A significant and positive asymmetry parameter shows that the positive shocks (good news) have smaller impact than negative shocks (bad news) on the following period volatility (conditional variance). The ARCH-LM test statistics do not show any remaining ARCH effects which refer the model successfully estimated volatility in the return series, except for Korea's KOSPI index.

The PGARCH (1,1) model is different than its counterparts by estimating standard deviation with a power parameter instead of estimating conditional variance. The results in tables for PGARCH (1,1) model indicate that asymmetry parameter (γ) has positive value in all indices and it is statistically significant at 1% confidence level. Thus, there is a presence of leverage effect and positive shocks induce higher volatility than negative shocks. The power term (δ) is significant at 1% level in all return series, and it has the lowest value with 1.012809 in SSE index and the highest value with 1.641220 in PSE index. These results confirm the constraints of the model (δ >0). Moreover, the estimated power parameter has values other than unity or two in all series which is supporting the use of the model. The ARCH-LM test statistics didn't indicate any remaining ARCH effects which imply the model was able to remove all heteroscedasticity in the residuals except Malaysia's KLCI index.

Table 3.6: Model comparison for the estimated models under t-student distribution

NIKKEI INDEX	GARCH (1,1)	EGARCH (1,1)	TGARCH (1,1)	GARCH-M (1,1)	PGARCH (1,1)
AIC	3.401824	3.380279	3.386826	3.402044	3.379535
SIC	3.418046	3.397660	3.404208	3.419426	3.398075
HQIC	3.407470	3.386328	3.392876	3.408094	3.385988
HANG SENG INDEX					
AIC	3.339570	3.326013	3.328567	3.339910	3.325210
SIC	3.346516	3.334117	3.336671	3.348014	3.334471
HQIC	3.341987	3.328833	3.331387	3.342730	3.328433
STRAITS TIMES INDEX					
AIC	2.702712	2.693898	2.693663	2.703112	2.693220
SIC	2.710969	2.703531	2.703297	2.712745	2.704230
HQIC	2.705615	2.697285	2.697051	2.706499	2.697091
SET INDEX					
AIC	3.234291	3.227500	3.229793	3.234637	3.226980
SIC	3.245953	3.240328	3.242621	3.247465	3.240974
HQIC	3.238351	3.231967	3.234260	3.239103	3.231852
KUALA LUMPUR COMPOSITE INDEX					
AIC	2.330992	2.321173	2.325600	2.330936	2.321364
SIC	2.349557	2.340898	2.345325	2.350661	2.342249
HQIC	2.337454	2.328039	2.332466	2.337802	2.328633
JAKARTA COMPOSITE INDEX					
AIC	3.194326	3.188479	3.189914	3.194513	3.188992
SIC	3.215376	3.210700	3.212134	3.216734	3.212382

HQIC	3.201656	3.196217	3.197652	3.202251	3.197137
SSE COMPOSITE INDEX					
AIC	3.520408	3.512490	3.51960	3.519445	3.514265
SIC	3.529802	3.523058	3.530168	3.530013	3.526007
HQIC	3.523680	3.516171	3.523281	3.523126	3.518355
TAIEX INDEX					
AIC	3.154292	3.140886	3.146266	3.154602	3.14105
SIC	3.163366	3.151093	3.156473	3.164809	3.152392
HQIC	3.157446	3.144434	3.149814	3.158150	3.144993
KOSPI INDEX					
AIC	3.339994	3.329591	3.331967	3.338382	3.329325
SIC	3.349002	3.339725	3.342101	3.348516	3.340585
HQIC	3.343123	3.333112	3.335488	3.341903	3.333237
PSE COMPOSITE INDEX					
AIC	3.139018	3.136360	3.133955	3.138730	3.133692
SIC	3.148311	3.146815	3.144410	3.149185	3.145308
HQIC	3.142253	3.139999	3.137594	3.142370	3.137735

The log likelihood values of the estimated models show that the best performing model is PGARCH (1,1) for all selected Asian stock market indices except for China's SSE which is EGARCH (1,1) model. According to the Table 3.6, Akaike information criteria (AIC), Schwarz information criteria (SIC) and Hannah Quinn information criteria (HQIC) values also confirm that for NIKKEI, HANG SENG, PSE and SET indices. However, the outcomes of the data indicate that the TGARCH (1,1) model outperformed for STI index, while EGARCH (1,1) for KLCI, JCI, SSE, KOSPI and TAIEX indices. These results show the difficulty of modelling stock market volatility where there is no single outperforming model for selected indices. Nevertheless, asymmetric GARCH models outperformed symmetric GARCH models in daily returns of selected indices which confirms the study of Poon and Granger (2003).

3.5.2 Estimation Results and Their Economic Meaning for Weekly Return Series

The detail estimation output of GARCH, EGARCH, TGARCH, GARCH-M, and PGARCH models are reported in Appendix A for weekly return series from Table A.11 to Table A.20. p -values are presented in the parentheses while Student-t statistic in square brackets. The values in log likelihood represent the maximized log likelihood value. Residual diagnostics test results are also attached in the tables to look whether there are any remaining ARCH effects in the estimated GARCH models. Durbin-Watson test statistic is added to check autocorrelation.

One of the most simple, yet common volatility model has been introduced in this work is the GARCH (1,1) model. The sum of ARCH and GARCH coefficients close to unity for all estimated index returns except NIKKEI index which is slightly lower compared to results. This indicates that there is a high degree of persistence in the shocks to the conditional variance. The first three coefficient variance intercept term (ω), ARCH term (α) and GARCH term (β) have high statistical significance at 10% level for all estimated models with the only exception of constant term in SET index. Statistically significant terms refer that lagged conditional variance (GARCH term) and Arch term has an influence on current volatility, in other words, the news from previous periods have impact on current volatility. The ARCH-LM heteroscedasticity test results indicate that there are no remaining ARCH effects in the residuals of the model. Thus, variance equations are well specified in all selected indices.

The mean equation of GARCH-M model estimated by using risk premium feature which is denoted by λ on the function of the conditional variance. If the risk premium has a positive value and statistical significance, it indicates that the return series is positively correlated with its volatility. This means investors have greater returns for the higher risk taken.

The estimation of risk premium parameter (λ) is negative in HANG SENG, STI, SET and TAIEX indices, while positive in the rest. However, it is insignificant for all estimated indices. The economic interpretation of this result is; the conditional variance which has been used as a proxy for risk of return is not related to the level of return. Although the results confirm the well-known risk-return spectrum of higher risk is associated with greater probability of higher return and lower risk with a greater probability of smaller return, the insignificant risk premium indicates that investors are not compensated for bearing higher risk for the selected indices. The ARCH (α) and GARCH (β) coefficients are statistically significant and the sum of the two coefficients are close to unity which is similar to GARCH estimation. The ARCH-LM test statistics didn't indicate any remaining ARCH effects which refer the model successfully estimated the volatility in the return series.

Leverage effects have been investigated by three asymmetrical models EGARCH (1,1), TGARCH (1,1) and PGARCH (1,1) on selected return series. The first estimated model EGARCH (1,1) shows statistically significant parameters at 1% in almost all series with the only exception of asymmetry parameter (γ) in SSE index which is insignificant. A negative and significant leverage parameter indicates that negative news has a greater effect on conditional variance than the positive news with the same magnitude. The null hypothesis of no heteroscedasticity is accepted in all selected return series.

The other asymmetric model to test leverage effect is the TGARCH (1,1) model. The results report that ARCH term is insignificant except SET, SSE, KOSPI and JCI indices which implies no feedback about volatility from the previous period, while GARCH term and the asymmetry term are positive and statistically significant at 1% confidence level for all selected markets with the only exception of SSE and SET indices for asymmetry parameter. A significant and positive asymmetry coefficient shows that the positive shocks (good news) have a smaller impact than negative shocks (bad news) on the following period volatility (conditional variance). The ARCH-LM test statistics do not show any remaining ARCH effects which refer the model successfully estimated the volatility in the return series.

The results in tables for PGARCH (1,1) model indicate that the estimated asymmetry parameter (γ) has positive value in all indices and it is statistically significant, except for China's SSE which is negative and insignificant. Thus, there is a presence of leverage effect and positive shocks induce higher volatility than negative shocks. The power term (δ) is significant at 1% level in all return series except HSI index which is insignificant. It has the lowest value with 0.984765 in JCI index and the highest value with 2 in HSI index. These results confirm the constraints of the model (δ >0). The ARCH-LM test statistics didn't indicate any remaining ARCH effects except Hong Kong's HANG SENG index which implies the model was able to remove all heteroscedasticity in the residuals.

Table 3.7: Model comparison for the estimated models under t-student distribution

NIKKEI	**GARCH (1,1)**	**EGARCH (1,1)**	**TGARCH (1,1)**	**GARCH-M (1,1)**	**PGARCH (1,1)**
AIC	4.925823	4.903761	4.909014	4.926451	4.903973
SIC	4.967407	4.949502	4.954756	4.972193	4.953873
HQIC	4.941468	4.92097	4.926224	4.943661	4.922747
HANG SENG INDEX					
AIC	5.007466	5.001865	4.998661	5.008753	5.575592
SIC	5.049159	5.047727	5.044523	5.054615	5.625623
HQIC	5.023155	5.019123	5.015918	5.02601	5.594418
STRAITS TIMES INDEX					
AIC	4.358661	4.337807	4.336224	4.360709	4.337272
SIC	4.388731	4.372889	4.371306	4.395791	4.377366
HQIC	4.370104	4.351158	4.349575	4.37406	4.35253
SET INDEX					

AIC	4.962915	4.959826	4.964271	4.964478	4.961093
SIC	5.004608	5.005688	5.010133	5.01034	5.011124
HQIC	4.978604	4.977083	4.981528	4.981735	4.979919
KUALA LUMPUR COMPOSITE INDEX					
AIC	4.151791	4.142793	4.14234	4.153382	4.141297
SIC	4.201887	4.197065	4.196612	4.207653	4.199743
HQIC	4.170643	4.163217	4.162764	4.173805	4.163291
JAKARTA COMPOSITE INDEX					
AIC	4.970624	4.960355	4.964521	4.97223	4.960636
SIC	5.037951	5.03189	5.036056	5.043765	5.036378
HQIC	4.995973	4.987288	4.991455	4.999164	4.989153
SSE COMPOSITE INDEX					
AIC	5.189628	5.185639	5.191304	5.190402	5.187402
SIC	5.215285	5.215572	5.221237	5.220335	5.221611
HQIC	5.199297	5.196921	5.202585	5.201684	5.200294
TAIEX					
AIC	4.864278	4.852795	4.856807	4.865768	4.853979
SIC	4.889509	4.882231	4.886243	4.895204	4.887621
HQIC	4.873777	4.863877	4.86789	4.87685	4.866645
KOSPI					
AIC	5.058984	5.056871	5.058593	5.060016	5.057835
SIC	5.125868	5.127935	5.129657	5.13108	5.133079
HQIC	5.084156	5.083616	5.085338	5.086762	5.086153
PSE COMPOSITE INDEX					
AIC	4.910941	4.899828	4.901236	4.912373	4.900099
SIC	4.952634	4.94569	4.947097	4.958235	4.95013
HQIC	4.92663	4.917085	4.918493	4.929631	4.918925

The log likelihood values of the estimated models show that the best performing model is PGARCH (1,1) for all selected Asian stock market indices except for HANG SENG index. However, as Table 3.7 indicates above, Akaike information criteria (AIC), Schwarz information criteria (SIC) and Hannah Quinn information criteria (HQIC) values report that EGARCH (1,1) outperforms in almost all selected indices, while TGARCH (1,1) is the best performing model for KLCI, STI, and HANG SENG indices. These results prove the difficulty of modelling stock market volatility where there is no single outperforming model. Nevertheless, the modeling performance of asymmetric GARCH models is better than symmetric GARCH models in all chosen criteria for weekly returns of selected indices.

3.5.3 Estimation Results and Their Economic Meaning for Monthly Return Series

The estimation output of GARCH, EGARCH, TGARCH, GARCH-M, and PGARCH models are reported for monthly return series in Appendix A from Table A.21 to Table A.30. p-values are presented in the parentheses while Student-t statistic in square brackets. Log-likelihood refers to the maximized log likelihood value. Residual diagnostics test results are also attached in the tables to look whether there are any remaining ARCH effects in the estimated GARCH models. Durbin-Watson test statistic is added to see autocorrelation.

According to the GARCH (1,1) estimates, the sum of ARCH and GARCH coefficients close to unity for all estimated index returns except NIKKEI index which is around 0.79 and HANG SENG index which is negative. These results sign that observed shocks in the current time will have no influence upon next period conditional variance. The first three coefficient variance intercept term (ω), ARCH term (α) and GARCH term (β) either have lower statistical significance in different confidence levels or completely lose their significance. Insignificant terms refer that lagged conditional variance (GARCH term) and ARCH term do not affect current volatility. The ARCH-LM heteroscedasticity test indicates that there are no remaining ARCH effects in the residuals of the model. Thus, variance equations are well specified in all selected indices.

The risk premium parameter (λ) has been estimated in GARCH-M (1,1) model and it has a positive value in JCI, KLCI, KOSPI, NIKKEI, and STI indices, while negative in the rest. Nonetheless, it is insignificant for all estimated indices. Although, positive risk premium confirms the well-known risk-return spectrum of a higher risk is associated with greater probability of higher return and lower risk with a greater probability of smaller return, the insignificant risk premium indicates that investors are not compensated for bearing higher risk for the selected indices. The ARCH (α) and GARCH (β) coefficients are statistically significant in different levels and the sum of the two coefficients are close to unity which is similar with GARCH estimation. The only exception is the ARCH term in NIKKEI index, which is insignificant, therefore volatility persistence is also far from unity. The ARCH-LM test statistics didn't show any remaining ARCH effects which refer the model successfully estimated the volatility in the return series.

Leverage effects have been investigated by three asymmetrical models EGARCH (1,1), TGARCH (1,1) and PGARCH (1,1) on selected return series. The first estimated model EGARCH (1,1) shows mixed results in asymmetry parameter (γ) which is significant in various levels for NIKKEI, HANG SENG, STI, PSI, and KLCI indices, while insignificant in the remaining indices. However, it has a negative value in all indices with the only exception of the SSE index. A negative and significant leverage parameter indicates that negative news has greater effect on conditional variance than the positive news with the same magnitude. The null hypothesis of no heteroscedasticity is accepted in all selected return series.

The other asymmetric model to test leverage effect is the TGARCH (1,1) model. The results report that ARCH term is insignificant in all indices except for TAIEX which implies no feedback about volatility from the previous period, while the results for GARCH term and the asymmetry term are mixed. The ARCH-LM test statistics didn't show any remaining ARCH effects except for NIKKEI, STI and SSE indices which refers the model successfully estimated the volatility in the return series.

The results in tables for PGARCH (1,1) model indicate that the estimated asymmetry parameter (γ) has a positive value and statistical significance at %1 confidence level in all indices. Thus, there is a presence of leverage effect and positive shocks induce higher volatility than negative shocks. The power term (δ) is significant at 1% level in NIKKEI, STI, KOSPI, and JCI return series, while at 5% level in PSE and at 10% level in HSI and KLCI series. In SET, SSE and TAIEX indices, the power term is insignificant. It has a positive value in all return series which confirms the constraints of the model (δ >0). The ARCH-LM test statistics didn't indicate any remaining ARCH effects which imply the model was able to remove all heteroscedasticity in the residuals.

Table 3.8: Model comparison for the estimated models under t-student distribution

NIKKEI	**GARCH (1,1)**	**EGARCH (1,1)**	**TGARCH (1,1)**	**GARCH-M (1,1)**	**PGARCH (1,1)**
AIC	6.320312	6.314044	6.360114	6.326991	6.291706
SIC	6.420545	6.426807	6.472876	6.439754	6.416998
HQIC	6.360452	6.359203	6.405272	6.372149	6.341882
HANG SENG INDEX					
AIC	6.692214	6.599782	6.585249	6.5759	6.574557
SIC	6.767203	6.687269	6.672736	6.663388	6.674543
HQIC	6.722242	6.634814	6.620281	6.610932	6.614594
STRAITS TIMES INDEX					
AIC	5.914181	5.924191	6.036342	5.920663	5.911486

SIC	6.066969	6.092258	6.204409	6.088729	6.094832
HQIC	5.97586	5.992039	6.104189	5.98851	5.985501
SET INDEX					
AIC	6.693669	6.693296	6.70024	6.700174	6.687249
SIC	6.768658	6.780784	6.787728	6.787661	6.787235
HQIC	6.723697	6.728328	6.735272	6.735206	6.727286
KUALA LUMPUR COMPOSITE INDEX					
AIC	5.939881	5.92642	5.927809	5.945764	5.934566
SIC	6.040114	6.039183	6.040571	6.058527	6.059858
HQIC	5.980021	5.971578	5.972967	5.990922	5.984742
JAKARTA COMPOSITE INDEX					
AIC	6.599535	6.607822	6.605358	6.606287	6.611714
SIC	6.699768	6.720584	6.71812	6.71905	6.737006
HQIC	6.639675	6.65298	6.650516	6.651445	6.66189
SSE COMPOSITE INDEX					
AIC	7.050242	7.044736	7.168416	7.056958	7.04456
SIC	7.175846	7.182899	7.30658	7.195121	7.195284
HQIC	7.100548	7.100072	7.223753	7.112294	7.104927
TAIEX					
AIC	6.430408	6.438027	6.435285	6.437182	6.439613
SIC	6.505398	6.525514	6.522772	6.52467	6.539598
HQIC	6.460436	6.473059	6.470317	6.472215	6.479649
KOSPI					
AIC	6.487047	6.497987	6.493249	6.488195	6.490283
SIC	6.587281	6.610749	6.606012	6.600957	6.615575
HQIC	6.527188	6.543145	6.538407	6.533353	6.540458
PSE COMPOSITE INDEX					
AIC	6.574061	6.554654	6.562313	6.580282	6.560935
SIC	6.674295	6.667416	6.675076	6.693045	6.686227
HQIC	6.614202	6.599812	6.607471	6.62544	6.611111

The log likelihood values of the estimated models show that the best performing model is PGARCH (1,1) for all selected Asian stock market indices except for HANG SENG index which is in line with weekly results. However, as shown in the Table 3.8, Akaike information criteria (AIC), Schwarz information criteria (SIC) and Hannah Quinn information criteria (HQIC) values report different results compared to daily and weekly results. GARCH (1,1) outperforms for STI, SET, JCI, TAIEX and KOSPI indices, while GARCH-M (1,1) is the best performing model for HANG SENG indices. Asymmetric models only outperformed in NIKKEI with PGARCH (1,1), while KLCI, SSE and PSE indices with EGARCH (1,1). These results confirm the difficulty of modelling stock market volatility where there is no single outperforming model.

3.6 Conclusion

To summarize the change of the important values depending on each frequency and model, Table 3.9 was created. This table compares the values of ARCH term, GARCH term and volatility persistence for all selected models. Furthermore, leverage effect values have been compared for all asymmetric models. In GARCH-M and PGARCH models, risk premium coefficient and power parameter values have been included respectively in each market for all selected frequencies.

The coefficient of ARCH term is mostly significant at 1% confidence level and has a positive value in all daily return series except for the second sample of KOSPI and TAIEX for TGARCH model which is insignificant. However, the significance level of ARCH term is reduced or completely lost in weekly and monthly series. These results indicate that the low-frequency data is less influenced by the lagged error terms compared with high-frequency data. The findings are in line with the studies of Thomas (1995), Caiado (2004) and Rafique (2011), who found same results in Portuguese Stock Index, Bombay Stock Index, and Karachi Stock Index respectively.

According to the table below, the coefficient of GARCH term is significant in full samples of all frequencies with the only exception of TGARCH model of NIKKEI, STI and SSE indices in monthly series, and EGARCH model of NIKKEI index in monthly series. In terms of sub-samples, daily and weekly series have strong significance level, while some of the monthly series experienced loss of significance. It has high value in all return series which shows that the past innovations have strong effect on the conditional variance. In other words, significantly positive GARCH term refers that the previous period volatility has strong impact on the current period conditional variance. In contrast to findings of Umar et al. (2021), the current study did not find any evidence of declining GARCH effect with the reducing frequencies.

The values of volatility persistence mostly close to unity which indicate that the volatility of the returns dies at a slow pace. The presence of volatility persistence in the daily, weekly, and monthly frequencies shows that the higher-frequency data has greater value than the lower-frequency data. Although the findings of Chambers (1998) show that the degree of persistence is irrespective in terms of frequency of data, the present study finds that reducing frequency decreases the persistence of volatility, especially in the developed stock markets of Asia. On the other hand, emerging markets of Asia such as JCI, KLCI, PSI, and KOSPI exhibit increasing volatility persistence with the reducing frequency which contradicts with the findings of Caiado (2004) and Panait and Slavescu (2012). Therefore, investors in emerging markets may expose volatility shocks not only in short run but also in the long run compared to the developed stock markets.

Based on the empirical results, the following conclusion can be drawn:

- The study finds strong evidence that the return series of emerging and developed stock markets of Asia could be characterized by the linear and non-linear GARCH models in all selected frequencies. Specifically, PGARCH (1,1) model for the daily and weekly return series, and GARCH (1,1) model for the monthly return series is found superior.
- By measuring the risk premium coefficient using GARCH-M (1,1) model, the present paper finds investors are rewarded with extra return by taking higher risk in daily series of KOSPI, PSE and SSE indices, which is in line with economic significance as revealed by Wang (2022). On the other hand, HANG SENG index penalizes its investors with negative risk-return trade-off in the long run and investors should be careful when considering Hong Kong stock market.
- Based on the estimations of non-linear GARCH-family models of EGARCH (1,1), TGARCH (1,1), and PGARCH (1,1), existence of significant leverage effect is found in higher frequency data for all selected stock markets, while in the lower frequencies the significance of asymmetry parameter is lost. Therefore, symmetric GARCH models could be preferred in lower frequency data which is in line with the findings of Lim and Sek (2013) and Lee et al. (2017). Moreover, the results of the leverage effect coefficient indicate that there is no significant correlation with the frequency of data.
- The overall results reveal that Asian stock markets exhibit high persistence of volatility, non-normality, high kurtosis, and volatility clustering in daily return series, while weekly and monthly return series indicate lower volatility which makes it possible to have higher profits but also leads to market inefficiency (Mittal et al., 2012).

Table 3.9: Comparison of values for all the return series and frequencies

	HANG SENG INDEX								
	Daily			**Weekly**			**Monthly**		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.050684*	0.064617*	0.057690*	0.058056*	0.072113*	0.065919*	-0.053153	0.254651**	0.108169***
Garch Term (β)	0.945017*	0.930564*	0.938032*	0.935228*	0.909466*	0.922007*	-0.432653	0.658860*	-0.324227
Volatility Persistence	0.995701	0.995181	0.995722	0.993284	0.981579	0.987926	-0.485806	0.913511	-0.216058
EGARCH (1,1)									
Arch Term (α)	0.116217*	0.138079*	0.124954*	0.139927*	0.161001*	0.147493*	0.083232	0.484690*	0.338346*
Garch Term (β)	0.989289*	0.987252*	0.988867*	0.986382*	0.964735*	0.976693*	-0.768678*	0.850559*	0.921664*
Leverage Effect (γ)	-0.062873*	-0.06348*	-0.061484*	-0.046174***	-0.076308*	-0.066562*	0.060839	-0.026339	-0.027863
Volatility Persistence	0.989289	0.987252	0.988867	0.986382	0.964735	0.976693	-0.768678	0.850559	0.921664
TGARCH (1,1)									
Arch Term (α)	0.015343***	0.026803*	0.021426*	0.034255	0.01284	0.016311	-0.061609	0.249253	0.148217***
Garch Term (β)	0.937757*	0.923792*	0.932587*	0.928460*	0.901117*	0.915166*	-0.352299	0.657764*	0.778096*
Leverage Effect (γ)	0.076409*	0.077171*	0.073611*	0.049437	0.110109*	0.092542*	0.197174	0.009179	0.037661
Volatility Persistence	0.9913045	0.9891805	0.990606	0.962715	0.9690115	0.977748	-0.315321	0.9116065	0.9451435
GARCH-M (1,1)									
Arch Term (α)	0.050791*	0.064736*	0.057826*	0.056987*	0.071390*	0.065012*	0.110697***	0.250643**	0.171907*
Garch Term (β)	0.944893*	0.930413*	0.937866*	0.936467*	0.910609*	0.923213*	0.857546*	0.669168*	0.783789*
Volatility Persistence	0.995684	0.995149	0.995692	0.993454	0.981999	0.988225	0.968243	0.919811	0.955696
Risk Premium (λ)	0.005226	0.006293	0.007987	-0.063794	-0.053858	-0.064086	-0.351372	-0.257102	-0.314083***
PGARCH (1,1)									
Arch Term (α)	0.059089*	0.072231*	0.064743*	0.068884*	0.054578	0.15	-0.070091	0.06889	0.024672
Garch Term (β)	0.942441*	0.926674*	0.936472*	0.927737*	0.901210*	0.600000***	0.359609	0.563113**	0.610312*
Leverage Effect (γ)	0.556930*	0.469603*	0.506202*	0.294117	0.512548	0.05	-0.071703	-0.102858	0.01969
Power Parameter (δ)	1.164146*	1.230886*	1.169995*	1.407131**	1.976171*	2	1.977865	6.048771	7.274523**
Volatility Persistence	1.00153	0.998905	1.001215	0.996621	0.955788	0.75	0.289518	0.632003	0.634984

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

SSE COMPOSITE INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.132883*	0.058227*	0.084449*	0.179140*	0.135438*	0.141400*	-0.041954	0.276372**	0.152200**
Garch Term (β)	0.840028*	0.944511*	0.915927*	0.717776*	0.863858*	0.841136*	1.062974*	0.726383*	0.792039*
Volatility Persistence	0.972911	1.002738	1.000376	0.896916	0.999296	0.982536	1.02102	1.002755	0.944239
EGARCH (1,1)									
Arch Term (α)	0.261671*	0.134717*	0.188165*	0.287930*	0.253573*	0.245197*	-0.119899	0.620480*	0.242947*
Garch Term (β)	0.957875*	0.995127*	0.986137*	0.908692*	0.984296*	0.969435*	0.987734*	-0.672023*	0.953083*
Leverage Effect (γ)	-0.035124**	-0.005586	-0.023318*	-0.001432	0.044214***	0.004549	-0.083691**	0.171899	0.039971
Volatility Persistence	0.957875	0.995127	0.986137	0.908692	0.984296	0.969435	0.987734	-0.672023	0.953083
TGARCH (1,1)									
Arch Term (α)	0.108153*	0.058537*	0.071273*	0.188153*	0.162677*	0.142878*	-0.051107*	0.298315**	-0.034248
Garch Term (β)	0.842122*	0.944612*	0.913639*	0.713364*	0.874368*	0.841191*	1.030629*	0.846710*	0.590943
Leverage Effect (γ)	0.053970**	-0.000749	0.030100**	-0.020792	-0.068073***	-0.003247	0.089002***	-0.269432**	0.043292
Volatility Persistence	0.97726	1.0027745	0.999962	0.891121	0.968972	0.9824455	1.024023	1.010309	0.578341
GARCH-M (1,1)									
Arch Term (α)	0.132322*	0.058902*	0.084829*	0.186157*	0.135711*	0.143471*	0.738196*	0.274530**	0.150639**
Garch Term (β)	0.839018*	0.943709*	0.915029*	0.716622*	0.863719*	0.837749*	-0.181506*	0.727104*	0.793147*
Volatility Persistence	0.97134	1.002611	0.999858	0.902779	0.99943	0.98122	0.55669	1.001634	0.943786
Risk Premium (λ)	0.124437**	0.061639	0.083489*	0.32357***	-0.050812	0.084663	0.777757*	0.056555	-0.033965
PGARCH (1,1)									
Arch Term (α)	0.139949*	0.070562*	0.096956*	0.168512*	0.131269*	0.132375*	0.008106	0.137367***	0.129685**
Garch Term (β)	0.865505*	0.945105*	0.920956*	0.768464*	0.877749*	0.873577*	0.971762*	0.866162*	0.856793*
Leverage Effect (γ)	0.121454**	0.029601	0.121152*	-0.024163	-0.142295	-0.023390	1.000000	-0.624998	-0.257183
Power Parameter (δ)	1.149303*	1.160336*	1.012809*	1.405687**	1.724613*	1.155710*	0.067058	1.040742	0.710898
Volatility Persistence	1.005454	1.015667	1.017912	0.936976	1.009018	1.005952	0.979868	1.003529	0.986478

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

JAKARTA COMPOSITE INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.146420*	0.112323*	0.124770*	0.086075*	0.263437*	0.152439*	0.077065	0.348996***	0.084343**
Garch Term (β)	0.839532*	0.880203*	0.869142*	0.895167*	0.709455*	0.846452*	0.885100*	0.671854*	0.911087*
Volatility Persistence	0.985952	0.992526	0.993912	0.981242	0.972892	0.998891	0.962165	1.02085	0.99543
EGARCH (1,1)									
Arch Term (α)	0.286799*	0.211297*	0.245211*	0.198473*	0.414155*	0.279185*	0.140767	0.583929**	0.193904**
Garch Term (β)	0.963979*	0.977231*	0.974965*	0.964772*	0.911709*	0.958037*	0.928903*	0.869356*	0.978257*
Leverage Effect (γ)	-0.060956*	-0.079876*	-0.060150*	-0.073868*	-0.083106***	-0.101827*	-0.142507	0.063287	-0.062284
Volatility Persistence	0.963979	0.977231	0.974965	0.964772	0.911709	0.958037	0.928903	0.869356	0.978257
TGARCH (1,1)									
Arch Term (α)	0.102844*	0.055333*	0.085419*	0.036329	0.170105**	0.083428**	-0.178607**	0.439129	0.033856
Garch Term (β)	0.829546*	0.882250*	0.864587*	0.886820*	0.697768*	0.842579*	0.960536*	0.723649*	0.922950*
Leverage Effect (γ)	0.098280*	0.096204*	0.078200*	0.096496*	0.178874***	0.126610*	0.309414*	-0.209410	0.056134
Volatility Persistence	0.98153	0.985685	0.989106	0.971397	0.95731	0.989312	0.936636	1.058073	0.984873
GARCH-M (1,1)									
Arch Term (α)	0.146054*	0.119690*	0.125980*	0.086682*	0.276316*	0.152383*	0.076513	0.266797***	0.084692**
Garch Term (β)	0.839860*	0.872045*	0.868003*	0.894787*	0.697928*	0.846529*	0.890097*	0.753929*	0.910843*
Volatility Persistence	0.985914	0.991735	0.993983	0.981469	0.974244	0.998912	0.96661	1.020726	0.995535
Risk Premium (λ)	-0.011214	0.119328**	0.032987	-0.082054	0.151134	0.017588	-0.219349	0.279531	0.020288
PGARCH (1,1)									
Arch Term (α)	0.151004*	0.118155*	0.132132*	0.041603*	0.264342*	0.155755*	8.57E-05	-0.038315	0.018637
Garch Term (β)	0.832902*	0.889021*	0.872474*	0.876447*	0.712337*	0.846122*	0.837995*	0.553913	0.934191*
Leverage Effect (γ)	0.173254*	0.389278	0.208218*	0.252329***	0.265654***	0.430270*	0.732236	-0.010725	0.987911
Power Parameter (δ)	1.867080*	1.074357*	1.468024*	3.279166**	0.911293*	0.984765*	6.801301	2.02031	2.144288*
Volatility Persistence	0.983906	1.007176	1.004606	0.91805	0.976679	1.001877	0.923695	0.515598	0.952828

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

KUALA LUMPUR COMPOSITE INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.131632*	0.121700*	0.123133*	0.061185*	0.116914*	0.073144*	0.190312***	0.160499	0.169422*
Garch Term (β)	0.872196*	0.866181*	0.876560*	0.933862*	0.874074*	0.923577*	0.764028*	0.766525*	0.816892*
Volatility Persistence	1.003828	0.987881	0.999693	0.995047	0.990988	0.996721	0.95434	0.927024	0.986314
EGARCH (1,1)									
Arch Term (α)	0.221248*	0.205957*	0.207504*	0.133445*	0.240246*	0.166681*	0.215864	0.380407	0.251817*
Garch Term (β)	0.987368*	0.980849*	0.987996*	0.991639*	0.972965*	0.990882*	0.936186*	0.794467*	0.969479*
Leverage Effect (γ)	-0.061505*	-0.059444*	-0.058247*	-0.088456*	-0.039378	-0.063601*	-0.224251*	-0.187857	-0.134868*
Volatility Persistence	0.987368	0.980849	0.987996	0.991639	0.972965	0.990882	0.936186	0.794467	0.969479
TGARCH (1,1)									
Arch Term (α)	0.073648*	0.086940*	0.078769*	0.00922	0.094183*	0.022936	-0.020802	0.035914	0.050877
Garch Term (β)	0.880096*	0.865204*	0.879247*	0.938390*	0.872888*	0.930485*	0.812191*	0.692041*	0.829198*
Leverage Effect (γ)	0.101036*	0.067941*	0.081625*	0.094395*	0.041538	0.078306*	0.310155**	0.298643	0.179076**
Volatility Persistence	1.004262	0.9861145	0.9988285	0.9948075	0.98784	0.992574	0.9464485	0.727955	0.969613
GARCH-M (1,1)									
Arch Term (α)	0.131970*	0.121029*	0.123618*	0.061168*	0.128145*	0.073697*	0.190289***	0.278168***	0.175836*
Garch Term (β)	0.871856*	0.867865*	0.876245*	0.933887*	0.863389*	0.923088*	0.764453*	0.655962*	0.811274*
Volatility Persistence	1.003826	0.988894	0.999863	0.995055	0.991534	0.996785	0.954742	0.93413	0.98711
Risk Premium (λ)	0.010997	0.142304*	0.045165	-0.005619	0.209039***	0.016088	-0.016354	0.492057***	0.07121
PGARCH (1,1)									
Arch Term (α)	0.120637*	0.115129*	0.113611*	0.051635***	0.130930*	0.076790*	0.138475**	0.169425*	0.138474**
Garch Term (β)	0.899027*	0.891987*	0.902606*	0.938781*	0.875239*	0.924994*	0.816937*	0.701805*	0.834646*
Leverage Effect (γ)	0.284801*	0.258371*	0.280275*	0.665485	0.177190	0.409353*	0.994738*	0.507630	0.434444**
Power Parameter (δ)	1.104873*	1.244636*	1.142452*	1.608801*	1.128068***	1.410241*	0.709247	1.633553	1.545239***
Volatility Persistence	1.019664	1.007116	1.016217	0.990416	1.006069	0.999784	0.955412	0.87123	0.97312

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

KOSPI INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.059842*	0.073891*	0.067983*	0.061571*	0.147542*	0.092596*	0.090263	0.081264	0.097417**
Garch Term (β)	0.937454*	0.920159*	0.931828*	0.929258*	0.796526*	0.904830*	0.889235*	0.896732*	0.900876*
Volatility Persistence	0.997296	0.99405	0.999811	0.990829	0.944068	0.997426	0.979498	0.977996	0.998293
EGARCH (1,1)									
Arch Term (α)	0.140746*	0.142241*	0.147493*	0.103777*	0.265041*	0.170369*	0.093134	0.192416***	0.233849*
Garch Term (β)	0.993552*	0.985756*	0.994068*	0.990290*	0.928388*	0.988920*	0.975889*	0.987299*	0.988616*
Leverage Effect (γ)	-0.036704*	-0.090998*	-0.054973*	-0.041597*	-0.115524*	-0.043337**	-0.213491*	0.068738	-0.020814
Volatility Persistence	0.993552	0.985756	0.994068	0.99029	0.928388	0.98892	0.975889	0.987299	0.988616
TGARCH (1,1)									
Arch Term (α)	0.032062*	0.010588	0.035006*	0.020743	0.035488	0.064457*	-0.004368	0.13296	0.107549
Garch Term (β)	0.939220*	0.906704*	0.928570*	0.947704*	0.778215*	0.903177*	0.889618*	0.897034*	0.903695*
Leverage Effect (γ)	0.050134*	0.129160*	0.069006*	0.048970**	0.191727*	0.049627***	0.215141***	-0.082957	-0.026707
Volatility Persistence	0.996349	0.981872	0.998079	0.992932	0.9095665	0.9924475	0.9928205	0.9885155	0.9978905
GARCH-M (1,1)									
Arch Term (α)	0.059540*	0.075944*	0.068734*	0.059078*	0.168039*	0.093991*	0.111528***	0.08165	0.098332**
Garch Term (β)	0.937765*	0.917576*	0.931106*	0.932152*	0.761348*	0.903231*	0.866105*	0.894735*	0.899278*
Volatility Persistence	0.997305	0.99352	0.99984	0.99123	0.929387	0.997123	0.977633	0.976385	0.99761
Risk Premium (λ)	0.046615	0.131364**	0.112314*	0.133798	0.348137**	0.069046	0.058684	0.157422	0.189712
PGARCH (1,1)									
Arch Term (α)	0.066594*	0.076116*	0.078208*	0.044344***	0.127594*	0.090337*	0.001021	0.01678	0.011666
Garch Term (β)	0.937900*	0.920456*	0.933162*	0.948297*	0.782747*	0.917114*	0.881843*	0.864350*	0.880311*
Leverage Effect (γ)	0.250408*	0.673425*	0.363001*	0.315514*	0.492206**	0.259602**	0.121607	-0.235423	-0.190192**
Power Parameter (δ)	1.513723*	1.179664*	1.205649*	1.814067***	1.627777*	1.254649*	8.375515	5.134292	5.539115*
Volatility Persistence	1.004494	0.996572	1.01137	0.992641	0.910341	1.007451	0.882864	0.88113	0.891977

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

NIKKEI INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.062911*	0.111959*	0.084040*	0.049997**	0.072208*	0.068166*	0.047313	-0.064459*	0.102136***
Garch Term (β)	0.927172*	0.874411*	0.904749*	0.906368*	0.890531*	0.886145*	0.589989	0.562316	0.693902*
Volatility Persistence	0.990083	0.98637	0.988789	0.956365	0.962739	0.954311	0.637302	0.497857	0.796038
EGARCH (1,1)									
Arch Term (α)	0.130889*	0.185999*	0.158589*	0.065688	0.239532*	0.162885*	-0.164802	0.139129	0.006986
Garch Term (β)	0.975454*	0.966071*	0.971515*	0.912178*	0.822742*	0.8677*	0.631555*	-0.240368*	0.394711
Leverage Effect (γ)	-0.073341*	-0.122506*	-0.098558*	-0.090611*	-0.214887*	-0.153042*	-0.218067	-0.309975**	-0.239005*
Volatility Persistence	0.975454	0.966071	0.971515	0.912178	0.822742	0.8677	0.631555	-0.240368	0.394711
TGARCH (1,1)									
Arch Term (α)	0.020940**	0.025014***	0.024864*	-0.010720	-0.027956	-0.020039	-0.144716**	0.052438	-0.015881
Garch Term (β)	0.921098*	0.865227*	0.894844*	0.885796*	0.659310*	0.775805*	0.815395*	0.586566	0.567282
Leverage Effect (γ)	0.085622*	0.163007*	0.119263*	0.107765**	0.343169*	0.214144*	0.233954	-0.119352	-0.037853
Volatility Persistence	0.98485	0.9717445	0.9793395	0.9289485	0.8029385	0.862838	0.787656	0.579328	0.5324745
GARCH-M (1,1)									
Arch Term (α)	0.062649*	0.112548*	0.084521*	0.050184**	0.076695**	0.069554*	0.0504	0.122305	0.100583
Garch Term (β)	0.927559*	0.873352*	0.904047*	0.906246*	0.880185*	0.881727*	0.597152	0.787258*	0.695825*
Volatility Persistence	0.990208	0.9859	0.988568	0.95643	0.95688	0.951281	0.647552	0.909563	0.796408
Risk Premium (λ)	-0.02498	0.092503	0.037641	0.016887	0.204416	0.182855	0.212591	-0.08481	0.113763
PGARCH (1,1)									
Arch Term (α)	0.067317*	0.104153*	0.084889*	-0.033044*	0.128974*	0.085043*	-0.088266	-0.050908	-0.028330
Garch Term (β)	0.924114*	0.885968*	0.906585*	0.989897*	0.745096*	0.80709*	0.867614*	0.566083	1.017654*
Leverage Effect (γ)	0.557909*	0.741436*	0.668181*	-1.000000*	0.978693*	0.999966*	-0.952949	-0.016115	-0.968210
Power Parameter (δ)	1.165320*	0.938329*	1.022707*	0.805078*	0.946770*	1.03761*	1.30573	2.044518	2.166077*
Volatility Persistence	0.991431	0.990121	0.991474	0.956853	0.87407	0.892133	0.779348	0.515175	0.989324

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

PSE COMPOSITE INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.182601*	0.134362*	0.160264*	0.063286**	0.106066*	0.075067*	0.025174	-0.045115*	0.094668**
Garch Term (β)	0.767956*	0.832143*	0.796884*	0.891817*	0.865980*	0.905150*	0.818612*	0.578887	0.867912*
Volatility Persistence	0.950557	0.966505	0.957148	0.955103	0.972046	0.980217	0.843786	0.533772	0.96258
EGARCH (1,1)									
Arch Term (α)	0.280494*	0.225976*	0.258619*	0.093340**	0.237095*	0.146477*	-0.152669***	-0.330052	0.134692
Garch Term (β)	0.942436*	0.957085*	0.952287*	0.969098*	0.946549*	0.973798*	0.854814*	-0.609292	0.938778*
Leverage Effect (γ)	-0.056358*	-0.081773*	-0.064332*	-0.071346*	-0.073269**	-0.064438*	-0.291852*	-0.060567	-0.121894**
Volatility Persistence	0.942436	0.957085	0.952287	0.969098	0.946549	0.973798	0.854814	-0.609292	0.938778
TGARCH (1,1)									
Arch Term (α)	0.122125*	0.066671*	0.097146*	-0.007402	0.048278	0.016213	-0.110302*	-0.010307	-0.026055
Garch Term (β)	0.779407*	0.838415*	0.807278*	0.928256*	0.846455*	0.908727*	0.885104*	0.575882*	0.827266*
Leverage Effect (γ)	0.103846*	0.109545*	0.104535*	0.092322**	0.109981**	0.094737*	0.236798*	-0.048713	0.206509*
Volatility Persistence	0.953455	0.9598585	0.9566915	0.967015	0.9497235	0.9723085	0.893101	0.5412185	0.9544655
GARCH-M (1,1)									
Arch Term (α)	0.183594*	0.135836*	0.161911*	0.067836**	0.106548*	0.075991*	0.027358	0.154724*	0.092924**
Garch Term (β)	0.766843*	0.829155*	0.794586*	0.882112*	0.864974*	0.903837*	0.749003**	0.735300*	0.869804*
Volatility Persistence	0.950437	0.964991	0.956497	0.949948	0.971522	0.979828	0.776361	0.890024	0.962728
Risk Premium (λ)	0.03802	0.116064***	0.083910***	0.120433	0.102291	0.054893	0.570806	0.127982	-0.086965
PGARCH (1,1)									
Arch Term (α)	0.170881*	0.121466*	0.147388*	0.022406	0.128351*	0.069671*	0.075247	-0.039118	0.083459*
Garch Term (β)	0.790077*	0.854317*	0.823474*	0.918215*	0.850081*	0.912792*	0.823515*	0.581138*	0.843279*
Leverage Effect (γ)	0.155194*	0.321489*	0.200023*	0.998843	0.339669**	0.491843**	0.998638*	0.047429	0.999958*
Power Parameter (δ)	1.804940*	1.430850*	1.641220*	2.019620*	0.998227**	1.357636*	0.474031	2.031761	1.036193**
Volatility Persistence	0.960958	0.975783	0.970862	0.940621	0.978432	0.982463	0.898762	0.54202	0.926738

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

SET INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.087564*	0.125138*	0.108899*	0.058716*	0.094008*	0.071768*	0.134162***	0.192104*	0.135201*
Garch Term (β)	0.902062*	0.877895*	0.896090*	0.932248*	0.895865*	0.926993*	0.841392*	0.808326*	0.864964*
Volatility Persistence	0.989626	1.003033	1.004989	0.990964	0.989873	0.998761	0.975554	1.00043	1.000165
EGARCH (1,1)									
Arch Term (α)	0.202694*	0.196957*	0.199566*	0.134946*	0.216142*	0.156062*	-0.056262	0.710880*	0.215761*
Garch Term (β)	0.977850*	0.978585*	0.984879*	0.988254*	0.968373*	0.991456*	-0.571984	0.212054	0.991843*
Leverage Effect (γ)	-0.034381*	-0.057563*	-0.041092*	-0.027458	-0.034796	-0.027100***	0.165915	-0.101222	-0.039580
Volatility Persistence	0.97785	0.978585	0.984879	0.988254	0.968373	0.991456	-0.571984	0.212054	0.991843
TGARCH (1,1)									
Arch Term (α)	0.073859*	0.074785*	0.081439*	0.042688***	0.084146***	0.063981*	0.055595	0.209356	0.120322
Garch Term (β)	0.887336*	0.871019*	0.888567*	0.932625*	0.895513*	0.926837*	0.870034*	0.810007*	0.869323*
Leverage Effect (γ)	0.054697*	0.101865*	0.069991*	0.029290	0.015845	0.013803	0.088579	-0.028064	0.01695
Volatility Persistence	0.9885435	0.9967365	1.0050015	0.989958	0.9875815	0.9977195	0.9699185	1.005331	0.99812
GARCH-M (1,1)									
Arch Term (α)	0.083844*	0.125871*	0.109021*	0.056897*	0.092321*	0.071502*	0.136779***	0.183965**	0.136832*
Garch Term (β)	0.906270*	0.877625*	0.896000*	0.934122*	0.897931*	0.927245*	0.845349*	0.812480*	0.863618*
Volatility Persistence	0.990114	1.003496	1.005021	0.991019	0.990252	0.998747	0.982128	0.996445	1.00045
Risk Premium (λ)	-0.066732	0.050549	0.005301	-0.140386	0.086438	-0.023841	-0.387357	0.154398	-0.046038
PGARCH (1,1)									
Arch Term (α)	0.104324*	0.118632*	0.113150*	0.067178*	0.105513*	0.082710*	0.005931	0.105991**	0.079667***
Garch Term (β)	0.892180*	0.892120*	0.903183*	0.932423*	0.896701*	0.928114*	0.890725*	0.896183*	0.917373*
Leverage Effect (γ)	0.151038*	0.297130*	0.208300*	0.194007	0.132245	0.175122	0.295890	0.315635	0.412816
Power Parameter (δ)	1.671580*	1.227961*	1.303004*	1.354935***	1.310313*	1.111710*	5.743661	0.20022	0.15494
Volatility Persistence	0.996504	1.010752	1.016333	0.999601	1.002214	1.010824	0.896656	1.002174	0.99704

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

STRAITS TIMES INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.102472*	0.068174*	0.085134*	0.090516*	0.118654*	0.110813*	0.117586	0.250397	0.210919***
Garch Term (β)	0.891204*	0.922393*	0.910978*	0.920152*	0.847298*	0.881633*	0.858205*	0.639847*	0.764384*
Volatility Persistence	0.993676	0.990567	0.996112	1.010668	0.965952	0.992446	0.975791	0.890244	0.975303
EGARCH (1,1)									
Arch Term (α)	0.180048*	0.115856*	0.148231*	0.173446*	0.173052*	0.156068*	0.354623***	0.404459**	0.253035**
Garch Term (β)	0.976508*	0.991768*	0.988367*	0.960487*	0.977967*	0.977365*	0.979451*	0.874774*	0.938372*
Leverage Effect (γ)	-0.076435*	-0.066611*	-0.067960*	-0.148439*	-0.123756*	-0.114928*	0.122268	-0.183004	-0.131183***
Volatility Persistence	0.976508	0.991768	0.988367	0.960487	0.977967	0.977365	0.979451	0.874774	0.938372
TGARCH (1,1)									
Arch Term (α)	0.049360*	0.017403***	0.035462*	0.001884	0.021069	0.008829	0.526829	0.107549	-0.012080
Garch Term (β)	0.889499*	0.936330*	0.918673*	0.880340*	0.874322*	0.903549*	0.833235*	0.669712*	0.568593
Leverage Effect (γ)	0.094252*	0.074616*	0.077430*	0.198033*	0.164876*	0.138742*	-0.449967	0.247992	-0.064496
Volatility Persistence	0.985985	0.991041	0.99285	0.9812405	0.976727	0.981749	1.1350805	0.991257	0.524265
GARCH-M (1,1)									
Arch Term (α)	0.102243*	0.069103*	0.085234*	0.083219*	0.120053*	0.110709*	0.239344	0.244203	0.204478***
Garch Term (β)	0.891697*	0.921196*	0.910860*	0.927548*	0.846885*	0.881750*	-0.242124	0.648653*	0.769810*
Volatility Persistence	0.99394	0.990299	0.996094	1.010767	0.966938	0.992459	-0.0011896	0.892856	0.974288
Risk Premium (λ)	-0.043045	0.120347***	0.013935	-0.123535	0.164344	-0.005573	9.868147	0.346163	0.12864
PGARCH (1,1)									
Arch Term (α)	0.096196*	0.053329*	0.075048*	0.081576	0.090234*	0.068050**	0.084662	0.153508	0.007879
Garch Term (β)	0.897604*	0.939465*	0.923770*	0.881698*	0.901101*	0.908905*	0.796781*	0.709584*	0.774798*
Leverage Effect (γ)	0.346908*	0.489916*	0.368467*	0.986038	0.735957**	0.737841**	-0.449276**	0.814745*	0.983276
Power Parameter (δ)	1.462370*	1.576693*	1.513681*	1.388491*	1.169265**	1.509956*	4.454873***	0.050149	3.726697*
Volatility Persistence	0.9938	0.992794	0.998818	0.963274	0.991336	0.976955	0.881443	0.863092	0.782677

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

TAIEX INDEX

	Daily			Weekly			Monthly		
	Sample 1	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**	**Sample 1**	**Sample 2**	**Full Sample**
GARCH (1,1)									
Arch Term (α)	0.064852*	0.059263*	0.058657*	0.079747*	0.083608*	0.084120*	0.031573	0.213614**	0.158778*
Garch Term (β)	0.928515*	0.935694*	0.939505*	0.901714*	0.908262*	0.911643*	0.565956	0.773837*	0.835718*
Volatility Persistence	0.993367	0.994957	0.998162	0.981461	0.99187	0.995763	0.597529	0.987451	0.995958
EGARCH (1,1)									
Arch Term (α)	0.153239*	0.123876*	0.127188*	0.150786*	0.160343*	0.163687*	0.081847	-1.320668**	0.302423*
Garch Term (β)	0.978553*	0.989670*	0.989788*	0.966150*	0.978402*	0.981337*	0.850642*	0.955037*	0.973387*
Leverage Effect (γ)	-0.066497*	-0.068174*	-0.063347*	-0.060008***	-0.065685*	-0.058562*	-0.135463	-0.020750	-0.048439
Volatility Persistence	0.978553	0.98967	0.989788	0.96615	0.978402	0.981337	0.850642	0.955037	0.973387
TGARCH (1,1)									
Arch Term (α)	0.035347*	0.015399	0.025270*	0.004767*	0.020272	0.021973	-0.121924**	0.215957	0.124367***
Garch Term (β)	0.912815*	0.929806*	0.918673*	0.914768*	0.917749*	0.922498*	0.831031*	0.773600*	0.837193*
Leverage Effect (γ)	0.078717*	0.080416*	0.063130*	0.101204*	0.080997**	0.080721*	0.254854*	-0.003144	0.057718
Volatility Persistence	0.9875205	0.985413	0.975508	0.970137	0.9785195	0.9848315	0.837809	0.987985	0.96156
GARCH-M (1,1)									
Arch Term (α)	0.066351*	0.060600*	0.059103*	0.078722*	0.083533*	0.084218*	0.015131	0.221385**	0.159076*
Garch Term (β)	0.926707*	0.934038*	0.939026*	0.903517*	0.908231*	0.911607*	0.700677**	0.767671*	0.835492*
Volatility Persistence	0.993058	0.994638	0.998129	0.982239	0.991764	0.995825	0.715808	0.989056	0.994568
Risk Premium (λ)	0.034	0.066866	0.015878	-0.091169	0.021283	-0.03377	1.777309	-0.094164	-0.006074
PGARCH (1,1)									
Arch Term (α)	0.083309*	0.061980*	0.068308*	0.045015***	0.074841**	0.085008*	-0.004585	0.02943	0.040415
Garch Term (β)	0.915455*	0.936019*	0.937748*	0.932963*	0.912973*	0.915582*	0.562768	0.674336*	0.793791*
Leverage Effect (γ)	0.470674*	0.551365*	0.498676*	0.162216	0.426596*	0.370815**	-0.970634	-0.094509	0.039986
Power Parameter (δ)	0.965110*	1.273477*	1.054546*	0.007075	1.381953**	1.081369*	3.064082	7.281787***	5.228952
Volatility Persistence	0.998764	0.997999	1.006056	0.977978	0.987814	1.00059	0.558183	0.703766	0.834206

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level.

In attempting to model conditional variance, symmetric and asymmetric GARCH models have been applied in daily, weekly, and monthly return series of Asian stock markets over 25 years of data from 1993 to 2018. The results indicate that the applied models were able to remove heteroscedasticity successfully in the return series. To identify the best-fitted model among the selected GARCH applications, Akaike information criteria (AIC), Schwarz information criteria (SIC) and Hannah Quinn information criteria (HQIC) are used as well as comparison of log likelihood values. Although asymmetric GARCH models outperform in daily and weekly return series according to the criteria mentioned above, symmetric GARCH models would seem to outperform in monthly return series.

The findings of the study also showed that there is strong persistence of volatility, which means impact of shocks continues for a long period on return series. Although higher volatility creates more opportunities for individual and institutional traders, it also leads to market inefficiency (Akhtar and Khan, 2016).

McMillan et al. (2000) state that short-term investment decisions focus on short-term predictions of volatility, and the valuation of long-lived equities require longer-term predictions of volatility. In this context, the present study examines the sensitivity of results in three different frequencies to address this gap in Asian financial markets and provide further evidence on volatility characteristics from the countries such as, the Philippines, Thailand, and Taiwan which tend to be ignored. The results indicate that examining volatility with different frequencies provides different results which may have implications for making decisions and it concludes that different frequencies have their own structure and characteristics with one common point that higher frequency data is more volatile than lower frequency data, therefore market participants should be aware of the structure of volatility in these markets at different time horizons.

CHAPTER 4

Volatility Forecasting Exercise: Evidence from Ten Asian Markets

Abstract

Volatility forecasting is a key factor in predicting the values of financial instruments, value-at-risk analysis and, more broadly, measuring the risks of investments and developing hedging strategies. Thus, proper methods and accurate forecasts of volatility are needed for the application and evaluation of asset pricing models and hedging strategies. In this context, the present chapter aims to examine the relative out-of-sample predictive ability of different GARCH models for ten Asian markets by using three different frequencies and two different methods, considering the features of volatility clustering, leverage effect and volatility persistence phenomena, which the evidence of existence are found in the data. Five measures of comparison are employed in this research and a further dimension is investigated based on the classification of the selected models in order to identify the existence or not of any differences between the recursive and rolling window methods. The empirical results reveal that asymmetric models with the lead of EGARCH model provide better forecasts compared to symmetric models in higher frequencies. However, when it comes to lower frequencies of data symmetric GARCH models tend to outperform over their asymmetric counterparts. Furthermore, GARCH type models can appropriately adopt to the volatility behaviour of Asian stock indices and provide satisfactory degree of forecast accuracy in all selected frequencies. These results are also supported by Diebold-Mariano (DM) pairwise comparison test. Finally, the present paper did not find any significant superiority between employed recursive and rolling window methods.

4.1 Introduction

Volatility is the degree of variation of a trading price series over time, and usually measured by the standard deviation of logarithmic returns. As an important concern for traders, investors, companies, and financial regulatory authorities, volatility forecasts of asset returns have been studied over the years for risk management, security valuation, portfolio diversification, and monetary policy making purposes. Furthermore, especially with the stock market crash in 1987, volatility modelling and forecasting has attracted finance professionals and academics since the main reason for the crash was attributed to high volatility (Haugen et al., 1991).

The behaviour of stock market volatility is time-varying. The early prominent empirical works of Mandelbrot (1963) and Fama (1965) revealed that small (large) changes of asset prices tend to be followed by small (large) price changes with same magnitude, indicating the phenomenon of volatility clustering. Throughout the empirical applications over the last five decades, evidence suggests that volatility changes of return series are predictable, particularly in the long term (Fama and French, 1989; Wurgler, 2000; Cochrane, 2008; Campbell and Thompson, 2008). Therefore, numerous empirical models and methods have been developed and applied to identify and accurately predict the volatility behaviour of return series. Nevertheless, earlier studies reveal no consensus neither regarding model nor method provide the most accurate forecasts of asset returns.

Early studies tried to predict future volatility through simple statistical approaches based on averaging and smoothing methods. However, these simple models had limited prediction capacity as financial time series tend to accompany some special characteristics such as volatility clustering. In order to deal with this issue, Engle (1982) developed the first generation of heteroscedasticity models with the seminal idea on ARCH models. Bollerslev (1986) took another step and put forward its generalized version which is called GARCH model. Although ARCH and GARCH models took incredible attention from researchers and practitioners and proved their empirical success, these models cannot capture the stylized fact of volatility asymmetry which is later named as leverage effect by Black (1976). This constraint has been solved by the development of more adaptable and advanced versions. A noteworthy and popular example of these new class models are the Exponential GARCH (EGARCH) model of Nelson (1991), the Power GARCH (PGARCH) model of Ding et al. (1993), and the Threshold GARCH (TGARCH) model of Zakoian (1994). There are more than 330 GARCH-type models with various specifications in the literature and a number of studies are devoted to review the important GARCH family models such as Poon and Granger (2003), Bauwens et al. (2006), Silvennoinen and Teräsvirta (2009).

The aim of the present paper is to investigate and evaluate the relative out-of-sample forecasting ability of various GARCH models by comparing the three different frequencies and two different methods. Although there are competitive alternatives such as stochastic volatility and EWMA models, SV models have limitations in empirical applications due to the intractability of the likelihood function and EWMA models have shortcomings in addressing characteristics of the stock market volatility (Koopman and Hol Uspensky, 2002; Roh, 2007). In the recent years, the HAR model of Corsi (2009) is becoming increasingly popular among researchers due to its modelling accuracy (Patton and Sheppard, 2015), yet this model is also excluded in this study due to the lack of data for realized variance, especially in emerging markets of Asia. Evaluation of predicted GARCH family models is not an easy task and one of the major issues is the "true" volatility series is not observed. To overcome this problem, the squared return series is used as a proxy for the unobserved volatility process since squared returns are unbiased gauge for volatility as revealed by Andersen and Bollerslev (1998). With the usage of squared returns, proper evaluation of estimated models is ensured in terms of selected error statistics. The recent studies of Reschenhofer et al. (2020) and Nybo (2021) also show that the squared returns can be used as a true volatility proxy. Furthermore, Patton (2011) states "*…and so the squared daily return is a valid proxy*" (pp.249) and supports the usage of squared returns. Although Kambouroudis et al. (2016) find that realized variance is preferred over squared returns, this study implements squared returns as a volatility proxy due to the limitation on alternative dataset in some of the selected markets.

Another important aspect of the paper is covering a broad range of Asian markets including emerging economies. Although there are a significant number of papers on forecasting stock market volatility, there are limited studies examining the Asian markets, particularly on emerging markets such as McMillan and Kambouroudis (2009). The review of Poon and Granger (2003) reports that only five studies out of 93 papers on volatility forecasting cover Asian markets, namely New Zealand, Australia, and Japan, while no emerging Asian markets were covered. Some recent papers have individually examined stock market volatility in Asian markets such as Lux and Kaizoji (2007) for Japan, Bhattacharyya et al. (2009) for India, and Tzang et al. (2009) for Taiwan. However, the stock markets of emerging countries such as

Indonesia, Thailand, Malaysia, and the Philippines, which together constitute 66% of the market capitalization of the ASEAN economies as of 2016 (Ganbold, 2021), tend to be ignored in volatility exercises. In addition, volatility dynamics in emerging stock markets of Asia is expected to influence the global stock markets through the "leverage effect" and idiosyncratic risk factors (Atanasov, 2018; Bouri et al., 2020), and hence further indicating the importance of generating more accurate and comprehensive forecasts in this bloc. Therefore, this paper aims to extend the literature of volatility forecasting by selecting ten Asian markets with up-to-date data and covering periods of both financial crisis and recent developments.

It is broadly acknowledged by the financial literature that an increase in data frequency is accompanied by excess kurtosis, which challenges the capabilities of forecasting models due to the fat-tailed distribution on return series (Mandelbrot, 1963). Under assumption of normality for errors, the results of the models would be biased. Therefore, the present paper considers student-t distribution in all selected frequencies to capture anomalies in the return series. Furthermore, it aims to contribute to the ongoing debate for determining the best model between linear (symmetric) and non-linear (asymmetric) GARCH family models for producing the most accurate volatility forecasts.

This research adds to the current academic literature in three ways. First, it finds that GARCH-type models can appropriately adapt to the volatility behaviour of Asian stock indices and provide a satisfactory degree of forecast accuracy in all selected frequencies. The superiority of asymmetric models is more evident for higher frequencies of data, while symmetric models tend to outperform asymmetric ones in lower frequencies. Second, given the level of risk associated with investment in stock markets, day traders, investors, financial analysts, and empirical finance professionals should consider alternative error distributions while specifying a predictive volatility model, as less contributing error distributions implies incorrect specification, which could lead to loss of efficiency in the model. Investors should also not ignore the impact of news while forming expectations of investments. Finally, the obtained results report that frequency of data and choice of forecast method have a strong effect on the performance of the models, and therefore, depending on the investment perspective and risk sensitivity, correct method and data period should be applied.

The remainder of the chapter is organized as follows: Section 4.2 provides a broad review of volatility forecasting applications on various markets with an emphasis on Asian markets.

Section 4.3 reports the data and methodology used. Section 4.4 provides the empirical analysis and results. And finally, Section 4.5 discusses the findings and present a conclusion.

4.2 Literature Review

4.2.1 Introduction

Volatility forecasting is a key aspect of finance due to its central role in financial market analysis, especially for market participants to assess and measure the risks of investments and develop hedging strategies to manage and minimize the risks of portfolios. Volatility is also the essential part of pricing financial derivatives, including options, which makes volatility forecasting even more crucial for banks and other financial institutions after risk management has been placed to a key role with the release of Market Risk Amendment by Basel Committee on Banking Supervision (BCBS) in 1996.

There are numerous studies in the existing literature that have applied various approaches, yet a consensus still could not be reached for a superior forecasting model. Furthermore, even for the same stock market the conclusions are mostly different depending on the data sets, frequencies and estimation methods. Since volatility is inherently latent, observable variables are used for estimations. In principle two methods have been used widely to forecast conditional variance. The first approach applies return series based on historical prices, while the second one derives and estimates volatility from option prices which is called implied volatility. With the development of ARCH and GARCH models, changing variance can be forecasted by using both methods.

In this context, related studies on forecasting financial markets will be presented and important findings will be discussed. Then the scope of the literature will be narrowed to forecasting applications on Asian stock markets which aims to provide an insight for the volatility behaviour in selected markets.

4.2.2 Background

The vast majority of the stock market volatility related literature has been focused on western markets, particularly developed markets such as the United States, United Kingdom, and Germany (see, Poon and Taylor, 1992; Bluhm and Yu, 2001; Wilhelmsson, 2006; Minkah, 2007).

One of the first prominent works regarding the US stock market volatility by using ARCH family models is delivered by French et al. (1987). Their findings showed that there is negative correlation between unpredictable alterations in volatility and unexpected stock market returns. They used daily and monthly return series from January 1928 to December 1984. Chou (1988) followed similar approach on weekly data of the US stock market from July 1962 through December 1985. He claims that the stock market volatility is highly impacted by the persistence of shocks which supports the study of French et al. (1987). However, his findings strongly contradict with the study of Poterba and Summers (1984), where they found that unpredictable changes on volatility does not have persistent impact on the return series. Baillie and DeGennaro (1990) joined this argument by defending that predictable return series and volatility do not exhibit signs of strong connection. They covered the same sort of data from the US market by using daily and monthly frequencies for the period from January 1970 through December 1987, and from February 1928 through December 1984 respectively.

Cao and Tsay (1992) examined the NYSE using monthly return series over the period of January 1928 to December 1989. Out-of-sample forecasts was used to compared TAR, ARMA, GARCH, and EGARCH models. They concluded that EGARCH model outperforms for the long-term volatility forecasts, while GARCH underperforms compared to other three models in multi-step ahead forecasts. Brooks (1998) also studied the NYSE based on daily observations starting from November 1978 through June 1988. He used GARCH, GJR-GARCH and EGARCH models to compare out-of-sample forecasting performance and supported the study of Cao and Tsay (1992) for the superiority of EGARCH, while GJR-GARCH and GARCH models is considered inferior which are recommended by Brailsford and Faff (1996), and Akgiray (1989) respectively. For further comparison see, Pagan and Schwert (1990), Day and Lewis (1992), Najand (2002), Ederington and Guan (2005), Awartani and Corradi (2005), Mootamri (2011), Sharma (2016), and McMillan (2020).

One of the first GARCH family applications on volatility in the UK stock market was investigated by McMillan et al. (2000) using three different time horizons from 2 January 1984 to 31 July 1996. Out of 10 forecasting models, including 4 GARCH family models, GARCH and EGARCH models are favoured, especially for the higher frequencies. With a comparatively shorter time horizon and different dates, Pederzoli (2006) forecasted volatility on FTSE100 from the period of 1 January 1990 to 31 December 2001. He compared ARCH type and stochastic volatility (SV) models using daily return series and the results indicated that the

EGARCH model outperforms SV and GARCH models on out-of-sample comparison. This is in line with Obodoechi et al. (2018) and Devi (2018), for which they recommended EGARCH model for the UK market as well. However, Loudon et al. (2000) were more sceptical about the outperformance of different GARCH models on daily UK stock returns for the period of 1971 to 1997. They claimed that the performance of the model is period-specific and differs from in-sample inferences to out-of-sample inferences for each model within the same selected period.

The powerhouse economy of Europe, Germany, is an important market in the international framework which has been studied over the years. Bluhm and Yu (2001) forecasted daily DAX index returns from 01 January 1988 to 30 June 1999 by conducting the historical mean model, EWMA model, four GARCH family models and SV model. The results showed that there is no single outperforming model, yet the GARCH family models are useful. Moreover, they claim that there is no superiority of time series models over implied volatilities for forecasting volatility which supports the studies of Jorion (1995) and Blair et al. (2001). Claessen and Mittnik (2002) joined this argument following the DAX index from Germany and suggested that out-of-sample performance of GARCH models can be improved by combining GARCH and implied volatility information which minimize the bias induced from IV. Focusing solely on GARCH models, Peters (2001) studied DAX 30 using daily frequency over a 15-years period. He recommended GJR-GARCH model over the GARCH, APARCH, and EGARCH models. On the other hand, Reher and Wilfling (2016) favoured GARCH-in-Mean model over the EGARCH and other selected models on the daily German DAX index between 2000 and 2009. For further discussion, see, Franses and Van Djik (1996), Taylor (2004), and Namdari and Durrani (2018).

Forecasting exercise has also been studied in many other countries, including some of the exotic markets. Balaban et al. (2006) investigated prediction capability of a wide range of volatility forecasting models for 15 stock markets using monthly return series over the 10-year period from 1987 to 1997. Based on the findings of the study, ARCH family models are the worst forecasting models according to the standard error functions. However, under the asymmetric loss functions, GARCH family models are found superior which is consistent with the findings of Brailsford and Faff (1996) and Asarkaya (2010). On the other hand, AbdElaal (2011) argued that EGARCH model outperforms other models under the standard evaluation statistical metrics for Egyptian stock markets which he studied from 1998 to 2009. Miron and Tudor (2010) supported his findings over EGARCH superiority for Romanian stock market. While

Gokcan (2000) studied seven emerging markets including Argentina, Mexico, Colombia, Philippines, Taiwan, Brazil and Malaysia from 1988 to 1997, and recommended the linear GARCH model over the EGARCH model in terms of forecasting performance. Srinivasan and Ibrahim (2010) supported the forecasting capability of symmetric GARCH models over the asymmetric GARCH models for Indian stock market.

The ongoing argument on performance of forecasting models has also leaped into Asian stock markets. Some Asian markets have been studied deeply over the years using various models. Among these markets, Japan took the lead as the second largest stock exchange globally by market capitalization. Tse (1991) examined Tokyo Stock Exchange between the first trading day of 1986 to the last trading day of 1989. Naïve forecast based on the sample variance, EWMA and ARCH/GARCH models are applied for prediction. The forecast performance of EWMA is found superior compared to other models, as they claimed this might be due to the turbulent volatility during these years. This result is also supported by Kuen and Hoong (1992). Lux and Kaizoji (2007) studied comparatively longer horizon from 1975 to 2001 for the NIKKEI 225 index and the findings showed that GARCH family models are able to present good forecast performance compared to naïve sample variance models. They concluded that the time series models are well suited for predicting large realizations of volatility. Ishida and Watanabe (2009) extended the research in the Japanese stock market by focusing on minute-to-minute data in a sample period spanning from 1996 to 2007. They combined GARCH model with ARFIMA and predicted realized variance successfully. For further research on Japanese stock market, see, Ng and McAleer (2004), Shibata (2008), Guidi (2010), and Lee et al. (2017).

Studies on volatility in Chinese stock markets began relatively later than Japan, yet with the rapid economic progress and explosive investments to China's financial market, researcher's interest also grew gradually. Ding (1999) studied one of the earliest ARCH family applications on Chinese stock market by applying ARCH (1) and ARCH (2) models. Wei (2002) employed GARCH, GJR-GARCH, and QGARCH models to predict the Shanghai Stock Exchange Composite Index (SSE Index) and the Shenzhen Stock Exchange Composite Index (SZ Index). He used weekly data from 1992 to 1998 which covers seven years in total and the empirical results recommend that QGARCH is the best prediction model for China's stock market volatility in two of the four cases, while Random Walk model and GARCH model are also preferred in one case and GJR-GARCH model is not recommended at all. In contrast, Gu and Cen (2011) expanded the models for the same two markets and the results revealed that

GARCH and CGARCH models are preferred for more accurate prediction of volatility, and TGARCH and EGARCH are better to capture asymmetric effects of the volatility behaviour in Chinese stock markets. They also suggested that GARCH type models are more accurate for better forecasting compared to SV models for China's capital markets. Lin (2018) compared the adaptability of the GARCH models on the SSE Index and SX Index using daily returns from 2013 to 2017. Through the empirical analysis and forecast evaluation, he pointed out that the EGARCH model outperforms ARCH, TARCH, GARCH and ARIMA models and it is more competent to predict volatility behaviour in selected indices. For further research, see, Lee et al. (2001), Liu et al. (2009), Chen and Wu (2011), and Wei et al. (2018).

Following Japan and China, volatility behaviour of East Asian newly industrialized countries was particularly interesting for academics and researchers. These countries can be defined as South Korea (KOSPI), Taiwan (TAIEX), and Hong Kong (Hang Seng). These export-oriented countries are very charming for international investors and companies who are not willing to take extra risk to invest in more riskier emerging economies. There have been a number of earlier papers on these three markets over the years which have investigated volatility behaviour using a large variety of models.

Duan and Zhang (2001) examined Hang Seng Index using daily data to construct weekly returns and the findings showed that GARCH family models outperforms the Black-Scholes model either in turbulent or calm times. Chan and Fung (2007) revealed that GARCH models can provide good forecast results in the Hong Kong Stock Index when historical, implied, or realized volatility combined with the standard GARCH model. Liu and Morley (2009) compared historical volatility models with GARCH family models, and they found that although not all GARCH models outperform historical averaging, the EGARCH model provides superior forecast performance for Hang Seng index returns. Similar outcome has been reported by Sabiruzzaman et al. (2010) in the Hong Kong stock market that non-linear models outperform linear GARCH models due to the presence of asymmetric information in the daily data.

Kim et al. (2005) studied Korean stock market for the period of 1995 to 2001. The GARCH family applications has revealed that in pre-crisis period volatility is only related to domestic volume whereas after crisis period foreign volume has more impact on volatility. Kim and Won (2018) studied multiple GARCH type models with some further combinations of hybrid models for KOSPI 200 Index from 2001 to 2011. The study revealed that EGARCH provides the best out-of-sample forecast followed by GARCH and EWMA respectively. Furthermore, when it comes to Neural Network models, the ranking is identically the same with the order of GARCH type models. Chen (2003) investigated Taiwanese stock market using daily data from 01 January 1992 to 31 January 2001. Four innovation distribution assumptions are compared using GARCH models and for characterizing Taiwan stock index returns EGARCH-GED model is recommended while in-sample forecasting estimation recommended GARCH-n model and out-of-sample results demonstrated the superiority of EGARCH-M-GED model. Hung (2009) examined three Asian countries including Taiwan from 2004 to 2006. He proposed a new model and compared the forecasting performance with standard GARCH type models and the empirical results suggest that GJR-GARCH and EGARCH models are more successful than other models including standard GARCH in capturing asymmetric effects and forecasting in the Taiwanese stock market; see, Pyun et al. (2000), Choudhry (2000), and Huh et al. (2015) among others.

With an estimated combined GDP of $3.3 trillion US as of 2020, and a critical hub for global trade, Association of Southeast Asian Nations (ASEAN) have attracted international investors in the past few decades. The founding group of countries; Thailand (SET), Indonesia (JCI), Malaysia (KLCI), Singapore (STI), and Philippines (PSI) form the biggest part of the association with the exponentially growing capital markets. The growing attention also lead scholars and financial econometricians to focus more on these rapidly growing markets.

The early findings about volatility behaviour in ASEAN nations are fairly mixed. Laurence (1986), Saw and Tan (1989), and Kok and Goh (1994) revealed that random walk model is preferred to track volatility characteristics in Malaysian stock index. Lian and Leng (1994) also captured mean-reverting conditional variance for Malaysia, whereas Mansor (1999) and Pan et al. (1999) found strong ARCH effects. Sareewiwathana (1986) and Saw and Tan (1986) also found that the volatility behaviour is far from following random walk for Thailand and Singapore stock markets respectively.

Wong and Kok (2005) compared the forecasting capability of six different models using daily returns of the ASEAN-5 equity markets (Indonesia, Malaysia, Singapore, Thailand, and the Philippines) by covering the data from 2 January 1992 to 12 August 2002. They separate the results as pre-crisis, crisis and post-crisis periods and the findings suggest that forecast results are most reliable in pre-crisis and post-crisis periods, while is the least reliable in the crisis period. Furthermore, TARCH and ARCH-M models are found superior for pre-crisis period, ARCH-M and Random Walk models outperform for crisis period, while TARCH and EGARCH models are the best for post-crisis period for the selected ASEAN countries. Evans and McMillan (2007) examined the volatility forecasts of equity returns with the focus of asymmetric and long memory dynamics in more than 30 economies including ASEAN-5 countries. Eleven years of daily data is covered from 1994 to 2005. By comparing 5 GARCH family and 4 simple pre-ARCH class of models, they found that HYGARCH model for Singapore, CGARCH model for Thailand, and EGARCH model for Indonesia outperforms based on the RMSE error statistic. On the other hand, moving average method provides the best forecast results for Malaysia and the exponential smoothing method is the best model predicting the volatility of the Philippines stock market. Guidi and Gupta (2012) studied the same ASEAN-5 stock markets for the period of 02 January 2002 to 30 January 2012. APARCH model have been employed under two different distributions to predict the volatility of the returns and the empirical results reveal that APARCH with the t-distribution is a good prediction model for the selected indices. They concluded that the Indonesian stock market gives the largest response to volatility shocks among ASEAN countries.

Country specific studies have also been conducted for the ASEAN-5 countries over the years. Chong et al. (1999) investigated the prediction ability of GARCH model and its modifications for the Kuala Lumpur Composite Index (KLCI) using daily observations from 01 January 1989 to 31 December 1990. According to the empirical results, they recommend that EGARCH model is superior compared to random walk and other GARCH family models in terms of capturing skewness and one-step-ahead forecasting, while the Integrated GARCH model is the poorest model in both respects. Conversely, Lim and Sek (2013) compared the forecasting performance of GARCH, TGARCH and EGARCH models for the KLCI index from 1990 to 2010. Their findings suggest that during the pre-crisis and post-crisis periods, symmetric GARCH model outperforms. Whereas, during the turbulent period asymmetric GARCH model is preferred. Etac and Ceballos (2018) conducted a similar research on the Philippines stock market and the results showed that the GARCH family models are the most appropriate approach to estimate volatility in the Philippines stock market.

Kuen and Hoong (1992) conducted one of the earliest studies for Singaporean stock market volatility and out-of-sample forecast results based on the monthly return variances indicated that EWMA model is preferred over the historical sample variance and GARCH family models for Singapore. While Shamiri and Hassan (2007) examined both Malaysian and Singaporean capital markets by employing four different methods over a 14-year period. They revealed that fat-tailed asymmetric densities are captured successfully with asymmetric GARCH models. Furthermore, in terms of the best out-of-sample forecasts, GJR-GARCH model outperforms in the KLCI Index, while EGARCH model is preferred for Singapore's STI index.

Wiphatthananthakul and Sriboonchitta (2010a) studied SET Index from Thailand using ARMA-GARCH, EGARCH, GJR-GARCH and PGARCH models. The findings are very mixed as they found asymmetric effects in all models yet there was no existence of leverage effect. Moreover, the findings did not report clear superior model while ARMA-PGARCH produces the lowest AIC criteria value, EGARCH outperforms according to the SBIC value, and MAPE and RMSE criteria highlight the GJR-GARCH model for Thailand's stock market volatility. Moreover, Wiphatthananthakul and Sriboonchitta (2010b) employed long memory models to estimate Thailand's SET Index in a separate study, and they recommended ARMA-FIAPARCH model as the best performing model. Sattayatham et al. (2012) investigated the SET Index by using standard GARCH family models and Markov Regime Switching GARCH (MRS-GARCH) model by considering the day of the week effect. Based on the empirical estimations, they report that GARCH family models can capture one day and a week's forecasts successfully, while MRS-GARCH model is more successful for predicting longer horizons (two weeks and a month).

4.2.3 Summary and Remarks

The existing volatility forecasts literature has been reviewed by discussing multiple developed and emerging economies with the focus of selected Asian markets. The related studies in this chapter have shown that a vast range of models and methods have been employed to predict the behaviour of conditional variance. Although the reviewed literature has considerably enhanced the understanding of forecasting performance of a variety of models and volatility behaviour in emerging and developed markets, the findings from the previous studies are significantly unclear given that they were highly dependent on the selection of countries, range of the data period, and the methods followed. However, there is no ultimate procedure for selecting a proper model.

As it can be seen from the discussed literature, there is a gap of literature for Asian stock markets, particularly emerging capital markets in the region. Thus, the current paper is expected to be one of the first empirical works regarding forecast comparison in ten Asian markets using three different frequencies with 24 years of data, which includes two major crises that hit the selected economies at different magnitudes. Moreover, this research addresses the true nature of financial market volatility in countries that tend to be ignored, such as, the Philippines, Thailand, and Taiwan. In addition, identifying excess kurtosis by using student's t-distribution and using recursive and rolling window methods for the selected GARCH models is expected to contribute to the gap in methodology in the field of stock market volatility of Asian countries.

4.3 Data and Methodology

4.3.1 Data

The same dataset from Chapter 3 has been applied. Daily, weekly, and monthly time series data is obtained from Bloomberg database. Table 4.1 shows the selected markets and indices for the present chapter. Closing price data from the selected indices is converted to the return series by taking the logarithmic differences. Figures A.1, A.3, and A.5 from Appendix A present that return series are fluctuating around zero which sign the evidence of volatility clustering phenomenon.

The overall sample period covers 24 years in total as mentioned in Chapter 3 in detail. Table 4.2, 4.3 and 4.4 below report the descriptive statistics of in-sample period for each frequency. According to the tables, the mean and median are centred around zero in daily return series while with the reducing frequency tendency of deviation increase, which is expected. Looking at the skewness of the series, NIKKEI and STI indices have negative values for all selected time horizons which implies asymmetric distributions skewed to the left, while KLCI, SET and SSE indices report positive skewness for each frequency suggesting asymmetric distributions skewed to the right. For the remaining five indices, the direction of skewness changes depending on the selected frequency. If the kurtosis is considered, the given values from all tables indicate leptokurtic characteristic which signify the existence of fatter tails. Lastly, the Jarque-Bera test statistic for normality rejects the null hypothesis that return follow a normal distribution.

Table 4.1: Markets and Indices

Market	Index	Index Code
Japan	The Nikkei 225 Index	NIKKEI
Singapore	The Straits Times Index	STI
Hong Kong	The Hang Seng Index	HANG SENG
Malaysia	The Kuala Lumpur Composite Index	KLCI
Indonesia	The Jakarta Composite Index	JCI
Thailand	The SET Index	SET
China	The Shanghai Composite Index	SSE
Taiwan	The Taiwan Capitalization Weighted Stock Index	TAIEX
South Korea	The KOSPI Index	KOSPI
The Philippines	The PSE Index	PSE

Table 4.2: Summary of in-sample descriptive statistics for daily return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	-0.006896	-0.008975	0.02846	0.001518	0.039814	-0.02413	0.035713	0.013712	0.012371	-0.011758
Median	-0.002262	0.028592	0.036591	0.002292	0.058451	-0.058689	0.025033	-0.00769	0.050867	-0.038199
Maximum	7.660481	7.531083	17.2471	20.81737	13.12768	11.34953	26.99277	6.172055	8.16129	16.1776
Minimum	-7.233984	-8.695982	-14.73468	-24.15339	-12.73214	-10.02803	-17.90509	-6.975741	-12.8047	-9.744158
Std. Dev.	1.440705	1.323858	1.641641	1.632034	1.695683	1.753001	1.817131	1.53731	1.990682	1.503186
Skewness	-0.022372	-0.398517	0.119978	0.594985	0.032216	0.497725	0.876601	-0.055486	-0.189095	0.755579
Kurtosis	4.863499	7.481252	14.40016	46.90451	10.89784	7.216725	27.64449	4.889879	5.932565	15.04423
Jarque-Bera	416.2318	2024.212	15564.62	230598.5	7384.241	2227.573	71902.92	432.3149	1082.671	17515.88
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	2875	2345	2873	2869	2841	2848	2827	2895	2972	2853
Sample	12/09/1994 8/11/2006	8/31/1999 12/30/2008	1/10/1995 8/29/2006	1/10/1995 9/04/2006	1/11/1995 8/25/2006	1/11/1995 8/24/2006	1/10/1995 9/11/2006	1/11/1995 3/23/2006	1/10/1995 5/02/2006	1/11/1995 7/17/2006

Table 4.3: Summary of in-sample descriptive statistics for weekly return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	-0.04703	-0.036714	0.096331	-0.027284	0.16798	-0.125584	0.151207	-0.008768	0.028492	-0.04337
Median	0.070721	0.10386	0.196187	0.023564	0.22806	-0.009112	0.1595	0.202186	0.197534	0.044041
Maximum	11.04704	11.43806	13.9169	24.57857	18.80297	21.83839	38.07101	18.31817	14.70595	16.18463
Minimum	-11.29215	-16.46836	-19.92123	-19.02678	-17.8541	-17.24383	-22.6293	-16.40812	-19.14189	-21.98549
Std. Dev.	2.874453	2.967102	3.499748	3.428855	4.091328	4.134383	3.918802	3.590463	4.507016	3.587097
Skewness	-0.081482	-0.724046	-0.471968	0.278927	-0.049843	0.219675	1.295237	-0.150573	-0.199036	-0.264552
Kurtosis	3.901964	7.396589	6.420523	11.41934	6.898372	5.431559	19.9507	5.59161	4.444065	7.697924
Jarque-Bera	21.56245	435.6816	322.6443	1824.41	389.0519	156.4536	7289.664	172.1637	57.40346	572.7302
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	616	488	615	615	614	615	595	607	614	615
Sample	9/23/1994 7/14/2006	9/03/1999 1/09/2009	10/21/1994 8/04/2006	10/21/1994 8/04/2006	10/21/1994 7/28/2006	10/21/1994 8/04/2006	10/21/1994 9/29/2006	10/22/1994 7/22/2006	10/23/1994 7/30/2006	10/28/1994 8/04/2006

Table 4.4: Summary of in-sample descriptive statistics for monthly return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	-0.132043	-0.198429	0.361043	-0.030609	0.655951	-0.360376	0.315205	0.312537	0.407225	-0.084081
Median	0.582549	0.901965	0.94774	0.192732	0.609101	-0.200538	-0.10265	0.337473	-0.174881	-0.150691
Maximum	14.96626	11.31864	26.45214	29.44212	25.01933	28.42753	85.52026	33.23789	41.0616	33.16657
Minimum	-18.30893	-27.36404	-34.82366	-28.4632	-37.8555	-28.16608	-34.03195	-21.50303	-31.81042	-29.89063
Std. Dev.	5.856204	6.214737	8.024243	8.577219	9.078728	10.06465	11.0501	8.325613	9.702619	8.49973
Skewness	-0.259136	-1.347471	-0.132261	0.145642	-0.780137	0.122933	3.041904	0.371143	0.38633	0.210962
Kurtosis	2.867726	6.212182	5.671145	5.047541	5.767228	3.794966	25.90612	4.319366	4.991361	5.865271
Jarque-Bera	1.764292	82.77637	44.43075	26.37649	62.23404	4.269925	3463.836	14.13225	28.13555	51.72477
Probability	0.4139	0.0000	0.0000	0.0000	0.0000	0.1182	0.0000	0.0009	0.0000	0.0000
Observations	148	113	148	148	148	148	148	148	148	148
Sample	1993m10 2006m02	1999m08 2009m01	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02	1993m10 2006m02

4.3.2 Modelling Conditional Variance

There are more than 300 GARCH-type models (Hansen and Lunde, 2005) in the existing literature which some of the important ones are discussed under the "Empirical Literature" title in Chapter 2. Therefore, for compactness, the current paper confines the employed models with the most common and traditional specifications. The selected models are namely, GARCH (Bollerslev, 1986), GARCH-M (Engle et al., 1987), EGARCH (Nelson, 1991), PGARCH (Ding et al., 1993) and TGARCH (Zakoian, 1994). The return specification is given by:

$$r_t = \mu + \varepsilon_t \tag{4.1}$$

where μ is the constant mean and $\varepsilon_t = h_t z_t$ refers the returns of residual with 0 mean and 1 variance *(i.i.d.)*.
The conditional variance specifications of the chosen models are as follow:

$$\text{GARCH: } h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \mathrm{h}_{t-1}^2 \tag{4.2}$$

$$\text{GARCH-M: } h_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \beta h_{t-1}^2 \tag{4.3}$$

$$\text{EGARCH: } \ln\left(h_t^2\right) = a_0 + \beta_1 \ln(h_{t-1}^2) + a_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} \tag{4.4}$$

$$\text{PGARCH: } h_t^\theta = a_0 + \sum_{k=1}^{p} \beta_k h_{t-1}^\theta + \sum_{l=1}^{q} a_l (|\varepsilon_{t-l}| - \gamma_l \varepsilon_{t-1})^\theta \tag{4.5}$$

$$\text{TGARCH: } h_t^2 = a_0 + a_1 \varepsilon_{t-1}^2 + \gamma D_{t-1} \varepsilon_{t-1}^2 + \beta_1 h_{t-1}^2 \tag{4.6}$$

where h_t^2 is the time-dependent conditional variance and ε_t is the returns of residual. α_0, a_1, β, γ and θ are the parameters estimated using the maximum likelihood method.

4.3.3 Forecasting Methodology

Out-of-sample tests are widely considered as the "gold standard" of the forecast evaluation, and according to the "conventional wisdom" the forecasts of the estimated models should be evaluated by conducting out-of-sample fit rather than generating the same set of data that was used to estimate the model's parameters which is called "in-sample" forecast. Bartolomei and Sweet (1989), and Pant and Starbuck (1990) show that even the best in-sample forecasts may not be successful to forecast post-sample data. Furthermore, throughout the empirical studies in-sample forecasting performance is found less reliable compared to out-of-sample test which may be due to the vulnerability to outliers and data mining (White, 2000). Therefore out-of-sample forecast has seen as the "ultimate test of forecasting model" by econometricians and forecasters (Stock and Watson (2007, p. 571)). For further discussion see, West and Harrison (2006) and Clark and McCracken (2013).

Out-of-sample forecasts can be estimated using two different methods which known as recursive forecast and rolling window forecast. The recursive forecast sets a fixed initial sample data starting from $t = 1, \dots, T$ to fit the models, and L step ahead forecast is computed for out-of-sample prediction starting from time T until there is no more L step ahead forecast can be counted. On the other hand, the rolling window forecast sets a fixed initial sample data starting from $t = 1, \dots, T$ to estimate the model and specify the window length. Out-of-sample forecast begins from time T and both the start and the end estimation dates consecutively increase by one observation where the model is re-estimated each time from $t = 2, \dots, T + 1$. L step ahead out-of-sample forecast is computed beginning with time $T + 1$ until no more L step ahead forecast can be counted.

For each index, forecasting models are estimated using recursive and rolling window methods and assessed by out-of-sample performance. Maximum likelihood method has been used to estimate parameters. The choice of window size for out-of-sample forecast is controversial since there is no satisfactory solution for the optimal length. However, to robust the competence of the estimated parameters and to refrain from non-convergence problem, adequately large estimation size is recommended especially in the applications of richly parameterized GARCH family models (Pesaran and Timmermann, 2007; and Inoue et al., 2014). Therefore, the whole sample period is divided into two sample in each frequency and hold-out sample for out-of-sample forecast is chosen as second half where parameters are estimated based on the first half. In this context, similar procedure has been followed with earlier works such as Akgiray (1989), Pagan and Schewert (1990), Brailsford and Faff (1996), and Brooks (1998). Sample periods and sample sizes can be seen in Table 4.5.

Table 4.5 Sample Periods and Sample Sizes for Selected Countries and Frequencies

Country	Frequency	Estimation Period	Estimation Size	Forecast Period	Forecast Size	Full Sample Size
	Daily	12/09/1994 8/11/2006	2874	8/14/2006 5/02/2018	2876	5750
Japan	Weekly	9/23/1994 7/14/2006	616	7/21/2006 4/27/2018	617	1233
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	8/31/1999 12/30/2008	2344	12/31/2008 5/02/2018	2346	4690
Singapore	Weekly	9/03/1999 1/09/2009	486	1/16/2009 4/27/2018	489	975
	Monthly	1999m08 2009m01	112	2009m02 2018m04	114	226
	Daily	1/10/1995 8/29/2006	2874	8/30/2006 5/03/2018	2877	5751
Hong Kong	Weekly	10/21/1994 8/04/2006	614	8/11/2006 5/04/2018	616	1230
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/10/1995 9/04/2006	2871	9/05/2006 4/30/2018	2869	5740
Malaysia	Weekly	10/21/1994 8/04/2006	612	8/11/2006 4/20/2018	616	1228
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/11/1995 8/25/2006	2847	8/28/2006 4/26/2018	2841	5688
Indonesia	Weekly	10/21/1994 7/28/2006	603	8/04/2006 2/09/2018	615	1218
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/11/1995 8/24/2006	2855	8/25/2006 4/25/2018	2848	5703
Thailand	Weekly	10/21/1994 8/04/2006	613	8/11/2006 4/27/2018	616	1229
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/10/1995 9/11/2006	2828	9/12/2006 5/03/2018	2829	5657
China	Weekly	10/21/1994 9/29/2006	593	10/13/2006 5/04/2018	596	1189
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/11/1995 3/23/2006	2997	3/24/2006 5/02/2018	2895	5892
Taiwan	Weekly	10/22/1994 7/22/2006	606	7/29/2006 4/28/2018	608	1214
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/10/1995 5/02/2006	2970	5/03/2006 5/02/2018	2973	5943
South Korea	Weekly	10/23/1994 7/30/2006	613	8/06/2006 4/29/2018	615	1228
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296
	Daily	1/11/1995 7/17/2006	2875	7/18/2006 5/02/2018	2853	5728
Philippines	Weekly	10/28/1994 8/04/2006	612	8/11/2006 5/04/2018	616	1228
	Monthly	1993m10 2006m02	147	2006m03 2018m04	149	296

4.3.4. Forecast Performance Evaluation

Great decisions are based on great forecasts. There is wide selection of procedures available in the literature to evaluate the most accurate forecasts. In this study, the most common and important error measures are chosen to evaluate the predictive accuracy of selected volatility models. Nevertheless, there is no consensus about which error function is more suitable to assess the models. Therefore, instead of focusing on a single criterion, five different loss functions are determined for producing forecasts. These loss functions are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Quasi-Likelihood (QLIKE) and Mean Squared Error (MSE).

Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. The mean absolute error is given by:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\sigma_t^2 - \hat{\sigma}_t^2| \qquad (4.7)$$

where n denotes the rank of forecasted data, σ_t^2 is the true volatility series which is obtained by the squared return series and $\hat{\sigma}_t^2$ is the forecasted conditional variance at time t acquired by using GARCH family models.

Mean Absolute Percentage Error (MAPE)

MAPE is the sum of the individual absolute errors divided by each period separately. In other words, it is the average of the percentage errors. The advantage of the MAPE is that it is easy to interpret and helpful to compare the performance of the estimated volatility models. The mean absolute percentage error is defined as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\sigma_t^2 - \hat{\sigma}_t^2|}{\sigma_t^2} \qquad (4.8)$$

Root Mean Square Error (RMSE)

RMSE is the square root of the average of squared differences between prediction and actual observation. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable. Its value can only be positive, and a value of zero (almost never achieved in practice) would indicate a perfect fit to the data. In general, a lower RMSE is better than a higher one. However, comparisons across different types of data would be invalid because the measure is dependent on the scale of the numbers used. The following formula is given for the root mean square error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2} \quad (4.9)$$

Quasi-Likelihood Loss Function (QLIKE)

The term quasi-likelihood function was introduced by Robert Wedderburn in 1974 to describe a function that has similar properties to the log-likelihood function. In Qlike loss function, the mean and the variance is specified in the form of a variance function giving the variance as a function of the mean.

$$QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left(\log(\hat{\sigma}_t^2) + \left(\frac{\sigma_t^2}{\hat{\sigma}_t^2}\right)\right) \quad (4.10)$$

Patton and Sheppard (2009), Patton (2011), and Conrad and Kleen (2019) revealed that the squared error loss tends to be more sensitive to extreme observations than QLIKE which provides further motivation for using QLIKE in volatility forecasting applications.

Mean Squared Error (MSE)

MSE is another popular accuracy measure in the empirical financial literature developed by Bollerslev et al. (1994) to gauge the forecasting performance of the volatility models. As a distinctive feature, it has the tendency of penalizing large forecast errors compared to other loss functions, thus it is recognized as one of the most appropriate measures in terms of dealing with imperfect volatility proxy (Patton, 2011). The mean squared error is given as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{4.11}$$

Forecast Comparison Test (DM-test)

In order to evaluate the predictive accuracy of two competing models, the Diebold-Mariano (hereafter, the DM test) test is employed. Diebold and Mariano (2002) introduced an approach for testing of the null hypothesis of no difference for the equal forecast accuracies between two sets of competing models. The test can be applied with any error criterion such as straight differences, absolute differences, or squared differences. Furthermore, it is able to incorporate with autocorrelation between the given series. The DM test is widely employed in the empirical finance literature with various adaptations, see Xekalaki and Degiannakis (2010), Curto and Pinto (2012), Gilleland and Roux (2015), and Coroneo and Iacone (2018).

Consider two sets of competing forecast sequences defined as:

$$\{f_{it}: t = 1, 2, \dots T\}, \quad i = 1, 2 \tag{4.12}$$

and define the equation of difference between actual value y_t $\{y_t: t = 1, 2, \dots T\}$ and the predicted value f_{it} as:

$$e_{it} = f_{it} - y_t \tag{4.13}$$

The accuracy of each forecast is gauged by the loss function:

$$L(e_{it}) = e_{it}^2 \tag{4.14}$$

The loss functions adopted for this study are the absolute-error loss function and the squared-error loss function.

Absolute-error loss function:

$$L_1(e_{it}) = \sum_{t=1}^{T} |e_{it}| \tag{4.15}$$

Squared-error loss function:

$$L_2(e_{it}) = \sum_{t=1}^{T} (e_{it})^2 \tag{4.16}$$

and the loss differential between the two forecasts is defined by:

$$d_t = L(e_{1t}) - L(e_{2t}) \tag{4.17}$$

To assess whether the two competing forecasts have same predictive ability, the equal accuracy hypothesis is considered. The null hypothesis of DM test is given:

$$H_0 : E(d_t) = 0 \tag{4.18}$$

versus the two-sided alternative hypothesis of one of the two forecasts have better accuracy:

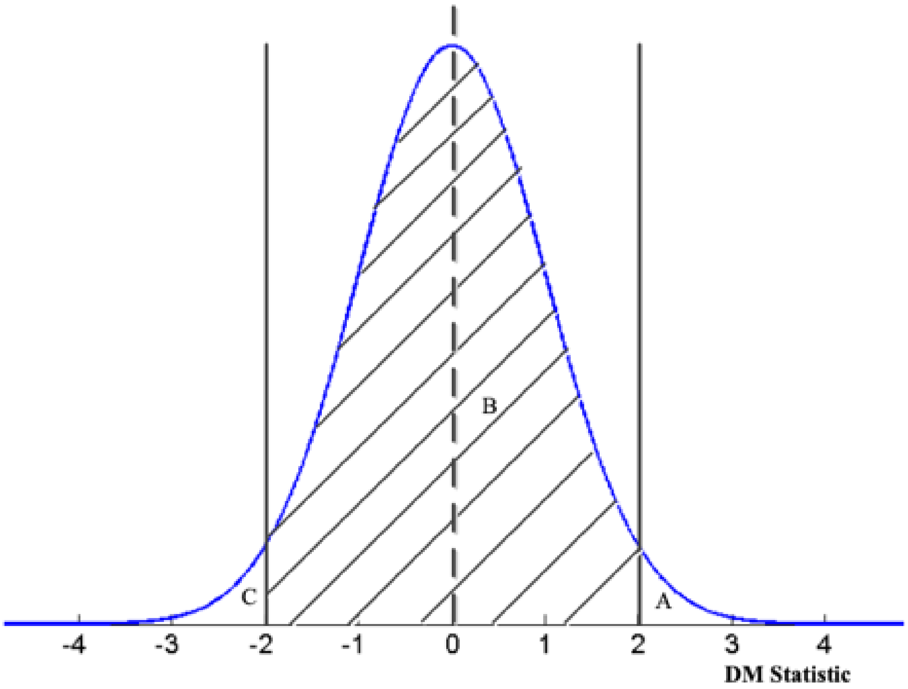
$$H_1 : E(d_t) \neq 0 \tag{4.19}$$

Then, the DM test statistic can be expressed as:

$$DM = \frac{\bar{d}}{\sqrt{\widehat{\omega}/T}} \sim N(0,1) \tag{4.20}$$

where $\bar{d} = \frac{1}{T}\sum_{t=1}^{T} d_t = \frac{1}{T}\sum_{t=1}^{T}[L(e_{1t}) - L(e_{2t})]$ and $\widehat{\omega}$ is a consistent estimator of the asymptotic variance of $\bar{d}\sqrt{T}$. The null hypothesis of H_0 is rejected if $|DM| > 1.96$ which can be shown in Figure 1 as the area A and area C. Conversely, the null hypothesis of H_0 cannot be rejected in the event of $|DM| \leq 1.96$ which corresponds to the area B in the following figure.

Figure 1: The standard normal distribution



4.4 Empirical Results

Table 4.6 demonstrates the forecasting performance for daily return series based on the calculation of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Quasi-Likelihood (QLIKE) and Mean Squared Error (MSE) using the recursive approach. The overall results of forecasting performance inform that EGARCH and TGARCH models perform better than the rest of the models in HANG SENG, STI, SET, JCI, TAIEX, KOSPI and PSE indices. These findings are also in line with the study of Liu and Morley (2009) and Wei-Chong et al. (2011), where they found that asymmetric models outperform in stock markets of Hong Kong and Japan respectively. The results also indicate that GARCH-M model outperforms in KLCI index based on MAE and QLIKE statistics, while GARCH and GARCH-M models equally outperform in SSE index, which is steady with the findings of Liu et al. (2009). KLCI index is the only index that shows mixed results since EGARCH has minimum values for both RMSE and MSE loss functions while GARCH-M indicates smallest numbers under the MAE and QLIKE statistics. Lim and Sek (2013) had similar results on Malaysia stock market which shows that Malaysian market tends to produce more complicated results and requires more detailed examination.

On the other hand, based on Table 4.7, which reports the results for Rolling Window method, there is no symmetric model that performs more superior than asymmetric models. Asymmetric models dominate in all the selected markets with the leading of EGARCH model except for HANG SENG index where PGARCH model has clear superiority based on the 4 out of 5 statistics. The reason may arise from these two issues. First, due to the nature of symmetric GARCH models, they are not able to capture leverage effect of volatility and as Chapter 3 reveals Asian stock markets tend to exhibit volatility asymmetry phenomenon. Second, the rolling window method does not allow the use of all available data to generate forecasts as in the recursive method which may lead to potential estimation problem. However, as Table 4.6 shows, asymmetric models have superiority in most of the indices as well.

The values between recursive and rolling window methods is highly mixed. Regardless of the models, a comparison cannot be conducted based on the error statistics since each method provides results in their own terms. Therefore, the present paper did not find any significant superiority between these two methods.

A general conclusion for the daily forecasting results is that in most circumstances, the asymmetric models provide smaller loss function than the symmetric models. Based on the error measures no specific model emerges as unconditionally best. Yet, in the presence of EGARCH, asymmetric models seem to outperform especially in the developed markets, which contradicts at some extent with the findings of Liu et al. (2009). As asymmetric models reduce the forecast errors in emerging markets, the findings are relatively consistent and conclusive that asymmetric models perform best compared to the symmetric models. The conclusion is that asymmetric models provide smaller loss functions than symmetric models in some markets but symmetric models have no clear superiority for daily return series among ten Asian markets except for recursive GARCH and GARCH-M models in SSE Index. Therefore, according to the provided results, asymmetric models should be the best choice for market participants, regardless of their degree of risk preference.

Table 4.6: Comparison of recursive forecast performance measures for daily return series

	MAE	**MAPE**	**RMSE**	**QLIKE**	**MSE**
NIKKEI INDEX					
GARCH (1,1)	2.587036	104.8954	6.927287	1.562947	0.4798731
EGARCH (1,1)	**2.479166**	105.4572	6.880609	**1.536782**	0.4734279

TGARCH (1,1)	2.580439	**103.9552**	**6.801676**	1.542612	**0.4626279**
GARCH-M (1,1)	2.586122	104.9069	6.927472	1.562966	0.4798987
PGARCH (1,1)	2.527196	105.0626	6.869496	1.541884	0.4718997
HANG SENG INDEX					
GARCH (1,1)	2.561509	103.1643	7.264017	1.462073	0.5276595
EGARCH (1,1)	**2.484555**	102.2727	**6.958204**	1.456995	**0.4841661**
TGARCH (1,1)	2.528717	**101.3025**	6.991431	**1.449444**	0.4888010
GARCH-M (1,1)	2.559787	103.1133	7.251374	1.461458	0.5258242
PGARCH (1,1)	2.586652	101.3267	6.995891	1.462087	0.4894248
STRAITS TIMES INDEX					
GARCH (1,1)	**0.913886**	96.78284	1.976149	0.496195	0.0390516
EGARCH (1,1)	0.910986	**95.03708**	**1.972934**	**0.491629**	**0.0389246**
TGARCH (1,1)	0.924262	95.70385	1.980209	0.495537	0.0392122
GARCH-M (1,1)	0.914155	96.81738	1.976955	0.496303	0.0390835
PGARCH (1,1)	0.951394	95.25337	2.01328	0.497664	0.0405329
SET INDEX					
GARCH (1,1)	1.906175	105.3177	6.7179	1.206068	0.4513018
EGARCH (1,1)	**1.853941**	105.0882	**6.676276**	**1.153943**	**0.4457266**
TGARCH (1,1)	1.894362	**103.8586**	6.676794	1.181998	0.4457958
GARCH-M (1,1)	1.88913	105.4373	6.712436	1.20002	0.4505679
PGARCH (1,1)	1.951078	104.5026	6.756292	1.170807	0.4564748
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	0.679296	99.98197	2.277337	0.060023	0.0518626
EGARCH (1,1)	0.667403	100.4669	**2.235911**	0.053187	**0.0499929**
TGARCH (1,1)	0.701806	**99.28575**	2.313005	0.062458	0.0534999
GARCH-M (1,1)	**0.65096**	100.0444	2.254335	**0.044328**	0.0508202
PGARCH (1,1)	0.69291	99.79142	2.276221	0.062842	0.0518118
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	2.0441	101.4464	5.259287	1.197184	0.2766010
EGARCH (1,1)	**1.996598**	100.9008	**5.176766**	**1.184489**	**0.2679890**
TGARCH (1,1)	2.037848	**99.93267**	5.222167	1.193907	0.2727103
GARCH-M (1,1)	2.043408	101.4626	5.256121	1.196861	0.2762681
PGARCH (1,1)	2.041875	100.2851	5.226898	1.195188	0.2732046
SSE COMPOSITE INDEX					
GARCH (1,1)	3.362493	**104.7333**	6.933591	1.697384	0.4807468
EGARCH (1,1)	3.337777	105.1576	**6.908015**	1.686254	**0.4772067**

TGARCH (1,1)	3.369595	104.872	6.924792	1.690698	0.4795275
GARCH-M (1,1)	**3.331011**	104.787	6.914063	1.687951	0.4780427
PGARCH (1,1)	3.384766	104.7707	6.951167	**1.683974**	0.4831872
TAIEX INDEX					
GARCH (1,1)	1.565298	99.75422	3.162739	1.028196	0.1000292
EGARCH (1,1)	**1.55803**	98.361	**3.141356**	**1.018578**	**0.0986812**
TGARCH (1,1)	1.600145	**96.6748**	3.159284	1.024245	0.0998107
GARCH-M (1,1)	1.565305	99.73742	3.161918	1.028516	0.9997723
PGARCH (1,1)	1.617696	97.8082	3.197254	1.029186	0.1022244
KOSPI INDEX					
GARCH (1,1)	1.790022	100.6294	4.913339	1.005362	0.241409
EGARCH (1,1)	**1.767842**	100.9281	**4.821477**	0.996488	**0.2324664**
TGARCH (1,1)	1.792983	**98.68959**	4.854616	**0.993382**	0.235673
GARCH-M (1,1)	1.789475	100.7094	4.912992	1.005631	0.2413749
PGARCH (1,1)	1.83218	99.27255	4.895882	1.003648	0.2396966
PSE COMPOSITE INDEX					
GARCH (1,1)	1.844115	98.15845	5.102734	1.237161	0.260379
EGARCH (1,1)	**1.808021**	97.34699	**5.021987**	**1.222524**	**0.2522036**
TGARCH (1,1)	1.858834	97.14607	5.08543	1.226648	0.258616
GARCH-M (1,1)	1.853516	98.17373	5.101353	1.241222	0.260238
PGARCH (1,1)	1.847766	**97.04785**	5.05302	1.223938	0.2553301

Notes: Numbers in bold demonstrate the minimum forecast error.

Table 4.7: Comparison of rolling window forecast performance measures for daily return series

	MAE	MAPE	RMSE	QLIKE	MSE
NIKKEI INDEX					
GARCH (1,1)	2.604888	106.2082	6.948597	1.562196	0.48283
EGARCH (1,1)	**2.475121**	**105.0707**	6.861767	**1.523355**	0.4708385
TGARCH (1,1)	2.592102	105.2052	**6.824228**	1.545574	**0.4657008**
GARCH-M (1,1)	2.604134	106.2296	6.949402	1.562222	0.4829418
PGARCH (1,1)	2.554392	105.7776	6.887053	1.545749	0.474315
HANG SENG INDEX					
GARCH (1,1)	2.50233	104.4677	7.25271	1.459778	0.526018
EGARCH (1,1)	**2.415606**	104.2941	7.049965	1.447725	0.49702
TGARCH (1,1)	2.455935	104.1706	7.008374	1.445925	0.491173
GARCH-M (1,1)	2.500407	104.3844	7.23523	1.458975	0.5234855

PGARCH (1,1)	2.432685	**104.1031**	**6.97589**	**1.443245**	**0.4866304**
STRAITS TIMES INDEX					
GARCH (1,1)	0.902532	98.64766	1.972595	0.493296	0.0389113
EGARCH (1,1)	**0.898874**	97.70559	1.975188	0.487509	0.0390136
TGARCH (1,1)	0.902942	96.84493	**1.970554**	**0.481714**	**0.0388308**
GARCH-M (1,1)	0.902158	98.66443	1.973111	0.493004	0.0389316
PGARCH (1,1)	0.928567	**97.36197**	1.997833	0.494192	0.0399133
SET INDEX					
GARCH (1,1)	1.882887	105.6482	6.710712	1.201288	0.4503365
EGARCH (1,1)	**1.840981**	104.8121	6.707536	1.161184	0.4499104
TGARCH (1,1)	1.885422	**103.8788**	**6.67502**	1.180261	**0.4455589**
GARCH-M (1,1)	1.874154	105.8696	6.711776	1.199131	0.4504793
PGARCH (1,1)	1.900219	104.6202	6.74088	**1.158713**	0.4543946
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	0.651199	101.0546	2.265128	0.038902	0.0513080
EGARCH (1,1)	**0.646715**	**99.94341**	**2.232009**	**0.033492**	**0.0498186**
TGARCH (1,1)	0.669354	100.6234	2.302587	0.038076	0.0530190
GARCH-M (1,1)	0.646861	101.3661	2.260683	0.038132	0.0511068
PGARCH (1,1)	0.652764	100.3483	2.242972	0.039637	0.0503092
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	2.026501	101.0445	5.243836	1.194157	0.2749781
EGARCH (1,1)	**1.989233**	99.66616	**5.164053**	**1.186056**	**0.2666745**
TGARCH (1,1)	2.0316	**98.96727**	5.207676	1.195521	0.2711989
GARCH-M (1,1)	2.029872	101.0232	5.248425	1.19493	0.2754597
PGARCH (1,1)	2.016035	99.50494	5.193848	1.191246	0.2697605
SSE COMPOSITE INDEX					
GARCH (1,1)	3.193871	109.9976	6.867032	1.677965	0.4715613
EGARCH (1,1)	**3.169549**	**109.723**	**6.859287**	**1.673801**	**0.4704982**
TGARCH (1,1)	3.192872	109.9885	6.867631	1.677937	0.4716435
GARCH-M (1,1)	3.194051	109.9939	6.866919	1.677952	0.4715458
PGARCH (1,1)	3.197683	109.8056	6.873206	1.674948	0.4724097
TAIEX INDEX					
GARCH (1,1)	1.544914	102.0293	3.16788	1.019933	0.1003546
EGARCH (1,1)	**1.535502**	100.4965	**3.157702**	**1.004684**	**0.0997108**
TGARCH (1,1)	1.582406	**98.35006**	3.163942	1.011804	0.1001053
GARCH-M (1,1)	1.544532	102.0356	3.167174	1.019876	0.1003099

PGARCH (1,1)	1.586746	99.80402	3.190685	1.015073	0.1018047
KOSPI INDEX					
GARCH (1,1)	1.793941	100.3222	4.914529	1.00288	0.241526
EGARCH (1,1)	**1.785204**	97.88502	**4.809564**	**0.998141**	**0.231319**
TGARCH (1,1)	1.816324	96.6203	4.861871	0.998325	0.2363779
GARCH-M (1,1)	1.794187	100.4138	4.918188	1.003083	0.2418857
PGARCH (1,1)	1.851597	**96.52826**	4.897602	1.00824	0.239865
PSE COMPOSITE INDEX					
GARCH (1,1)	1.810068	99.04375	5.080439	1.226183	0.2581086
EGARCH (1,1)	**1.785333**	**97.08529**	**4.988173**	**1.210813**	**0.2488187**
TGARCH (1,1)	1.81548	97.48082	5.052796	1.214231	0.2553075
GARCH-M (1,1)	1.808635	99.05043	5.074122	1.226355	0.2574671
PGARCH (1,1)	1.806505	97.27733	5.017069	1.213596	0.2517099

Notes: Numbers in bold demonstrate the minimum forecast error.

Table 4.8 presents the recursive forecasting results for weekly return series and one can see that the values in loss functions are higher compared to the daily forecasts except for the MAPE which is expected since it provides percentage errors. For the JCI index, EGARCH model clearly outperforms based on the four out of five loss functions. For NIKKEI, STI, SSE and PSE indices, EGARCH model is still favourable since it provides the smallest errors in MAE, RMSE and MSE error statistics except for the QLIKE in all four cases. On the other hand, HANG SENG Index is dominated by TGARCH model which provides lowest values in all error statistics which is consistent with the study of Liu and Morley (2009). The remaining four indices are quite inconclusive where there is no single volatility model that is preferred based on all five error statistics. However, focusing on the KLCI index, GARCH-M outperforms under the MAE, RMSE and MSE error functions with GARCH model under the remaining two, which contradicts with the study of Wong and Kok (2005), yet supports the findings of Brailsford and Faff (1996). The best forecasting model for Thailand's SET index is PGARCH under the RMSE, QLIKE and MSE loss functions, EGARCH under MAE, and TGARCH under MAPE which is in line with the findings of Wong and Kok (2005). SSE and TAIEX indices are inconclusive where both the symmetric and the asymmetric models have superiority.

Table 4.9 shows the rolling window forecasts for weekly series which is slightly different compared to recursive forecast results. Asymmetric models have clear superiority for NIKKEI, HANG SENG, SET, JCI, TAIEX and PSE indices. These results are consistent with Awartani and Corradi (2005), and Evans and McMillan (2007) that reveal supportive evidence for asymmetric GARCH models which produce more accurate volatility prediction in volatility forecasting. The results also display that asymmetry effect should be considered by investors in the mentioned markets above when they deal with these Asian markets. Furthermore, STI, SSE and KOSPI indices present mixed results where volatility prediction can be examined by employing either symmetric or asymmetric GARCH models. KLCI index is dominated by predictions of symmetric models which does not support the findings of Balaban et al. (2006) where they recommended asymmetric models for Malaysian stock market. According to these results, it can be said that Malaysian stock market does not seem to follow an asymmetric volatility pattern. Therefore, investors can rely on predictions of symmetric GARCH models in the medium term.

Table 4.8: Comparison of recursive forecast performance measures for weekly return series

	MAE	**MAPE**	**RMSE**	**QLIKE**	**MSE**
NIKKEI INDEX					
GARCH (1,1)	10.24704195	109.7288047	34.60629227	3.197106	11.9759546
EGARCH (1,1)	**9.852790417**	110.9811024	**34.44267618**	3.165366	**11.8629794**
TGARCH (1,1)	10.2146914	**104.1148664**	34.87318235	**3.120967**	12.1613884
GARCH-M (1,1)	10.24704195	109.7288047	34.60629227	3.197106	11.9759546
PGARCH (1,1)	10.16925746	105.1745571	34.73206302	3.141197	12.0631620
HANG SENG INDEX					
GARCH (1,1)	9.32547705	97.54144908	20.61230543	3.067299	4.24867135
EGARCH (1,1)	9.339625916	96.69445478	20.37137611	3.063201	4.14992964
TGARCH (1,1)	**9.264218226**	**94.57426436**	**20.36580757**	**3.047739**	**4.14766118**
GARCH-M (1,1)	9.320921302	97.77387765	20.63026612	3.068798	4.2560788
PGARCH (1,1)	9.429220346	94.91954197	20.45221065	3.058514	4.18292920
STRAITS TIMES INDEX					
GARCH (1,1)	5.252157757	96.08916503	12.86998243	2.206019	1.65636447
EGARCH (1,1)	4.758979982	**94.10409623**	**12.51704479**	2.201988	**1.56676410**
TGARCH (1,1)	**4.689119989**	95.41533598	12.5355122	**2.201942**	1.57139066
GARCH-M (1,1)	5.245712123	96.39410246	12.86569795	2.205946	1.65526183
PGARCH (1,1)	4.739728191	94.80038753	12.54920083	2.204196	1.57482441
SET INDEX					
GARCH (1,1)	8.426017081	99.57559993	30.5917542	2.759791	9.35855424

EGARCH (1,1)	**8.256817365**	101.2233018	30.37921097	2.744206	9.22896459
TGARCH (1,1)	8.717362695	**98.15766856**	30.83602776	2.759911	9.50860607
GARCH-M (1,1)	8.423303418	99.80803376	30.59025658	2.761036	9.35763797
PGARCH (1,1)	8.113879608	100.6702069	**30.33050086**	**2.738054**	**9.19939282**
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	3.288348242	**102.4169325**	7.19721938	**1.843497**	0.51799966
EGARCH (1,1)	3.45261819	104.9358843	7.291681023	1.870931	0.53168612
TGARCH (1,1)	3.365769532	104.065921	7.229090199	1.879609	0.52259745
GARCH-M (1,1)	**3.285864066**	102.6715916	**7.196365017**	1.844444	**0.51787669**
PGARCH (1,1)	3.912468272	105.0466439	8.171850554	1.915069	0.66779141
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	10.62651772	104.5819448	28.38330434	2.925983	8.05611965
EGARCH (1,1)	**10.58209705**	105.0888898	**28.20886416**	**2.89873**	**7.95740017**
TGARCH (1,1)	10.99610195	103.1326459	28.63523156	2.924834	8.19976486
GARCH-M (1,1)	10.61432225	104.7936276	28.37364648	2.926143	8.05063814
PGARCH (1,1)	11.06978711	**102.7527687**	28.68031894	2.919125	8.22560694
SSE COMPOSITE INDEX					
GARCH (1,1)	14.97503352	94.91533057	26.8523909	**3.313693**	7.21050897
EGARCH (1,1)	**14.49030711**	97.06112885	**26.15783872**	3.316308	**6.84232526**
TGARCH (1,1)	15.15766964	96.24289017	27.10123656	3.321227	7.34477023
GARCH-M (1,1)	15.14179153	**94.79130681**	27.04246949	3.314682	7.31295156
PGARCH (1,1)	15.76411983	98.26341017	28.41487602	3.337693	8.07405179
TAIEX INDEX					
GARCH (1,1)	**6.951689345**	96.35269128	12.59628114	**2.684637**	1.58666298
EGARCH (1,1)	7.060191741	96.55368882	12.64390506	2.693367	1.59868335
TGARCH (1,1)	6.986236118	**94.10762126**	**12.50567897**	2.691082	**1.56392006**
GARCH-M (1,1)	6.972881414	96.6849187	12.61696945	2.686138	1.59187918
PGARCH (1,1)	7.114754507	99.21654335	12.9244641	2.703149	1.67041772
KOSPI INDEX					
GARCH (1,1)	8.946319583	97.52324323	26.6996366	2.688929	7.12870594
EGARCH (1,1)	**8.678639681**	102.4499881	27.0854921	2.706622	7.33623882
TGARCH (1,1)	9.022069322	**96.89577285**	26.48031987	2.689281	7.01207340
GARCH-M (1,1)	8.917973926	97.54169095	26.66787562	2.688099	7.11175590
PGARCH (1,1)	8.846015166	98.58714164	**26.43323642**	**2.686089**	**6.98715987**
PSE COMPOSITE INDEX					
GARCH (1,1)	8.767170108	94.1165022	21.82350589	2.854801	4.76265409

EGARCH (1,1)	**8.364475703**	97.36601358	**21.61199648**	2.851791	**4.67078392**
TGARCH (1,1)	8.78391413	**91.68777522**	21.6559497	2.852224	4.68980157
GARCH-M (1,1)	8.759685864	94.16410237	21.81974201	2.854756	4.76101141
PGARCH (1,1)	8.799686403	92.48756345	21.77040975	**2.848462**	4.73950740

Notes: Numbers in bold demonstrate the minimum forecast error.

Table 4.9: Comparison of rolling window forecast performance measures for weekly return series

	MAE	**MAPE**	**RMSE**	**QLIKE**	**MSE**
NIKKEI INDEX					
GARCH (1,1)	10.23903752	115.3234282	34.6895999	3.228608	12.0336834
EGARCH (1,1)	**10.02960406**	110.4678963	**34.4978507**	3.15849	**11.9010170**
TGARCH (1,1)	10.18490051	**105.5480224**	34.87293549	**3.118403**	12.1612163
GARCH-M (1,1)	10.50922895	111.6392732	34.6563506	3.665166	NA
PGARCH (1,1)	10.16097164	107.9813858	35.27289295	3.133957	12.4417697
HANG SENG INDEX					
GARCH (1,1)	9.347053394	97.75967218	20.65139571	3.068174	4.26480144
EGARCH (1,1)	**9.118997728**	96.74101014	**20.15971826**	3.052794	**4.06414240**
TGARCH (1,1)	9.219939215	**95.76319774**	20.47479875	**3.047555**	4.19217383
GARCH-M (1,1)	9.338574572	97.99313533	20.66608513	3.069463	4.27087074
PGARCH (1,1)	9.164710922	95.99475087	20.36375296	3.04891	4.14682434
STRAITS TIMES INDEX					
GARCH (1,1)	5.112268729	**97.89894806**	12.80623319	2.196915	1.63999608
EGARCH (1,1)	4.721304268	100.264789	12.55809201	2.212307	1.57705675
TGARCH (1,1)	**4.615153369**	100.1671187	**12.53723108**	2.205709	**1.57182163**
GARCH-M (1,1)	5.106817953	98.18061964	12.80253485	**2.196883**	1.63904898
PGARCH (1,1)	4.701966549	99.08547731	12.56324032	2.203582	1.57835007
SET INDEX					
GARCH (1,1)	8.559501846	100.7626483	30.71614474	2.795522	9.43481547
EGARCH (1,1)	**8.319327042**	100.9050598	**30.52793742**	**2.773872**	**9.31954963**
TGARCH (1,1)	8.994764986	**99.48470097**	31.0105933	2.818087	9.61656896
GARCH-M (1,1)	8.548545804	100.7025553	30.69755824	2.792438	9.42340081
PGARCH (1,1)	8.386810531	105.4101086	30.63860185	2.831149	9.38723923
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	3.297103816	**102.2603225**	7.211087021	**1.841896**	0.51999776
EGARCH (1,1)	3.369799	105.3390351	7.228977783	1.866069	0.52258119
TGARCH (1,1)	3.383946928	107.5000312	7.312593617	1.888627	0.53474025

GARCH-M (1,1)	**3.293692809**	102.4692105	**7.208588101**	1.842553	**0.51963742**
PGARCH (1,1)	3.42816284	107.3560786	7.37594915	1.890691	0.54404625
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	10.73660772	103.6236215	28.36464407	2.930556	8.04553033
EGARCH (1,1)	**10.69562249**	103.0196581	**28.11420106**	**2.908711**	**7.90408301**
TGARCH (1,1)	11.12750968	**101.3239555**	28.4687193	2.931287	8.10467978
GARCH-M (1,1)	10.75247188	103.8831999	28.3614357	2.932319	8.04371035
PGARCH (1,1)	11.32325464	101.9060386	28.57454283	2.936134	8.16504497
SSE COMPOSITE INDEX					
GARCH (1,1)	13.9018026	104.3783375	26.30870349	3.324486	6.92147879
EGARCH (1,1)	**13.40776975**	105.1831596	**25.90241788**	3.318551	**6.70935252**
TGARCH (1,1)	13.72463722	105.7850418	26.2520718	3.324384	6.89171273
GARCH-M (1,1)	13.89610633	**103.9302372**	26.22439829	**3.318003**	6.87719065
PGARCH (1,1)	13.85895519	105.9204464	26.49834026	3.33063	7.02162036
TAIEX INDEX					
GARCH (1,1)	6.929810747	97.44531374	12.64146631	2.680249	1.59806670
EGARCH (1,1)	6.94199152	96.96124223	12.63376083	**2.675296**	1.59611912
TGARCH (1,1)	**6.908039017**	**96.28216513**	**12.56213378**	2.685641	**1.57807205**
GARCH-M (1,1)	6.941396055	97.80271546	12.65337317	2.682452	1.60107852
PGARCH (1,1)	7.222127158	98.81056654	13.069708	2.694263	1.70817267
KOSPI INDEX					
GARCH (1,1)	9.076358544	95.78283164	26.6779072	2.681991	7.11710732
EGARCH (1,1)	**8.977506471**	95.28897378	**26.08869043**	2.693891	**6.80619768**
TGARCH (1,1)	9.273876861	**93.62840096**	26.4485096	2.687859	6.99523660
GARCH-M (1,1)	9.062519328	95.88973008	26.69104258	**2.680772**	7.12411753
PGARCH (1,1)	9.229063314	94.09587094	26.32159032	2.698456	6.92826117
PSE COMPOSITE INDEX					
GARCH (1,1)	8.781616991	93.4202291	21.82425782	2.841792	4.76298229
EGARCH (1,1)	**8.466831256**	95.19936853	**21.54344241**	**2.831211**	**4.64119910**
TGARCH (1,1)	8.778769695	92.38548657	21.69140553	2.845177	4.70517073
GARCH-M (1,1)	8.749702644	93.51903077	21.79605048	2.838839	4.75067816
PGARCH (1,1)	9.381787835	**91.39264257**	22.20446446	2.852795	4.93038242

Notes: Numbers in bold demonstrate the minimum forecast error.

Table 4.10 reports the monthly out-of-sample forecasting results based on recursive method. With the reducing frequency, statistical values increase compared to daily and weekly time periods which is expected, except for the percentage-based loss function MAPE. The results are very surprising compared to daily and weekly outcomes. The only superiority for asymmetric models is reported from the STI index where PGARCH and EGARCH models are recommended based on the MAPE and remaining loss functions respectively. NIKKEI, HANG SENG, SSE, KOSPI and PSE models indicate mixed results and are fairly incomplete in terms of the most preferred model yet either symmetric or asymmetric models can be conducted for prediction depending on the selected loss functions. Still, it can be said based on the estimated results that these five markets are indecisive and neither symmetric nor asymmetric models dominate each other, which supports the earlier work of Ng and McAleer (2004). On the other hand, symmetric models dominate in SET and TAIEX indices except for the MAPE statistic which suggests EGARCH superiority. The smallest error values are provided by the symmetric GARCH models under all statistics for KLCI and JCI indices which is in line with the findings of Minkah (2007) and Lee et al. (2017). Thus, GARCH and GARCH-M models can be the best forecast models in these two markets for either econometricians or other market participants.

Based on the Rolling Window forecast results as presented in Table 4.11, asymmetric models are clearly superior in NIKKEI and SET indices, while EGARCH model is the single superior model based on the statistics in JCI index. This is very surprising since recursive method recommends symmetric GARCH models for JCI index, whereas rolling window method does not recommend at all. Moreover, GARCH and GARCH-M models dominate in HANG SENG index which supports the findings of Gokcan (2000) yet contradicts with the study of Liu and Morley (2009), and Sabiruzzaman et al. (2010) where they recommended EGARCH and TGARCH models respectively for Hong Kong stock market returns. Remaining indices are indecisive and inconclusive in terms of the dominance of symmetric and asymmetric GARCH models yet supports the work of Etac and Ceballos (2018).

Table 4.10: Comparison of recursive forecast performance measures for monthly return series

	MAE	**MAPE**	**RMSE**	**QLIKE**	**MSE**
NIKKEI INDEX					
GARCH (1,1)	36.13937171	108.9165511	71.39343577	4.474199	50.9702267
EGARCH (1,1)	**33.74478972**	126.4161671	71.72815663	4.51878	51.4492845
TGARCH (1,1)	36.42051006	110.5662039	72.60488221	4.474801	52.7146892
GARCH-M (1,1)	36.11342058	108.2973356	**71.18787899**	**4.467483**	**50.6771411**
PGARCH (1,1)	43.50617923	**90.5801923**	79.97545547	4.53929	63.9607347

HANG SENG INDEX					
GARCH (1,1)	44.11303339	106.3745122	75.4767641	**4.515765**	56.9674192
EGARCH (1,1)	44.50939769	108.7900812	**74.96431533**	4.552106	**56.1964857**
TGARCH (1,1)	44.87925045	105.8944785	76.3272369	4.528689	58.2584709
GARCH-M (1,1)	**43.965541**	109.0935159	75.17715281	4.536132	56.5160430
PGARCH (1,1)	63.46523175	**94.40515162**	83.0831442	4.763705	69.0280885
STRAITS TIMES INDEX					
GARCH (1,1)	26.39027302	92.42545973	46.0282317	3.805429	21.1859811
EGARCH (1,1)	**24.17079656**	86.53822773	**41.85116394**	**3.774182**	**17.5151992**
TGARCH (1,1)	24.84527773	85.81235534	43.62661678	3.767626	19.0328169
GARCH-M (1,1)	26.38496415	92.90026529	45.97301665	3.812358	21.1351826
PGARCH (1,1)	27.50161943	**83.91430967**	49.34098297	3.788462	24.3453260
SET INDEX					
GARCH (1,1)	**40.14294886**	98.66219174	**114.4438535**	4.289066	**130.973956**
EGARCH (1,1)	46.57016969	**87.34734209**	115.5980647	4.351424	133.629125
TGARCH (1,1)	41.31889381	96.84485635	116.1339308	4.291495	134.870898
GARCH-M (1,1)	40.47797495	97.68903105	114.4799052	**4.28838**	131.056486
PGARCH (1,1)	40.16653678	96.68829158	115.8919697	4.309496	134.309486
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	15.81671405	**100.8019022**	29.94179975	**3.378925**	8.96511372
EGARCH (1,1)	15.76343036	104.3824237	29.29805807	3.387469	**8.58376206**
TGARCH (1,1)	16.39680944	120.7636268	30.44154928	3.601556	9.26687922
GARCH-M (1,1)	**15.74525061**	102.3368336	**29.91456572**	3.386437	8.94881242
PGARCH (1,1)	16.5589291	117.4855398	31.24939783	3.556378	9.76524864
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	48.42643097	**89.62353775**	**123.4907233**	4.50241	**152.499587**
EGARCH (1,1)	66.8645489	95.93257192	139.8322435	4.594498	195.530563
TGARCH (1,1)	57.13590737	102.9657686	130.2570443	4.675225	169.668975
GARCH-M (1,1)	**48.30416115**	89.83505255	123.5078662	**4.497987**	152.54193
PGARCH (1,1)	58.74737026	96.2757173	143.843966	4.579117	206.910865
SSE COMPOSITE INDEX					
GARCH (1,1)	95.8644111	**114.1801706**	153.1306091	**5.198126**	234.489834
EGARCH (1,1)	94.32650292	128.5285823	**149.8592953**	5.285649	**224.578084**
TGARCH (1,1)	98.91509954	117.0330358	159.0790699	5.225212	253.061504
GARCH-M (1,1)	**93.09644502**	273.0684384	153.2074552	5.216335	234.725243
PGARCH (1,1)	100.3712522	120.0527793	164.7702377	5.232148	271.492312

TAIEX INDEX					
GARCH (1,1)	**28.18671674**	95.04204526	**50.06840478**	**4.023104**	**25.0684515**
EGARCH (1,1)	43.19547421	**81.27518973**	52.2496524	4.259888	27.3002617
TGARCH (1,1)	31.25622181	86.49914406	50.84625876	4.044196	25.8534203
GARCH-M (1,1)	31.98645284	83.08716116	54.44363312	4.824353	NA
PGARCH (1,1)	34.09138681	90.51921831	55.12185896	4.120919	30.3841933
KOSPI INDEX					
GARCH (1,1)	32.62617527	94.65923674	66.50816143	4.047954	44.2333553
EGARCH (1,1)	32.17000663	101.205364	66.51652596	4.058136	44.2444822
TGARCH (1,1)	34.7002436	99.77480809	69.42858055	4.091565	48.2032779
GARCH-M (1,1)	32.42825266	**92.66106591**	66.39169416	**4.027558**	44.0785705
PGARCH (1,1)	**29.39189557**	99.71261927	**59.43565374**	4.037928	**35.3259693**
PSE COMPOSITE INDEX					
GARCH (1,1)	33.78831738	90.44866151	70.43109114	4.30187	49.6053859
EGARCH (1,1)	36.61106192	98.29816079	71.03252277	4.392878	50.4561929
TGARCH (1,1)	38.06951705	**84.10260598**	71.83112695	4.336803	51.5971079
GARCH-M (1,1)	**33.5974511**	91.90064622	70.59149337	**4.301618**	49.8315893
PGARCH (1,1)	34.03357458	90.58543272	**70.10124654**	4.307639	**49.1418476**

Notes: Numbers in bold demonstrate the minimum forecast error.

Table 4.11: Comparison of rolling window forecast performance measures for monthly return series

	MAE	MAPE	RMSE	QLIKE	MSE
NIKKEI INDEX					
GARCH (1,1)	35.68034204	137.6621932	71.37525994	4.607964	50.9442773
EGARCH (1,1)	**35.6192196**	110.5984806	**71.09597635**	**4.449931**	**50.5463785**
TGARCH (1,1)	36.62242496	114.3439591	73.04373464	4.471616	53.3538717
GARCH-M (1,1)	1.61E+27	114.5584416	1.95E+28	5.351015	3.82E+56
PGARCH (1,1)	46.30306072	**105.7651175**	81.02921426	4.670946	65.6573356
HANG SENG INDEX					
GARCH (1,1)	44.26956718	**109.7175226**	76.87958946	**4.525215**	59.1047127
EGARCH (1,1)	44.10793906	115.8362886	76.01769424	4.610958	57.7868983
TGARCH (1,1)	45.59502803	111.4239774	77.32264709	4.568397	59.7879175
GARCH-M (1,1)	**43.80363089**	112.7806508	**75.93705209**	4.548415	**57.6643588**
PGARCH (1,1)	52.77150671	117.5579398	78.68502738	4.746715	61.9133353
STRAITS TIMES INDEX					
GARCH (1,1)	24.51726305	**93.17751469**	42.46318504	3.778342	18.0312208

EGARCH (1,1)	22.5504177	104.3194475	40.63369021	3.796456	16.5109678
TGARCH (1,1)	**22.04210235**	102.7597891	**38.33341071**	3.775107	**14.6945037**
GARCH-M (1,1)	24.49186442	94.26876325	43.00772655	3.784755	18.4966454
PGARCH (1,1)	24.00816988	99.11157724	43.16818931	**3.736314**	18.6349256
SET INDEX					
GARCH (1,1)	40.89568127	96.97461538	116.1304944	4.284368	134.862917
EGARCH (1,1)	42.99820562	**87.30635411**	113.8064589	4.358476	129.519100
TGARCH (1,1)	41.27529169	87.89284013	116.8322756	**4.275816**	136.497806
GARCH-M (1,1)	41.05914869	95.55166231	115.5835173	4.280834	133.595494
PGARCH (1,1)	**37.90849038**	95.48605127	**111.9304698**	4.326555	**125.284300**
KUALA LUMPUR COMPOSITE INDEX					
GARCH (1,1)	**15.77922042**	**103.2035548**	30.07818857	**3.395053**	9.04697427
EGARCH (1,1)	15.94107972	104.8350858	**29.9386287**	3.413558	**8.96321488**
TGARCH (1,1)	16.99634379	114.2177454	31.27121235	3.529704	9.77888721
GARCH-M (1,1)	1.02E+242	104.8220037	NA	10.34143	NA
PGARCH (1,1)	22.52956236	124.1088923	34.18635538	3.846813	11.6870689
JAKARTA COMPOSITE INDEX					
GARCH (1,1)	46.0127606	89.11073762	122.7407655	4.421782	150.652955
EGARCH (1,1)	**42.60991903**	**88.74935183**	**116.8132784**	**4.295547**	**136.453420**
TGARCH (1,1)	50.18068336	92.53907147	127.6355682	4.433328	162.908382
GARCH-M (1,1)	47.04107957	90.91205072	123.2588292	4.449774	151.927389
PGARCH (1,1)	54.7163157	95.28763404	142.990259	4.486811	204.462141
SSE COMPOSITE INDEX					
GARCH (1,1)	83.77736342	**124.8769572**	139.3492393	**5.21587**	194.182105
EGARCH (1,1)	83.11516659	147.1610836	136.9202249	5.482313	187.471479
TGARCH (1,1)	80.09052779	206.1656405	139.5677941	5.947184	194.791691
GARCH-M (1,1)	7.50E+38	130.2258094	9.09E+39	5.879085	8.26E+79
PGARCH (1,1)	**79.60418389**	130.9162032	**134.4769281**	5.219584	**180.840442**
TAIEX INDEX					
GARCH (1,1)	**28.29841929**	96.42357262	50.47603031	4.018177	25.4782963
EGARCH (1,1)	33.05684801	**83.84097093**	53.0489444	4.029078	28.1419050
TGARCH (1,1)	29.12683151	92.9883831	**50.01473118**	4.028996	**25.0147333**
GARCH-M (1,1)	1.39E+197	93.71602343	NA	12.60411	NA
PGARCH (1,1)	28.30199991	89.98944316	50.28092746	**3.9715**	25.2817166
KOSPI INDEX					
GARCH (1,1)	**30.91354564**	109.2698937	**65.92265188**	**4.006989**	**43.4579603**

EGARCH (1,1)	34.37528301	99.65449925	69.43052129	4.070387	48.2059728
TGARCH (1,1)	33.64263426	109.9297935	70.90057768	4.017745	50.2689191
GARCH-M (1,1)	707.0296796	106.3544693	2251.795946	4.454703	50.7058498
PGARCH (1,1)	32.64005915	**99.78512706**	67.46846057	4.027628	45.5199317
PSE COMPOSITE INDEX					
GARCH (1,1)	**33.82456354**	97.96613715	**71.18282651**	**4.37822**	**50.6699479**
EGARCH (1,1)	39.1332937	92.95452889	73.20748989	4.391089	53.5933657
TGARCH (1,1)	42.35321892	86.68376403	80.85382678	4.429187	65.3734130
GARCH-M (1,1)	2.23E+304	248.0119527	NA	113.9237	NA
PGARCH (1,1)	39.36423634	**86.54202952**	72.57175236	4.427396	52.6665924

Notes: Numbers in bold demonstrate the minimum forecast error.

Tables from B.1 to B.10 in Appendix B report pairwise Diebold and Mariano test results for a further evaluation of the performance in selected forecasting models for each selected index. In the tables below, DM(A) and DM(S) indicate DM test statistics based on the absolute-error loss and the squared-error loss, respectively. Their corresponding *p*-values are also attached for each statistic to show the level of significance.

The conducted DM test results mostly in line with the forecasting results as can be seen from the tables in Appendix B. A considerable portion of the pairwise comparison shows that the forecasting accuracy of one of the selected models are better based on the value of the error loss. Specifically, the daily results provide more significant values based on the absolute-error loss criteria for both recursive and rolling window methods. EGARCH model defeats other models in most series which is in line with the outcome of the given loss functions. On the other hand, according to the daily results based on the squared-error loss, NIKKEI, STI, SET, SSE and TAIEX indices cannot provide a certain forecasting accuracy between compared models due to the weakness on DM test results.

The weekly results are more indecisive compared to the daily DM test results. The DM statistics for NIKKEI and HSI Indices are less than 1.96, therefore, the zero hypothesis cannot be rejected. Thus, the observed difference between the forecasting performance of selected models is not significant and might be due to stochastic interference. Similarly, the predictive ability of the nonlinear GARCH models is fairly stronger compared to linear GARCH models in most series. STI and KLCI indices also do not provide noteworthy test results based on the squared-error loss criterion. However, the remaining indices indicate similar results with empirical forecasting results for both recursive and rolling window methods.

Finally, the forecasting comparison for monthly return series report significant forecasting accuracy for superior models especially those based on the absolute-error loss. Specifically, symmetric GARCH models provide higher and more significant predictive performance in most series which supports the earlier results of the given loss functions. On the other hand, the DM statistics based on the squared-error criteria provide weaker results due to the smaller values for both recursive and rolling window methods therefore the zero hypothesis cannot be rejected.

Summarizing the results listed in the following tables shows that the DM test results are highly consistent with the empirical volatility forecasts, indicating the evaluation of the forecasts are strong and accurate as the outcomes are supported by the DM test statistics.

4.5 Summary and Conclusion

The present paper examines the volatility forecasting ability of the GARCH-type econometric models based on recursive and rolling window methods for ten Asian stock markets, inspired by the theoretical gap for model accuracy and the practical need for more comprehensive evidence for the selected markets and models. Five GARCH models are considered, namely GARCH, GARCH-M, EGARCH, TGARCH and PGARCH models where the first two represents symmetric and the remaining three represents asymmetric models. Daily, weekly, and monthly return series data have been used and the evaluation of the forecasts are determined by using five different error statistics.

Based on the empirical analyses, GARCH type models can appropriately adapt to the volatility behaviour of Asian stock indices in all selected frequencies. Superiority of asymmetric models are more evident for higher frequencies of data, while symmetric models tend to outperform in lower time periods. More precisely, the EGARCH model generates the most accurate volatility forecasts, closely followed by the TGARCH and PGARCH models for the daily and weekly frequencies, indicating that asymmetric specification of volatility dynamics needs to be considered. This outcome may also further imply that the asymmetric models might be more appropriate than the symmetric models when applying risk management strategies for Asian stock markets. However, when it comes to monthly return series, GARCH-M model gains more attention, and the superiority of asymmetric models decrease compared to higher frequencies of data. Moreover, using three different frequency implies that not only does the ranking differ when applying various error statistics, but also how significantly it can differ. There is an important controversy that one error statistic suggests that a particular model is the best and another error statistic suggests that the same model to be the worst. This highlights the importance of choosing a proper error statistic for the intended purpose of the forecast.

For a better visualization of the performance of the employed models and overall conclusion, Table 4.12, Table 4.13 and Table 4.14 are created. According to Table 4.12, EGARCH model is clearly superior for both methods, followed by TGARCH model. Performance records of GARCH, PGARCH, and GARCH-M models reports double digit numbers in terms of worst overall performance. Moreover, EGARCH model does not report any numbers among worst performers for both methods which makes the model a clear winner and highlights the asymmetric specification of volatility dynamics in daily return series. Rolling Window GARCH and GARCH-M models do not provide any accurate forecast values and become the worst performers. The results are consistent with Awartani and Corradi (2005) and Evans and McMillan (2007).

Table 4.13 indicates that EGARCH and TGARCH models provide the lowest error statistics in total compared to other models which make them the best performs for weekly return series. Surprisingly, PGARCH model becomes the worst forecasting model based on the reported values. GARCH and GARCH-M models increase forecasting powers compared to daily results which suggest that symmetric models should be considered for better risk management purposes in selected Asian markets for weekly returns series. The results are partially in line with Ng and McAleer (2004), Liu et al. (2009), and Sharma (2016).

Based on the reported values by Table 4.14, EGARCH still provides strong forecast performance record compared to its asymmetric counterparts, while GARCH seems to be the best forecasting model for monthly return series. This may be due to the reducing asymmetric volatility dynamics in the lower frequencies. Furthermore, GARCH-M model indicates mixed results which seems to be penalized more by rolling window method, while recursive method put it among the best performers. PGARCH model is the clear loser, followed by TGARCH model. These findings are in line with Balaban (2004) but contradict with Atoi (2014) which recommends PGARCH model as a best performer.

Table 4.12: Summary of performance ranking of the models for daily return series

Loss Function	MAE		MAPE		RMSE		QLIKE		MSE		TOTAL	
Performance/ Models	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**
Recursive GARCH	1	2	1	2	0	4	0	3	0	5	2	16
Rolling Window GARCH	0	2	0	3	0	2	0	4	0	3	0	14
Recursive EGARCH	7	0	1	4	9	0	6	0	9	0	32	0
Rolling Window EGARCH	10	0	4	0	6	0	7	0	6	0	33	0
Recursive TGARCH	0	1	7	0	1	1	2	0	1	0	11	2
Rolling Window TGARCH	0	3	3	0	3	1	1	1	3	1	10	6
Recursive GARCH-M	2	0	0	4	0	1	1	3	0	1	3	9
Rolling Window GARCH-M	0	0	0	7	0	4	0	2	0	2	0	15
Recursive PGARCH	0	7	1	0	0	4	1	4	0	4	2	19
Rolling Window PGARCH	0	5	4	0	1	3	2	3	1	4	8	15

Table 4.13: Summary of performance ranking of the models for weekly return series

Loss Function	MAE		MAPE		RMSE		QLIKE		MSE		TOTAL	
Performance/ Models	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**
Recursive GARCH	1	1	1	1	0	3	3	4	0	2	5	11
Rolling Window GARCH	0	3	2	1	0	1	1	0	0	1	3	6
Recursive EGARCH	6	0	6	3	5	1	0	1	5	1	22	6
Rolling Window EGARCH	7	0	0	2	7	0	4	0	7	0	25	2
Recursive TGARCH	2	2	1	0	2	1	3	0	2	2	10	5
Rolling Window TGARCH	2	2	6	1	2	1	2	1	2	1	14	6
Recursive GARCH-M	1	1	1	2	1	1	1	2	1	1	5	7
Rolling Window GARCH-M	1	1	1	3	1	2	3	2	1	2	7	10
Recursive PGARCH	0	6	1	4	2	4	3	3	2	4	8	21
Rolling Window PGARCH	0	4	1	3	0	6	0	7	0	6	1	26

Table 4.14: Summary of performance ranking of the models for monthly return series

Loss Function	MAE		MAPE		RMSE		QLIKE		MSE		TOTAL	
Performance/ Models	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**	**Best**	**Worst**
Recursive GARCH	2	0	3	2	3	0	4	0	3	0	15	2
Rolling Window GARCH	4	1	4	3	2	0	5	0	2	0	17	4
Recursive EGARCH	2	3	2	3	3	0	1	3	4	0	12	9
Rolling Window EGARCH	2	1	3	2	3	2	2	1	3	1	13	7
Recursive TGARCH	0	2	1	2	0	3	0	3	0	3	1	13
Rolling Window TGARCH	1	0	0	2	2	1	1	1	2	2	6	6
Recursive GARCH-M	5	0	1	3	2	0	5	2	1	0	14	5
Rolling Window GARCH-M	1	6	1	1	1	3	0	5	1	3	4	18
Recursive PGARCH	1	5	3	0	2	7	0	2	2	7	8	21
Rolling Window PGARCH	2	2	2	2	2	4	2	3	2	4	10	15

Through the analyses above, the following conclusion can be drawn.

- Symmetric and asymmetric GARCH models can be applied to Asian stock markets. Although these models were developed and widely used in the process of researching western financial markets, it does not obstruct the use of them in emerging or developed Asian financial markets.

- In terms of the time series perspective, the volatility behavior of Asian markets indicates considerable clustering and time-varying events. This is more evident during the turbulent times, such as the 1997-98 Asian crisis and the 2008 US subprime crisis, due to the information shock on the markets reflecting the phenomenon whereby large changes tend to be followed by large changes, of either sign, small changes tend to be followed by small changes.

- Given the level of risk associated in investment in stock markets, day traders, investors, financial analysts, and empirical finance professionals should consider alternative error distributions while specifying predictive volatility model as less contributing error distributions implies incorrect specification, which could lead to loss of efficiency in the model. Also, investors should not ignore the impact of news while forming expectations on investments.

- Frequency of the data and choice of forecast method have strong effect on performance of the models. Therefore, depending on the investment perspective and risk sensitivity, the correct method and data frequency should be applied.

The out-of-sample performance of the compared volatility models in terms of the different loss functions based on the three data sets thus suggests a bit of a challenge. It is far from evident which of the specific conditional volatility models outperforms the other. First, the ranking of models based on a specific loss function differs for the three data sets. Secondly, for the selected markets the best and worst model depends heavily on which loss function is used. To answer which model has the best out-of-sample performance one must first consider the specific data set used and then which loss function to use as the criteria.

CHAPTER 5

Do Artificial Neural Networks Provide Improved Volatility Forecasts: Evidence from Asian Markets

Abstract

Forecasts of stock market volatility is an important input for market participants in measuring and managing investment risks. Thus, understanding the most appropriate methods to generate accurate is key. In this context, this chapter examines the utility of Machine Learning methods, specifically focusing on the application of Artificial Neural Network (ANN) models to forecast volatility. The ANN models were estimated and assessed by comparing with traditional non-linear forecasting models in terms of prediction accuracy and robustness. Ten Asian markets have been studied using 24 years of daily data, while the first half is used for training and the second half is reserved for out-of-sample prediction. The empirical results for ANN models are promising. Out-of-sample forecast evaluation reveals that ANN models are superior for each index compared to benchmark models of GARCH and EGARCH which indicates improved forecasting accuracy and strong performance, thereby offering new exiting capabilities for market participants, academics, and policymakers. In addition to standard statistics forecast metrics, risk management measures are considered including the value-at-risk (VaR) average failure rate, the Kupiec LR test, the Christoffersen independence test, the expected shortfall (ES) and the dynamic quantile test. The findings report that VaR analysis of the models accurately capture market risk exposure in selected markets with the desired confidence horizon, which is also supported by the backtesting metrics, providing general support for the ANN and suggesting a fruitfull approach for financial risk management.

5.1 Introduction

Stock market volatility has been one of the most core issues in financial literature over the past several decades where considerable number of studies have been addressed by economists and researchers. Earlier works regarding the volatility phenomenon started with the aftermath of the first contemporary global financial crisis in October 1987, the day also known as Black Monday, where twenty-three major world markets experienced staggering collapse in a single day. More specifically, eight out of these twenty-three industrialized countries dropped by 20 to 29% while Mexico, Malaysia, and New Zealand stock markets slumped by 30 to 39%. The most affected country was Hong Kong with a decline of 45.8%, while the Austrian stock market was the least impacted among all with an 11.4% fall. According to Schaede (1991), the total estimated worldwide loss was US$1.71 trillion. Moreover, during the global financial crisis (GFC) in 2007-2008, the main benchmark index of the US stock market, S&P 500, saw the worst weekly drop ever with a more than 20% drop as well as Dow Jones Industrial Average (DJIA) with over 18% drop. The International Monetary Fund (IMF) estimated that US$2 trillion was wiped out from the World economy. Besides, one of the most dramatic stock market crashes has been seen in modern financial history due to the COVID-19 pandemic in March 2020 which led to the plunge of stock markets all over the World. The DJIA index slumped more than 26% in four trading days, while the price of WTI crude oil fell into negative territory for the first time in recorded history. The global stock markets lost over US$16 trillion within 52 days. As the history indicates, the wide swings in the stock markets lead to greater uncertainties that is usually followed up by anticipation of a pending financial crisis. Thus, the interest in modelling and forecasting financial markets has grown over the years to understand crises, tail events, and systematic risks better. In 1982, Robert Engle addressed volatility estimation by developing the ARCH model which is considered one of the most significant theoretical developments in financial literature. It is followed by the GARCH model which was developed by Engle's student Tim Bollerslev in 1986 and the RiskMetrics variance model (also known as Exponential Smoother) in 1989 by the Chairman of JP Morgan, Dennis Weatherstone. Furthermore, the Volatility index (VIX) was developed by the Chicago Board Options Exchange (CBOE) to measure stock market expectations in 1993, based on S&P 500 index options. The VIX index is also referred as a fear gauge by market participants. Additionally, CBOE extended the volatility index for other indexes, namely the VXN for the NASDAQ 100 Index, the VXD for the DJIA Index and finally the RVX for the Russell 2000 index. Today, many countries have adopted this method to create their own volatility indexes such as VKJ for NIKKEI 225 index, VHSI for HANG SENG Index, and so on. All the mentioned methods above have received great attention both by financial academia and industry over the years, and today these methods are still trusted metrics in use. Nevertheless, the characteristic constraints on the historical volatility models and the growing transformation of financial markets with the new technologies show the necessity for more advanced solutions and improved volatility models. Thus, machine learning models based on Artificial Intelligence (AI) technology has significantly improved in recent years, although the controversy between academics and finance professionals still exists in terms of accuracy power and applications of AI based volatility models.

Although the stock market prediction has been one of the most trending topics among researchers and market professionals throughout the years due to its marketable and economic implementation, its popularity has levelled up with the adaptation of Machine Learning (ML) technology on financial instruments. A complete explanation of stock market prediction in a computational approach is given by McNelis (2005) as: "*Questions of finance and market success or failure are first and foremost quantitative. Applied researchers and practitioners are interested not only in predicting the direction of change but also how much prices, rates of return, spreads, or likelihood of defaults will change in response to changes in economic conditions, policy uncertainty, or waves of bullish and bearish behaviour in domestic or foreign markets. For this reason, the premium is on both the precision of the estimates of expected rates of return, spreads, and default rates, as well as the computational ease and speed with which these estimates may be obtained. Finance and market research is both empirical and computational*" (xi). There is no doubt that with the advent of the digital computer, stock market prediction has since moved into the technological realm. Moreover, the importance of computational speed has become more important than ever before for the banks, hedge funds or retail investors which they require to make investment decisions in a short period of time with today's massive quantity and constant inflow of news. Since news is now processed so quickly, there has been a huge increase in the volume of transactions which generates volatility and noisy data. This phenomenon specifically applies to stock markets where volatility is likely to create a ripple effect on asset prices. For instance, the Dow Jones Industrial Average (DJIA) collapsed 1,010.14 points (around 9%) within minutes (approximately 5 minutes) during the flash crash of 2010. Moreover, the NIKKEI 225 Index of Japan tumbled over 10% in a day after the nuclear catastrophe caused by the earthquake in 2011, which wiped off around US$287 billion from Tokyo stock market. As it can be seen, either financial or nonfinancial events can cause significant economic fallouts. So, the question of how to effectively filter the massive amount of information from dispersed signs of market for more comprehensive decision-making process or better smooth market functioning policy is the element of stock market forecasting exercise and core interest of financial academics. In response, statistical models have been developed and applied over the years. But such models are not able to capture sophisticated non-linear patterns. Thus, in order to overcome such restraints and effectively address today's noisy, fast paced, and non-linear markets, Neural Network (NN) methods based on Artificial Intelligence (AI) techniques have been proposed. The original definition of Artificial Intelligence is given by the founder of the term AI, John McCarthy, as: "*It is the science and engineering of making intelligent machines, especially intelligent computer programs. It is related to the similar task of using computers to understand human intelligence, but AI does not have to confine itself to methods that are biologically observable*" (2), McCarthy (2004). And more specifically, the notion of Computational Intelligence (CI) was first used in 1990, which is considered as a subset of AI, and the first clear definition was revealed by Robert Bezdek in 1994, as: "*A system is called computationally intelligent if it deals with low-level data such as numerical data, has a pattern recognition component and does not use knowledge in the AI sense, and additionally when it begins to exhibit computational adaptively, fault tolerance, speed approaching human-like turnaround and error rates that approximate human performance*" Bezdek (1994). Today, a variety of Machine Learning methods, such as Artificial Neural Network models, Fuzzy Sets, Swarm Intelligence models and Support Vector Machines, are in use and enabling the provision of solutions in numerous areas, including empirical finance and stock market prediction. See, Ciarlone and Trebeschi (2005), Pacelli et al. (2011), Ticknor (2013), Kristjanpoller et al. (2014), and Dunis et al. (2016).

The history of Neural Networks started with Warren McCulloch and Walter Pitts in 1943 who introduced the mathematical definition and network structure of a neuron. This seminal work led to further research on Neural Network methods and in the early 1950s, these networks translated onto computational systems with the first learning-based model on neural systems called Hebbian Network which was successfully implemented in 1954. However, the advance requirement of computational power for ANN models did not allow for further developments due to the weak and primitive computer technology at that time, and the growing enthusiasm for Neural Networks dwindled. The thawing of "the AI winter" began with the golden age of the technology where the computer systems developed tremendously. The invention of an associative neural network by Hopfield (1982), also known as the Hopfield Network, rekindled the interest of researchers for Artificial Intelligence in the early 1980s. At present, Neural Networks have a broad range of usage in various fields, including stock market prediction. The ANN models provide countless benefits when compared with conventional statistical linear forecasting methods such as tolerance of noisy and incomplete datasets, robustness in storing and processing data, dealing with non-linear problems, providing complex network connections, being self-adaptive, and enabling approximation for any continuous function to any desired degree of precision. But, as in every other forecasting model, ANNs also have some drawbacks. One of the main weaknesses of ANN models is difficulty of showing the problem to the network. Since ANNs can work with numerical information, problems have to be translated into numerical values before being introduced to ANN which directly influences the performance of the network. Therefore, it is very important to identify a suitable set of input parameters for more precise forecasting results. Another weakness is overfitting due to the structural complexity of the network. Sermpinis et al. (2013) showed that this problem can be solved by dividing the overall dataset into training period (in-sample) and testing period (out-of-sample). Although these limitations remain controversial for ANN models, the future of AI and ML is highly bright in terms of financial service and fintech perspective. Currently, AI technology holds a global market value of over US$30 billion where the Fintech's share is estimated around US$6 billion. It is forecasted that the global AI market will grow up to US$126 billion by 2025.

5.1.1 Outline and Research Contribution

Traditional market theories and methods are considered incompatible and inadequate with the modern financial analysis (Brav and Heaton, 2002). In recent years, Machine Learning methods have been used broadly for stock market forecasting due to their flexibility and feasibility (Bebarta et al., 2012). As these models are capable of learning any non-linear patterns and functions, they have also been demonstrated as universal function approximators (Hornik et al., 1989; Kosko and Toms 1993). Therefore, this chapter aims to contribute current financial literature with the application of sophisticated neural network and deep learning techniques to Asian stock market volatility and considering the volatility forecasts, including economic-based implications, against traditional benchmark econometric models. This research improves the forecasting capability of machine learning models by applying various learning algorithms in addition to fuzzy-logic methods with wide architecture selection. In doing so, the benchmark indices have been selected from ten emerging and developed Asian stock markets with 24 years of daily data frequency. Several prominent ANN models have been chosen among the broad range of AI family, including based on static, dynamic and supervised learning techniques and implemented for the forecasting exercise. The first 12 years of the overall sample period have been used for in-sample training and the remaining 12 years of data used for out-of-sample estimation. The performance of the ANN models has been compared with each other as well as with the benchmark models including the GARCH family models. The evaluation of the models is based on the widely accepted forecast error criteria, namely: RMSE, MAE, MAPE, MSE, and QLIKE. Finally, VaR and backtesting are performed by the average failure rate, the Kupiec LR test, the Christoffersen independence test, the expected shortfall and the dynamic quantile test of Engle and Manganelli for the risk management and model accuracy purposes.

5.2 Background

This section aims to briefly give an overview of the present state of the field of Machine Learning techniques for financial market forecasting. The section starts with the investment related theories namely, the Effective Market Hypothesis (EMH) and the Adaptive Market Hypothesis (AMH). It is followed by the overview of earlier forecasting attempts such as fundamental analysis and technical analysis to provide a further insight on these approaches and their incorporation with the ML systems. This is then followed by the related literature and finally, the parameters and the learning procedures of NN models will be discussed at the end of the section.

5.2.1 Efficient Market Hypothesis

Stock market prediction is considered one of the most demanding and challenging domains of empirical finance due to its dynamic and chaotic nature. The efficient market hypothesis (EMH), also known as the efficient market theory, is a hypothesis that states all available information about financial assets is already reflected into the prices of those securities by rational investors. Therefore, the asset prices will only be influenced by new information, and it is not possible to beat “the efficient” and unpredictable market constantly (Malkiel, 2003). Fama (1965) revealed the EMH for the first time and associated with the concept of “random walk” which is a theory stating that market prices move randomly and thus cannot be predicted. According to the random walk theory, past prices cannot be used to predict future prices, therefore no prediction model can be able to give a forecasting accuracy of more than 50%. Fama introduced three distinct forms of Efficient Market:

The Weak Form EMH: The weak level of efficiency suggests that the historical information is already priced in and reflected in the asset prices. Therefore, technical analysis cannot be used to evaluate future prices, but fundamental analysis can provide advantage in the short term (Hull, 2009; Hamid et al., 2017).

The Semi-Strong Form EMH: This level of efficiency follows the belief that all public information is already priced in and reflected in the current price of financial instruments. Therefore, neither fundamental analysis nor technical analysis can provide an advantage to predict future prices as everyone knows it (Shonkwiler, 2013; Degutis et al., 2014).

The Strong Form EMH: This form of efficiency implies that both public and private information is accounted into today's asset prices. Thus, there is no information that can be used by any investors to benefit from the market (Sewell, 2011).

The efficient market hypothesis was a hot debate topic especially during the 1980s and 1990s among financial researchers and market participants. A number of early studies unanimously supported the theoretical foundations of EMH. Jensen (1978) reviewed the methodology of EMH and stated that "*there is no other proposition in economics which has more solid empirical evidence supporting it than the Efficient Market Hypothesis*" (1). On the other hand, a decent number of studies either contradicted or detected anomalies with the theoretical and empirical framework of EMH (Shleifer, 2000; Ball, 2009; Lee et al., 2010; Lo, 2017; Lo, 2019). Moreover, Robert Shiller has been awarded with the Nobel prize in 2013, for showing that the markets are inefficient. On the other hand, Fama was also awarded with the Nobel prize in 2013 for his theory of Efficient Market Hypothesis.

5.2.2 Adaptive Market Hypothesis

The growing amount of criticism of the EMH's broad framework paved the way for the alternative theories and the Adaptive Market Hypothesis (AMH) has been proposed by Lo (2004). The AMH is an economic model that combines the principles of the EMH with behavioural finance. Lo (2004) asserts that the EMH is an inadequate model and less reliable compared to the AMH method for excluding investor behaviour which may create arbitrage opportunities. Lo (2012) writes that "*markets are not always efficient, but they are highly competitive and adaptive, and can vary in their degree of efficiency as the economic environment and investor population change over time*". According to the AMH, financial markets are predictable, and it is possible to benefit from the market as investors adapt to news flows and these adjustments provide opportunities for forecasting. However, the AMH also states that there are cycles that market conditions change, and the market follows random walk. For further studies on AMH, see, Neely et al. (2009), Zhou and Lee (2013), Urquhart and McGroarty (2016), and Kristjanpoller and Minutolo (2018).

5.2.3 Fundamental Analysis

Fundamental analysis in the stock market refers to a method of evaluating a company and determining the intrinsic value of its stock. Fundamental analysis mainly focuses on business's financial statements, balance sheets, competitors, and markets. More specifically, this type of analysis involves the overall state of the company and the economy including interest rates, earnings, GDP, management, industry conditions, the risk of natural disasters, political and social circumstances to analyse, and forecast equity prices and the stock index (Tsai and Hsiao, 2010; Krantz, 2016; Agarwal et al., 2017). Fundamental analysis aims to determine a security's real or intrinsic value and if the intrinsic value is less than the current asset price, the asset is considered overvalued. In this type of analysis, investors believe that markets may mispriced assets in the short run, but the correct price will eventually be achieved, therefore, it is possible to predict and benefit from the market in the long run. Although the nature of fundamental analysis does not enable the following of a structured path to predict future prices, the growth of computational intelligence has allowed financial researchers to develop automated forecasting method for stock market indices based on unstructured fundamental data (Nti et al., 2019).

5.2.4 Technical Analysis

Technical analysis is a method employed in financial markets to examine and forecast the direction of price movements by using historical price charts and market statistics such as asset price and volume. The logic behind the technical analysis is that history tends to repeat itself as market participants are humans who react in a similar manner under similar conditions. Technical analysis is built on some fundamental principles: 1. Price discounts everything; 2. Prices usually occur in trends; and 3. History repeats itself over time.

The debate over technical and fundamental analysis is contentious. Fundamental analysis is considered useful for long term market predictions, while technical analysis is considered more favourable to predict short term price movements and market timing. Both can also be combined to predict future movements over the medium and long term. Lo et al. (2000) describes the difference between two analyses as: "*It has been argued that the difference between fundamental analysis and technical analysis is not unlike the difference between astronomy and astrology. Among some circles, technical analysis is known as 'voodoo finance"* (pp 1705). The development of artificial neural network models has enabled the combination of traditional technical analysis rules with the intelligent systems where historical price and volume data can be used to forecast future prices on individual asset or market index (Park and Irwin, 2007; Wei et al., 2011; Gorgulho et al., 2011; Ticknor, 2013; Bisoi and Dash, 2014).

5.3 Artificial Neural Network Perspective and Implementation in Financial Markets

Forecasting financial markets is a prevalent topic that has attracted scholars over the years. A number of different approaches have been covered in the literature over the past few decades including, GARCH models, linear regression models, hybrid models, the support vector regression, fuzzy logic, genetic algorithms, and artificial neural networks. This section aims to give perspective on the theoretical and empirical works in the literature regarding stock market prediction in order to provide insight on the effectiveness of various approaches.

Yoon and Swales (1991) studied the returns data of 58 widely followed companies in Fortune 500 and revealed that the neural network model can learn a function that maps input to output and encoding it in the magnitudes of the weights in the network's connection. They also search for the performance of Neural Network and Multivariate Discriminant Analysis technique and revealed that NN can provide substantially accurate forecasts for the stock market returns. Wong et al. (1992) criticized the weakness of Neural Network approach and studied fuzzy neural systems to predict stock market returns as well as assessing country risk and rating stocks based on fuzzy rules. Moreover, Donaldson and Kamstra (1996) examined the applicability of the ANN approach by using time series data on four different developed stock markets. They conducted out-of-sample forecast using MSE criterion for comparison and revealed that ANN is superior on these markets compared to traditional linear models due to its flexibility with complex nonlinear dynamics. Ormoneit and Neuneier (1996) studied German DAX index using minutely data for the month of November 1994. They compared Multilayer Perceptron method (MLP) with the Conditional Density Estimating Neural Network (CDENN) and reported that CDENN easily outperforms MLP for the high-frequency data based on MSE criterion. Jasic and Wood (2004) analysed the statistical significance and potential profitability of one-step-ahead forecasts for DAX, FTSE, S&P 500 and TOPIX indices by using univariate neural network methods on daily closing prices. The results revealed that the Neural Network methods are more successful in terms of predictability of stock markets compared to benchmark model of AR (1). Kim and Lee (2004) proposed the feature transformation method based on Genetic Algorithm (GA) model and compared it with two conventional Neural Network methods. The results indicated that the GA method improves the prediction capability of Neural Network models as well as diminishes the negative impact of the feature space dimensionality and minimizes irrelevant factors for financial market forecasting. Altay and Satman (2005) implemented Neural Network methods on the emerging market of the Istanbul Stock Exchange using daily, weekly, and monthly data. They compared the out-of-sample forecasting results with the linear regression models based on RMSE, MAE and Theil-U criteria and reported that ANN is more superior only for weekly forecast results, while underperforming for daily and monthly data. Cao et al. (2005) studied ANN methods to predict individual price of the firms that traded on the Shanghai Stock Exchange. They compared the univariate and multivariate ANN models with the linear models and the results indicated that the neural network models are superior in terms of predicting future price changes and can be used as a tool for forecasting financial markets in emerging markets. On the other hand, Mantri et al. (2014) investigated the two benchmark indices of India (BSE SENSEX and NIFTY) from 1995 to 2008 by comparing GARCH, EGARCH, GJR-GARCH, IGARCH, and ANN model. The authors reported that the prediction capability of ANN model offers no differences to the statistical forecasting models henceforth the market participants and economists may remain neutral on estimation of volatility in emerging markets which contradicts with the findings of Cao et al. (2005). Dhar et al. (2010) constructed an ANN model to predict the National Stock Exchange of India (NSEI) and the results indicated that performance and prediction capability of the model is much better than satisfactory for the selected time frame.

Fernandez-Rodriguez et al. (2000) investigated the potential profitability of the ANN model for the Madrid Stock Exchange. The out-of-sample forecast test was conducted for the three different period which represents the bear market, stable market, and the bull market. The empirical results revealed that in the absence of trading costs, the ANN model provides superior predictions during stable and bear markets, while underperforming during bull markets. Moreover, Pérez-Rodríguez et al. (2005) analysed the Spanish Ibex-25 index by using daily returns for the sample period spanning December 1989 to February 2000. One-step-ahead and multi-step ahead forecasts are conducted by applying six competing models, namely the ESTAR, LSTAR and AR models, MLP, JCN and Elman Networks. Based on the given results, they concluded that the ANN models provide better fit for the selected markets in the case of one-step-ahead forecasting method, while in terms of multi-step-ahead forecasts, the ANNs are not able to provide advantages compared to other selected prediction models.

Several studies have also investigated the performance of different class of ANN models and hybrid models. Roh (2007) proposed a hybrid model between ANN and financial time series models for the KOSPI Index and forecast results report that hybrid models improve the volatility forecasting in terms of deviation and direction accuracy. Unlike Roh (2007), Guresen et al. (2011) analysed NASDAQ daily return prices by comparing standard MLP, GARCH-ANN and Dynamic Architecture Network model (DAN2), and the predicted results show that the hybrid models are not as successful as standard ANN models. Kristjanpoller et al. (2014) and Kristjanpoller and Michell (2018) proposed ANN-GARCH hybrid model for predicting three emerging stock markets from Latin-America namely, Mexico, Chile, and Brazil. The authors concluded that the hybrid models improve prediction capability and robustness of conventional time series models and can be applied in emerging South American markets. For further studies related to hybrid models, see, Leigh et al. (2002), Chakravarty and Dash (2009), Wei et al. (2011), Rather et al. (2015), Mingyue et al. (2016), Wang and Wu (2017), Kim and Won (2018), and Hao and Gao (2020).

From a different dimension, Adebiyi et al. (2012) investigated the efficiency of ANN approach in financial markets prediction from technical and fundamental standpoints. The authors proposed a novel model by combining technical and fundamental analysis to obtain feedforward multilayer perceptron model with backpropagation algorithm. The empirical results revealed that the proposed model enhances the quality of the decision-making process for investors by providing stronger prediction results compared to technical analysis-based approach which is consistent with the findings of Yao et al. (1999) and Sezer et al. (2017). Lam (2004), however, reported mixed results in terms of forecasting capability of integrated ANN models with fundamental and technical analysis. The experimental results of the study show that the integrated model works well when the economy is in recession, yet in terms of prediction efficacy, the proposed model is able to beat the maximum benchmark, which is decided as the top one-third returns in the market and the author concluded as inconclusive.

Some researchers have experimented neuro fuzzy and neuro evolutionary methods to evaluate stock market forecasting exercises. Quah (2007) used the DJIA index data spanning from 1994 to 2005 to compare the applicability of MLP, ANFIS and GGAP-RBF models. The comparison made based on the several benchmark metrics including generalize rate, recall rate, confusion metrics and appreciation. The study shows that ANFIS system provide more accurate results while GGAP-RBF underperforms in all selected criteria. Similar works have been undertaken separately by Chang et al. (2009), Boyacioglu and Avci (2010), and Yang et al. (2012) where they found fuzzy reasoning system can be used to predict stock market trend. Li and Xiong (2005) argued that the neural networks have limitations on dealing with qualitative information and suffers from the "black box" syndrome, proposing a neuro fuzzy inference system to overcome these drawbacks. The Shanghai stock market is chosen for prediction where they found that suggested fuzzy NN is more superior than the standard NN methods. Mandziuk and Jaruszewicz (2007) presented a neuro-evolutionary method to predict the change of closing price on German DAX index for the next day. The results revealed that the proposed model effectively produce high accuracy prediction for the market both in upward and downward directions. Additionally, Garcia et al. (2018) implemented a hybrid neuro fuzzy model to predict one-day ahead direction of the German DAX Index. The evaluation metrics showed that the proposed HyFIS model has 76.24% predictive accuracy. The authors concluded that the integration of traditional indicators may enhance the predictive accuracy of the model, yet it may generate too much noise in the prediction model together with over optimization. For more discussion on this issue, see, Gholamreza et al. (2010), D'Urso et al. (2013), Vlasenko et al. (2018) and Chandar (2019).

More recently, Selvin et al. (2017) discussed that the predictive capabilities of deep learning models are superior compared to other ANN algorithms, while Chen et al. (2015) revealed that LSTM algorithm is not satisfying in Chinese stock market. Cao and Wang (2020) further studied China's stock market and the experimental results show that neural networks are more effective combined with regularization algorithms. On top of that, Nelson et al. (2017) conducted series of analysis to show that deep learning models perform better when integrated with technical analysis indicators. Similarly, Kim and Kang (2019) compared various deep learning models and favoured LSTM network on Korean stock market. Meanwhile, Yap et al. (2021) find that deep learning models can be used to predict short term movements and trends in the financial markets confirming the earlier study of Atsalakis et al. (2016).

The above discussion demonstrates that the present state of the literature does not suggest a clear superiority either within the different ANN models, or over conventional forecasting methods. As discussed in Ravichandra and Thingom (2016), and Chopra and Sharma (2021), AI models do possess superior capabilities and the potential for more accurate volatility forecasts and thus, worthy of further research. This paper builds upon the research in the present literature on volatility forecasting capabilities of ML models to traditional models and extends the existing literature by evaluating a wider set of ANNs and utilising risk management measures and economic implications.

5.4 Machine Learning Methods in Stock Market Forecasting

The significant growth of the advanced machine learning systems and the recent innovations in data mining have enabled the building of complex intelligent forecasting systems to predict stock prices. The fundamental idea of machine learning is establishing and designing an intelligent architecture system that can recognize complex patterns and able to learn through trainings. Particularly for the stock market analysis where the data size is huge and also non-linear. Although Neural Network models have been widely recognized and proven to forecast financial markets, there is still no consensus on the best indicator or neural network architecture to constantly evaluate and predict the stock market precisely (Cavalcante et al., 2016).

Nelson and Illingworth (1991) states that there are unlimited possibilities to create a neural network model, although not more than twenty of them are effectively in use. There are some elements to forming of neural network models, inputs, outputs, activation functions, weights, number of neurons, and number of layers. In the following section, these parameters will be introduced, and related studies will be discussed.

5.4.1 Inputs

The input layer of a neural network is composed of artificial input neurons and brings the initial data into the system for further processing by subsequent layers of artificial neurons. The input layer is the very beginning of the workflow for the artificial neural network. Input data must be numerical, and transformation of data might be required depending on the work. In the empirical finance literature, technical and fundamental indicators are mostly applied for the financial market prediction. According to Cavalcante et al. (2016), computational intelligence approach stock market forecasting exercises are conducted mostly based on candidates of technical input variables. More specifically, they surveyed 56 articles between 2009 and 2015 that studies stock market prediction using Neural Network methods and revealed that 84% of the papers used technical variables and only 16% applied fundamental approach. They stated that the majority usage of the technical indicators is due to the applicability of the numerical format on ML systems since fundamental analysis such as web news and financial reports are in textual format and extracting this type of data includes difficulties. Another survey is studied by Krollner et al. (2010) where they categorized papers in different groups based on the technology used, forecasting timeframe, input selection and evaluation criteria. They indicated that 36 out of 46 articles employed technical input variables where the most widely used indicators in the reviewed literature are reported as the simple moving average (SMA), exponential moving average (EMA), relative strength index (RSI), moving average convergence/divergence (MACD) and average true range (ATR). Alhnaity (2015) conducted similar research and stated that the most common input parameters are the index opening price, closing price, highest daily price, and lowest daily price. Among the papers he reviewed, around 40% applied daily index prices as an input variable which supports the statement that soft computing methods use quite simple input data to provide predictions (Atsalakis and Valavanis, 2009). As the literature shows, technical indicators are more commonly utilized as inputs in the stock market prediction exercises which is probably due to the reliance on big data for neural network applications since technical indicators are more accessible compared to fundamental data.

5.4.2 Pre-processing Input Data and Feature Selection

The application of Neural Network models requires the transformation of raw data to computationally applicable form for avoiding problems such as noise, missing values, and inconsistencies. Pre-processing input data improves the quality of that data, and it is very crucial since it effects the performance of NN models and henceforth the accuracy of output. Atsalakis and Valavanis (2009) reviewed 25 articles regarding their data processing procedures, and they revealed that most of the papers find input data pre-processing is helpful and required. Maingi (2015) highlights the importance of data cleaning and states the significant negative impact of missing values on NN forecasting performance. There are various data cleaning procedures in the literature such as deletion methods (Pendharkar et al.,2005; Kosti et al., 2012; Rodríguez et al., 2012) and imputation methods (Minku et al., 2011; Kocaguneli et al., 2013). However, Romero and Balch (2014) states that the common approach for the missing data treatment should be "fill forward" method by using their last known value for the financial time series data.

Another critical step for more accurate forecasting estimation in addition to data pre-processing is feature selection methods. Feature selection (also called variable selection or attribute selection) refers to the process of selecting a subset of relevant features to be learned by the constructed model. The biggest benefit of feature selection is minimizing the impact of dimensionality which reduces the risk of overfitting and henceforth improves the forecasting accuracy (Tsai and Hsiao, 2010). According to Guyon and Elisseeff (2003) "*The objective of variable selection is three-fold: improving the prediction performance of the predictors, providing faster and more cost-effective predictors, and providing a better understanding of the underlying process that generated the data*" (pp 1157).

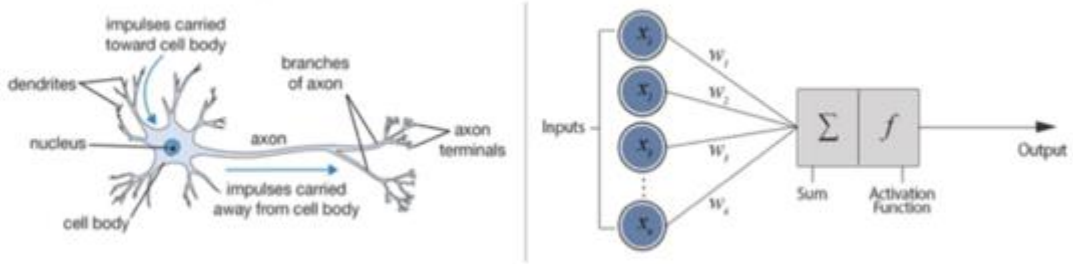
Torgo (2016) explains that there are two main classes for variable reduction methods which are filter methods and wrapper methods. Filter feature selection methods apply a statistical measure to rank the most relevant and important features independently based on ML metrics, whereas wrapper methods consider the selection of a set of features based on their advantage of a given algorithm. The main distinction between these two methods is that wrapper methods consider forecasting accuracy (out-of-sample) as a quality criterion, while filter methods ignore prediction approach. Therefore, as Hu et al. (2015) noted, filter methods tend to produce less successful prediction outputs due to the deficiency of guidance by forecasting accuracy for the network learning process. Therefore, wrapper methods are considered superior compared to filter methods for time series prediction applications due to the determination of feature subset based on forecasting approach (Kohavi and John, 1997).

5.5 Empirical Literature

5.5.1 Artificial Neural Networks

Artificial Neural Networks (ANNs) are one of the most essential applications in machine learning. ANN is a brain-inspired model which imitate the network of neurons in biological brain so that the computer will be able to learn and make decisions in a human-like manner.

Figure 5.1: Biological Neuron versus Artificial Neural Network



Source: DataCamp

The figure 5.1 above shows the structure of neurons in a biological brain and an ANN. Neurons are core elements of ANNs which are connected as networks. As shown in the biological brain, neurons have small arms called as dendrites, which receive inputs/signals. Axons transfer the information and provide connections between neurons.

Similarly, the artificial neuron receives signals/inputs then processes it and transmits to the other neurons that connected to it. The transmission is computed by the non-linear function of the sum of inputs. The transmission process between artificial neurons is weighted; the higher the number the greater effect one unit has on another.

Mathematically, the number of inputs $\{X_i\}$, $i = 1,2, \ldots n$ to the neuron and the weights , $k = 1,2, \ldots n$ are calculated by the following formula:

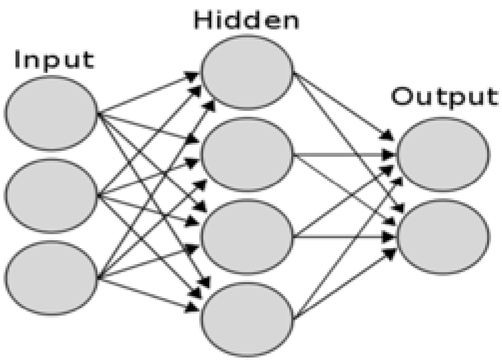
$$\bar{a} = \sum_{i,k=0}^{n} x_i w_k \qquad (5.1)$$

which creates the average input $\overline{a}$ for the activation function f. The activation function processes the information based on the stimulation level and produces the output as follow:

$$f(\overline{a}) = Y_j, \qquad j = 1,2, \dots n \qquad (5.2)$$

The connection between input and output variables is designed by the data structure of the network which is this architecture that makes ANN models are unique. The learning process of a neural network is performed with the layers. The key to note is that the neurons (also known as “nodes”) are placed within layers and each layer has its purpose. The neurons, within each of the layer of a neural network, perform the same function. They simply calculate the weighted sum of inputs and weights, add the bias, and execute an activation function. A simple ANN model is composed of minimum three layers which are input, hidden and output layers as shown in the following figure 5.2.

Figure 5.2: Standard architecture of ANN



The input layer is the first layer of the network which receives information from the outside world via the number of input nodes. There is no computation at this point as input nodes are only responsible for transferring the information. The output layer is the third layer and the output nodes compute and deliver information from the network to outside world. The hidden layer is the second and the most important layer where computation, data transformation and connection between input and output layers are facilitated. This transformation is exercised by activation function. There could be zero or more hidden layers in a neural network. One hidden layer is sufficient for the large majority of problems. Usually, each hidden layer contains the same number of neurons. The larger the number of hidden layers in a neural network, the longer it will take for the neural network to produce the output and the more complex problems the neural network can solve.

There are several types of ANN models developed for specific applications, including prediction of a pattern and financial forecasting. In this section, these network types will be introduced.

5.5.2 Multi-Layer Perceptron (MLP)

A multi-layer perceptron (MLP) is a feed-forward (where the information moves forward from input to output nodes) artificial neural network (ANN) and one of the most known and used neural network architectures in financial applications according to Bishop (1995). The basic feed-forward ANN model with a one hidden layer is given as follow:

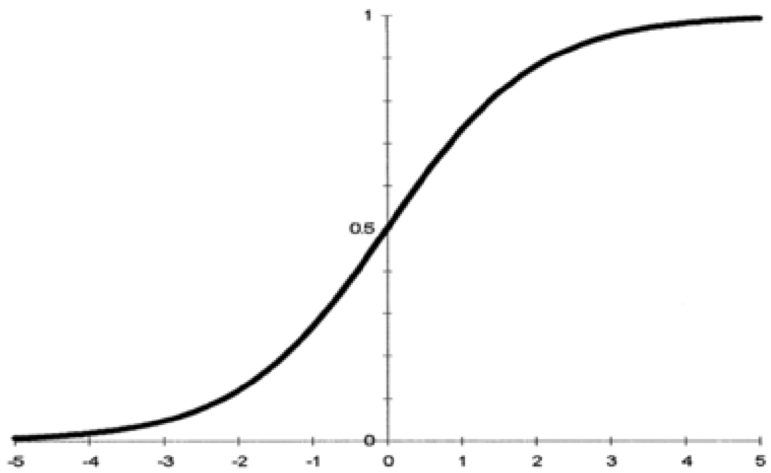
$$n_{k,t} = w_{k,0} + \sum_{i=1}^{i} w_{k,i} x_{i,t} \tag{5.3}$$

$$N_{k,t} = L(n_{k,t}) = \frac{1}{1 + e^{-n_{k,t}}} \tag{5.4}$$

$$Y_t = \lambda_0 + \sum_{k=1}^{k} \lambda_k N_{k,t} \tag{5.5}$$

where i shows the number of input data (x) and k represents the number of nodes (neurons). The activation (transfer) function is chosen as logistic sigmoid function due to its convenience and popularity which is represented by $L(n_{k,t})$ and defined as ${}^{1}/_{1 + e^{-n_{k,t}}}$. The logistic function is also can be illustrated as follow:

Figure 5.3: Log-sigmoid activation function $y = 1/\left(1 + exp(-x)\right)$



The training process starts with the input vector $x_{i,t}$, weight vector $w_{k,i}$, and the coefficient variable $w_{k,0}$. Combining these input vectors with the squashing function log-sigmoid, forms the neuron $N_{k,t}$, which then serves as an exogenous variable with the coefficient λ_k and the constant λ_0 to forecast output Y_t. This network architecture with the logarithmic sigmoid transfer function is one of the most popular methods to forecast financial time series data (Dawson and Wilby, 1998; Zhang, 2003).

A single hidden layer feed-forward ANN is capable of most of the forecasting problems. However, for more complex datasets (such as deep learning), additional layers can be helpful according to Hinton et al. (2006). When the size and number of layers in a Neural Network grow, the capacity of the network increases. That is, the space of representable functions grow as the nodes can collaborate to express many different functions. The MLP architecture with a two hidden layer is given as follow:

$$n_{k,t} = w_{k,0} + \sum_{i=1}^{M} w_{k,i} x_{i,t} \tag{5.6}$$

$$N_{k,t} = \frac{1}{1 + e^{-n_{k,t}}} \tag{5.7}$$

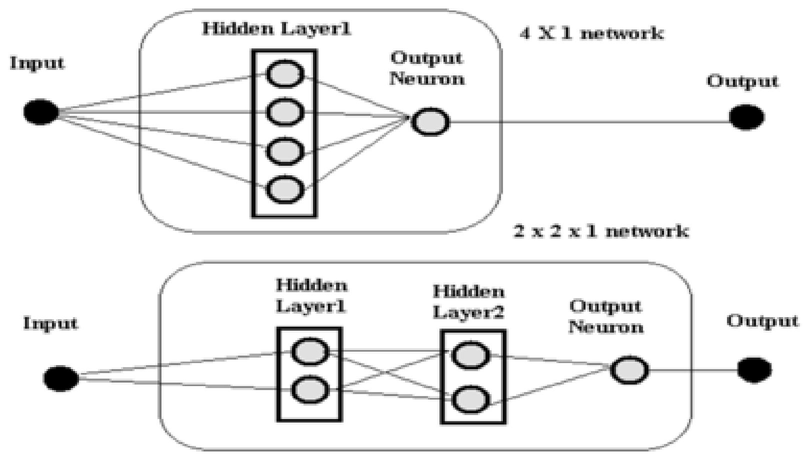
$$q_{c,t} = \vartheta_{c,0} + \sum_{k=1}^{Z} \vartheta_{c,k} N_{k,t} \tag{5.8}$$

$$Q_{c,t} = \frac{1}{1 + e^{q_{c,t}}} \tag{5.9}$$

$$Y_t = \lambda_0 + \sum_{c=1}^{H} \lambda_c Q_{c,t} \tag{5.10}$$

where M shows the number of input vectors, Z and H the number of nodes in the 1st and 2nd hidden layers, respectively. It can be clearly seen that, as the number of hidden layers rises, the components to be evaluated are also rising. Basically, in a single hidden layer MLP network with M inputs and Z nodes, $(M + 1)Z + (Z + 1)$ variables should be calculated, while in a two hidden layer MLP network with H nodes in the 2nd hidden layer $(H + 1)Z + (Z + 1)H + (H + 1)$ variables need to be calculated. The following figure shows MLP with single hidden layer and two hidden layers with same nodes in each, respectively.

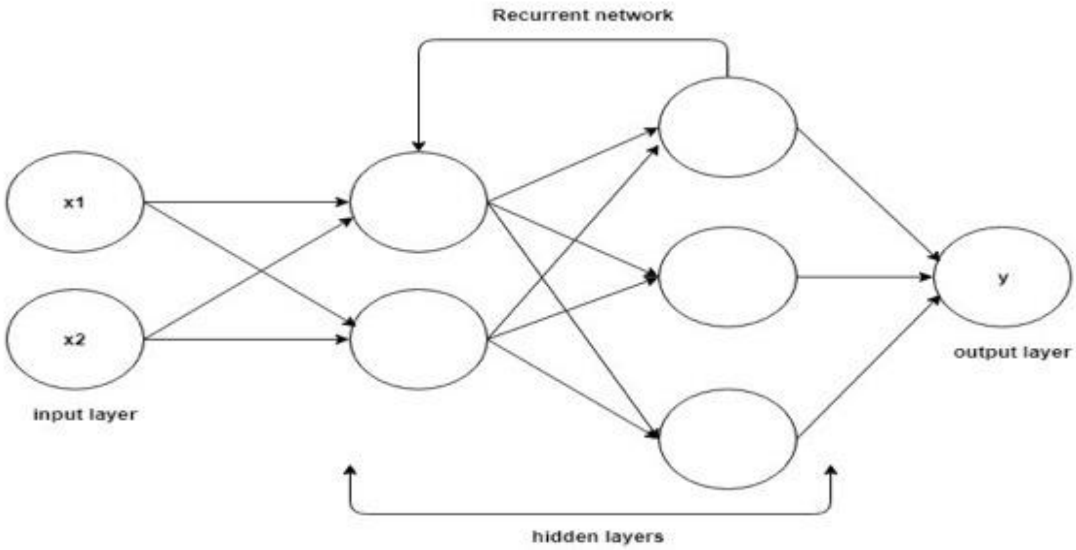
Figure 5.4: Single and two hidden layers MLP



5.5.3 Recurrent Neural Network (RNN)

A Recurrent Neural Network (RNN) is a class of artificial neural network which allows to process sequential information. In the RNN architecture, previous outputs can be used as inputs while having hidden states. The main difference between basic feedforward networks and RNN is that RNNs are able to have impact on the process of future inputs. In other words, feedforward networks can only “remember” things that they learnt during training, while RNNs can learn during training, in addition, they remember things learnt from prior input while generating output. The following figure represents the standard architecture of RNN:

Figure 5.5: Simple architecture of RNN



As in the Moving Average model where endogenous variable Y is a function of exogenous variable X and error term ε in the equation; likewise, nodes in the RNN is a function of input data and its previous value from $t-1$. The equation of RNN is given as follow:

$$n_{k,t} = w_{k,0} + \sum_{i=1}^{i} w_{k,i} x_{i,t} + \sum_{k=1}^{k} \varphi_k n_{k,t-1} \tag{5.11}$$

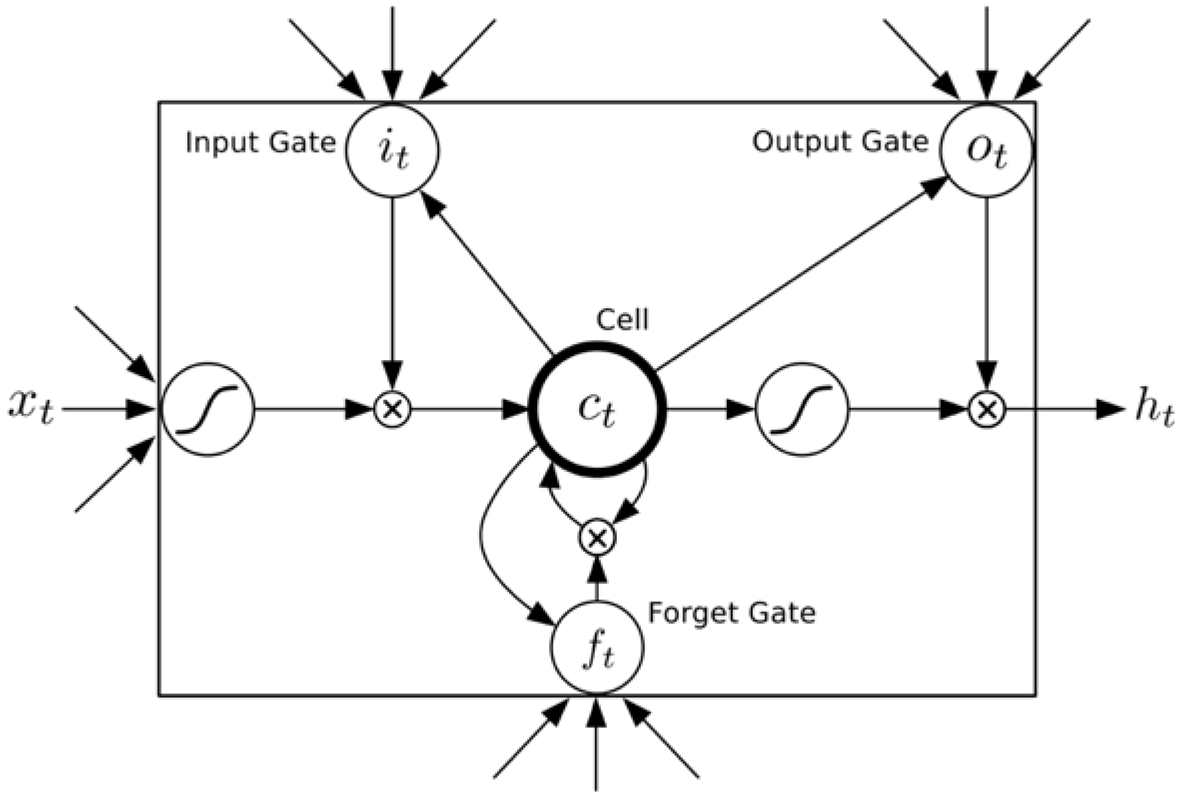
$$N_{k,t} = \frac{1}{1 + e^{-n_{i,t}}} \tag{5.12}$$

$$Y_t = \lambda_0 + \sum_{k=1}^{k} \lambda_k N_{k,t} \tag{5.13}$$

The main advantages of RNNs, which are having short term “memory” and the ability of processing sequential datasets, have attracted broad attention among financial researchers to predict financial time series and various applications have been conducted over the years (Rather et al., 2015; Gao 2016, Samarawickrama and Fernando, 2017; and Pang et al., 2020).

However, the difficulty of training and requirement of additional connections are the major drawbacks for RNN architectures. RNNs also prone to the problem of gradient vanishing which is the phenomena of difficulty to capture long term dependencies. It occurs when more layers using certain activation functions are added to network, which causes the gradients of the loss function approaches to zero and making the network hard to train. To overcome of this issue Hochreiter and Schmidhuber (1997) proposed the Long Short-Term Memory (LSTM) networks. LSTMs are proficient in training about long-term dependencies. They are not a different variant of RNNs, yet improved transformation with additional gates and a cell state. The following figure depicts the typical LSTM network:

Figure 5.6: Architecture of typical LSTM unit



The structure of LSTMs is slightly different than conventional RNNs where RNNs have standard neural network architecture with a feedback loop, while LSTMs contain three memory gates namely input gate, output gate, and forget gate as well as a cell. The purpose of these gates is:

- The input gate states which information to add to the memory (cell)
- The output gate specifies which information from the memory (cell) to use as output
- The forget gate describes which information to remove from the memory (cell)

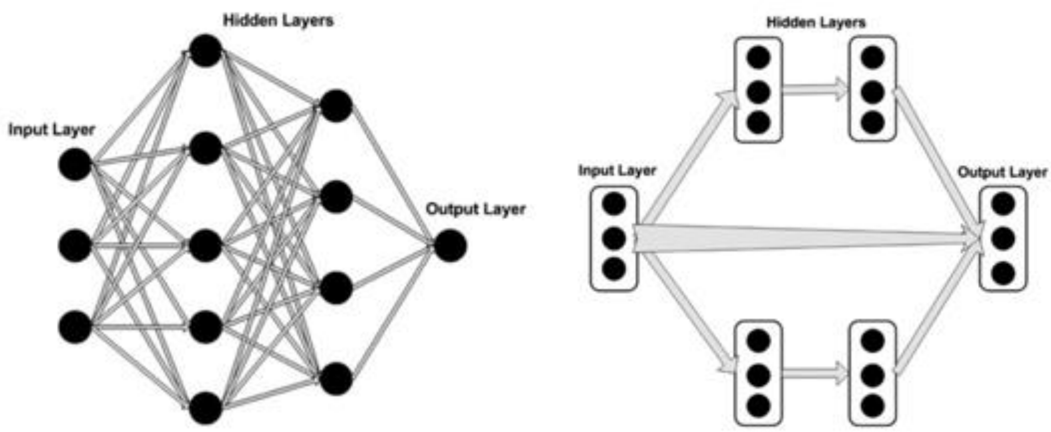
LSTMs are state of the art systems in forecasting time series data, pattern recognition and sequence learning.

5.5.4 Modular Feedforward Networks (MFNs)

The Modular Feedforward Networks (MFNs) are extension of typical feedforward NN architectures that are designed to reduce complexity and enhance robustness. The issues of learning weights and slow convergence in standard NN designing motivated researchers to study new designs to generate more efficient results.

The MFNs have a number of different networks that function independently and perform sub-tasks. The different networks do not really interact with or signal each other during the computation process. They work independently towards achieving the output. Figure 5.7 demonstrates the comparison between MLP and MFN, respectively.

Figure 5.7: The architecture difference of MLP and MFN

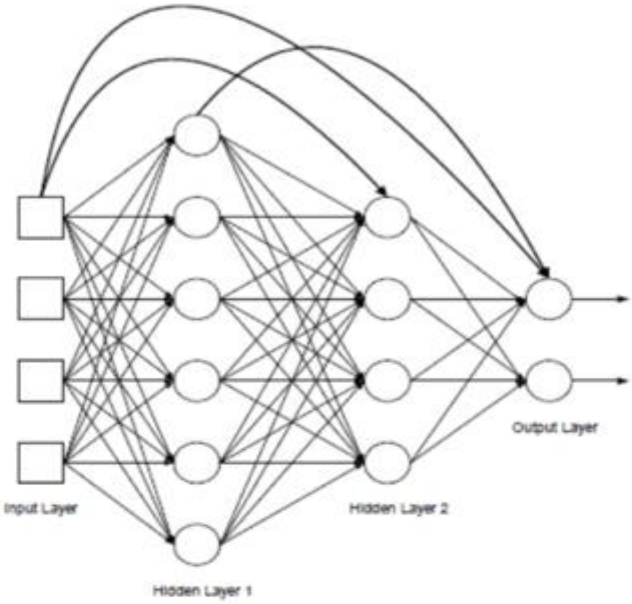


As the structure of MFN requires fewer weights and the networks are not interacting with each other, the computation speed increases, and a large and complex computational process can be done significantly faster. For further details, see Tahmasebi and Hezarkhani (2011).

5.5.5 Generalized Feedforward Networks (GFNs)

The Generalized Feedforward Networks (GFNs) are a subclass of Multi-layer Perceptron (MLP) networks that enable connections to jump over one or more than one layers. The direct connections between two separate layers provide raw information for the output layer along with the usual connection via the hidden layer. Figure 5.8 demonstrates the standard architecture of GFN:

Figure 5.8: Generalized Feedforward Network with two hidden layers



The most prominent feature of GFN is providing capability to send linear connections if the underlying elements consist of linear component. But, if the underlying elements require nonlinear connectivity, then the jump function will not be needed. Theoretically, MLP can provide solutions to every task that GFN architecture can overcome. However, practically GFNs offer more accurate and efficient solutions compared to standard MLP networks. The GFNs are applied in many areas, including time series forecasting, data processing, pattern recognition and complex engineering problems. For further information, see Arulampalam and Bouzerdoum (2003), Teschl et al. (2007), Celik and Kolhe (2013).

5.5.6 Radial Basis Function Networks (RBFNs)

The Radial Basis Function Networks (RBFNs) are a three-layered feedforward network that use radial basis function as activation function. The architecture was developed by Broomhead and Lowe (1988) to increase speed and efficiency of Multi-Layer Perceptron Networks as well as reducing the parameterization difficulty. The main differences between these two networks can be schematized as follow:

Radial Basis Function Networks	Multi-Layer Perceptron Networks
• The activation function is a function of the euclidean distance[1](between inputs and weights, which can be viewed as centers) of input vector and a certain vector.	• The activation function can be any nonlinear function which can serve the purpose.
• The final layer of RBFN don't use activation function, it rather linearly combines the output of the previous neuron.	• The final layer in MLP also uses the activation function before linearly combining it.
• There is only one hidden layer and one output layer.	• There can be more than one hidden layer.
• The final layer has only one neuron.	

The standard RBFN process is mathematically given by McNelis (2005) as follow:

$$Min_{<\omega,\mu,\tau>} \sum_{t=0}^{T} (y_{t-}\hat{y}_t)^2 \tag{5.14}$$

$$n_t = w_0 + \sum_{i=1}^{i^*} w_i x_{i,t} \tag{5.15}$$

$$R_{k,t} = \phi(n_t; \mu_k) \tag{5.16}$$

[1] Euclidean distance is a measure of the true straight-line distance between two points in Euclidean space.

$$= \frac{1}{\sqrt{2\pi\sigma_{n-\mu_k}}} exp\left(\frac{-[n_t - \mu_k]}{\sigma_{n-\mu_k}}\right)^2 \quad (5.17)$$

$$\hat{y}_t = \lambda_0 + \sum_{k=1}^{k^*} \lambda_k N_{k,t} \quad (5.18)$$

where:

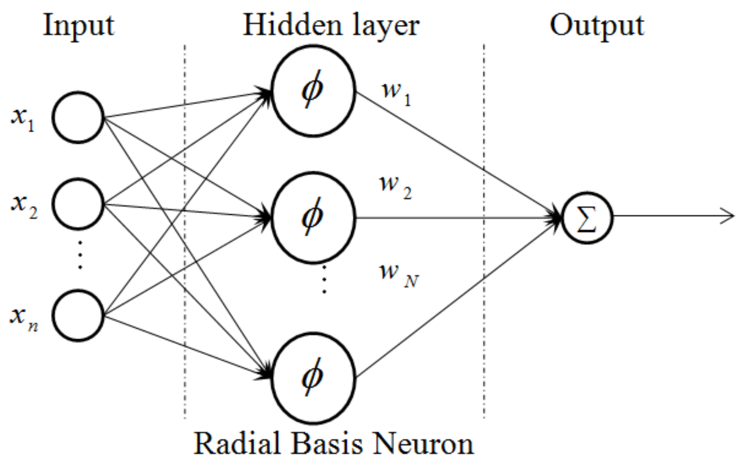
x = the set of input variables

n = the linear transformation of the input variables

w = weights.

The parameter k^* shows the number of centers for the transformation function of radial basis $\mu_k, k = 1,2, \ldots k^*$ compute error function generated by the separate centres μ_k, and obtain the k^* separate radial basis function, R_k. These parameters are then estimate the output $\hat{y}_t$ with weights λ via the linear transformation. Finally, the RBFN optimization occurs which includes determination of parameters w, λ with k^* and μ. The following figure represents a standard Radial Basis Feedforward Network:

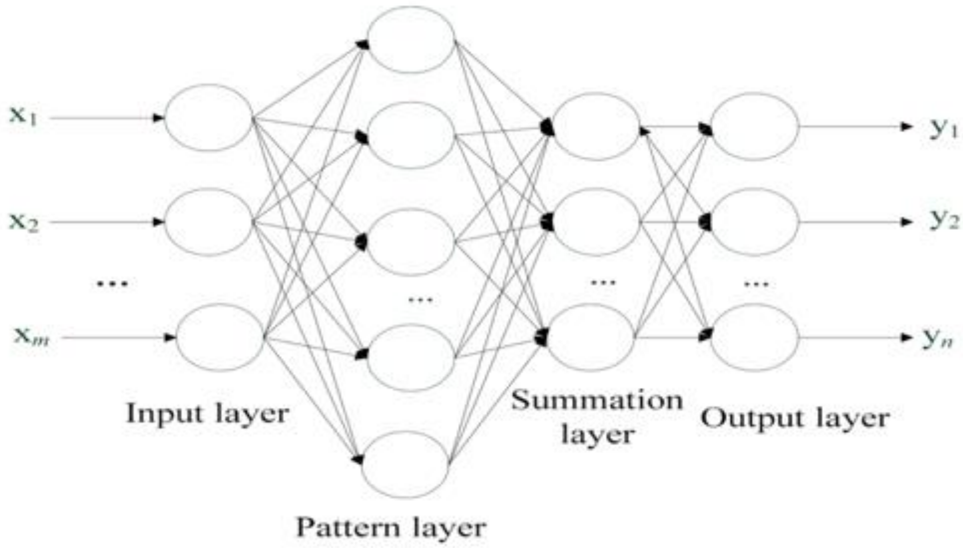
Figure 5.9: The Radial Basis Feedforward Neural Network architecture



5.5.7 Probabilistic Neural Networks (PNNs)

The Probabilistic Neural Networks (PNNs) was developed by Specht (1990) to overcome of classification issue which is caused by the applications of directional prediction. The structure of PNNs is formed of four layers which are the input layer, the pattern layer, the summation layer and the output layer. The following figure depicts the standard PNN architecture:

Figure 5.10: The Probabilistic Neural Network architecture

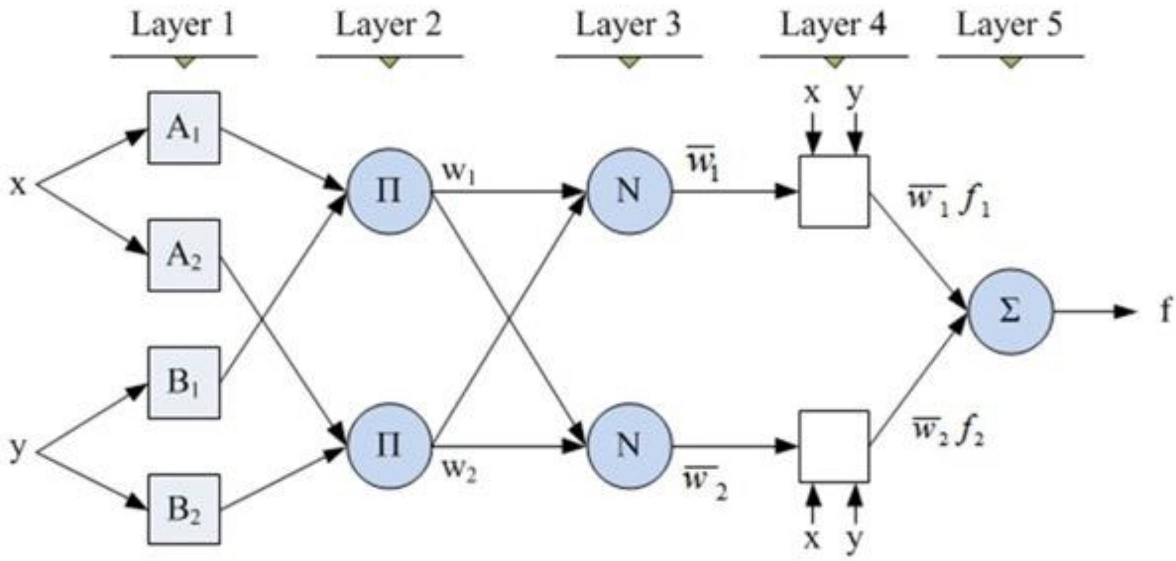


The linear and adaptive linear prediction designs of PNNs are the most popular functions in forecasting exercises of time series. The main advantages of PNNs compared to MLPs are requiring less training time, providing more accuracy and being relatively less sensitive to outliers. And the main disadvantage of the PNNs is requirement of more memory space to store the model.

5.5.8 Adaptive Neuro-Fuzzy Inference System (ANFIS)

The Adaptive Neuro-Fuzzy Inference System (ANFIS) is a subclass of ANNs which was introduced by Jang (1993). According to Yager and Zadeh (1994), the model is considered one of the most powerful hybrid models, since it is based on two different estimators, namely Fuzzy Logic (FL) and ANN, which are designed to produce accurate and reliable results by justifying the noise and ambiguities in complex datasets. The ANFIS architecture is based on the Takagi-Sugeno inference system which generates a real number as output. The structure of the model is similar to a MLP network with the difference on flow direction of signals between nodes and exclusion of weights. The figure 5.11 shows the architecture of ANFIS:

Figure 5.11: The ANFIS prototype



The simulation of the ANFIS model and the function of each layer is presented as follow:

Layer 1: Selection of input data and process of fuzzification

In this step input parameters are chosen and the fuzzification is initialized by transforming crisp sets into fuzzy sets. This process is defined as follow:

$$O_{1i} = \mu A_i(x_1), \qquad O_{2i} = \mu B_i(x_2), \quad for\ \ i = 1{,}2 \qquad (5.19)$$

where x_1 and x_2 are input parameters, A_i and B_i are linguistic labels of input parameters, O_{1i} and O_{2i} are membership grades of fuzzy set A_i and B_i.

Layer 2: Computation of firing strength

This layer is also called as rule layer and the outcome of this layer is known as firing strength. The nodes in this layer are fixed and represented by Π. These nodes are responsible for receiving information from previous layer and the output of this nodes is obtained by the following equation:

$$w_i = \mu A_i(x_1)\mu B_i(x_2) \quad for\ \ i = 1{,}2 \qquad (5.20)$$

Layer 3: Normalization of firing strength

Each node is fixed in the 3rd layer and defined as N. The nodes in this layer receives signals from each node in previous layer and calculate the normalized firing strength by given rule:

$$\overline{w}_i = \frac{w_i}{w_1 + w_2} \qquad for \;\; i = 1,2 \tag{5.21}$$

Layer 4: Consequent Parameters

The nodes in this layer are adaptive and process the information from 3rd layer by given rule which is showed as follow:

$$\overline{w}_i f_i = \overline{w}_i (p_i x_1 + q_i x_2 + r_i) \qquad for \;\; i = 1,2 \tag{5.22}$$

where $\overline{w}_i$ is the normalized firing strength and p_i, q_i, r_i are the parameter(s) set that can be determined by the method of least squares.

Layer 5: Computation of overall output

This layer is labelled as Σ and contains only a single node which calculates the overall ANFIS output by aggregating all the information received from 4th layer:

$$y = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \tag{5.23}$$

The mathematical details of ANFIS training procedure can be obtained in the studies of Jang (1993), Jang et.al. (1997), Nayak et al (2004), and Tahmasebi and Hezarkhani (2011).

5.5.9 Co-Active Neuro-Fuzzy Inference System (CANFIS)

The Co-Active Neuro-Fuzzy Inference System (CANFIS) is an extended version of ANFIS architecture which was introduced by Jang et al. (1997). The main advantage of CANFIS is to be able to deal with any number of input-output datasets by incorporating the merits of both

Neural Network (NN) and Fuzzy Inference System (FIS) (Mizutani and Jang, 1995; Aytek, 2009). The main distinctive elements of CANFIS system are the fuzzy axon (a) which applies membership functions (all the information in fuzzy set) to the inputs and a modular network (b) that applies functional rules to the inputs (Heydari and Talaee, 2011). The fuzzy axon produces output by computing given equation:

$$f_j(x,w) = Min\forall_i\left(MF\left(x_i, w_{ij}\right)\right) \tag{5.24}$$

where i is the input index, j the output index, x_i the input i, w_{ij} the weights, MF the membership function of the fuzzy axon. As in the ANFIS system, the CANFIS system is also based on Sageno function. Following Jang (1993), El-Shafie et al. (2007) described the rule set to initialize the CANFIS architecture with n inputs and m IF-THEN as follows:

$$\begin{gathered} RULE\ 1\text{: } If\ x_1\ is\ A_{11}\ and\ x_2\ is\ A_{12}\ ...\ and\ x_n\ is\ A_{1n} \\ then\ f_1 = p_{11}x_1 + p_{12}x_2 + \cdots + p_{1n}x_n + q_1 \end{gathered} \tag{5.25}$$

$$\begin{gathered} RULE\ 2\text{: } If\ x_1\ is\ A_{21}\ and\ x_2\ is\ A_{22}\ ...\ and\ x_n\ is\ A_{2n} \\ then\ f_2 = p_{21}x_1 + p_{22}x_2 + \cdots + p_{2n}x_n + q_2 \end{gathered} \tag{5.26}$$

$$\begin{gathered} RULE\ m\text{: } If\ x_1\ is\ A_{m1}\ and\ x_2\ is\ A_{m2}\ ...\ and\ x_n\ is\ A_{mn} \\ then\ f_m = p_{m1}x_1 + p_{m2}x_2 + \cdots + p_{mn}x_n + q_m \end{gathered} \tag{5.27}$$

The simulation of the CANFIS model and the function of each layer is introduces as follows:

Layer 1: Selection of input data and process of fuzzification

In this step input parameters are chosen and the fuzzification is initialized by transforming crisp sets into fuzzy sets. This process is defined as follow:

$$O_{1,ij} = \left|\mu A_{ij}(x_i)\right| < \mu A_{ij}(x_i) \qquad for\ \ 1 \le i \le n, 1 \le j \le m \tag{5.28}$$

where A_{ij} is the fuzzy set, $O_{1,ij}$ is the membership grade of a fuzzy set and x_i is the input parameter.

Layer 2: Computation of firing strength

This layer is also called as rule layer and the outcome of this layer is known as firing strength. The nodes in this layer are fixed and represented by Π. These nodes are responsible for receiving information from previous layer and the output of this nodes is obtained by the following equation:

$$O_{2,j} = w_j = \mu A_{i1}(x_1)\mu A_{i2}(x_2), \dots, \mu A_{in}(x_n) \qquad for\ \ 1 \le j \le m \tag{5.29}$$

Layer 3: Normalization of firing strength

Each node is fixed in the 3rd layer and defined as N. The nodes in this layer receives signals from each node in previous layer and calculate the normalized firing strength by given rule:

$$O_{3,j} = \overline{w}_j = \frac{w_j}{\sum_{j=1}^{m} w_j} \qquad for\ \ 1 \le j \le m \tag{5.30}$$

Layer 4: Consequent Parameters

The nodes in this layer are adaptive and process the information from 3rd layer by given rule which is showed as follow:

$$O_{4,j} = \overline{w}_j f_j = \overline{w}_j\left(p_{j1}x_1 + p_{j2}x_2 + \cdots p_{jn}x_n + q_j\right) \qquad for\ \ 1 \le j \le m \tag{5.31}$$

where $\overline{w}_i$ is the normalized firing strength and p_j, q_j are the parameter(s) set that can be determined by the method of least squares.

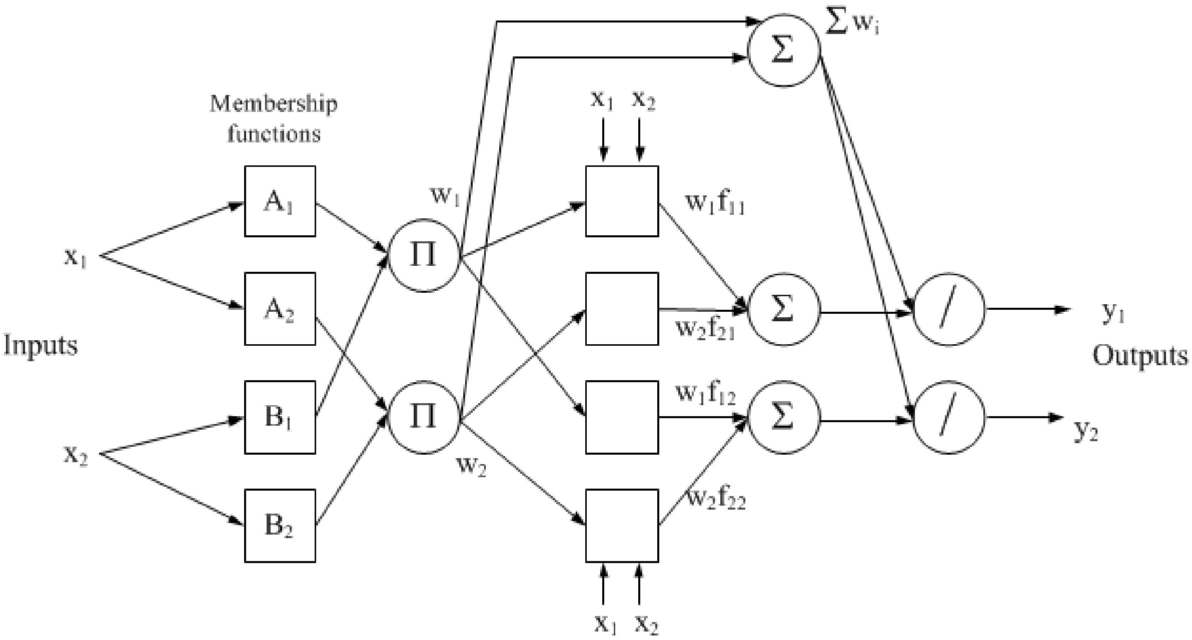
Layer 5: Computation of overall output

This layer is labeled as Σ which calculates the overall CANFIS output by aggregating all the information received from 4th layer:

$$O_{5,j} = y = \sum_j \bar{w}_j f_j = \frac{\sum_j w_j f_j}{\sum_j w_j} \tag{5.32}$$

The main contribution of CANFIS model is to provide multiple outputs, while the two biggest drawbacks of the system are (a) problem with dealing extreme values and (b) requirement of large dataset to train the model. The CANFIS structure with two inputs and two outputs is shown in Figure 5.12.

Figure 5.12: The CANFIS prototype with two inputs and two outputs



5.5.10 Forecast Combination

The combination of forecasts is generally considered a useful tool to improve performance of individual forecasts. The arithmetic average method can be used with various forecasting models which provides robustness and accuracy in overall results. This method is applied as follows:

$$Cf_t^{NN} = (f_t^{NN1} + f_t^{NN2} + \cdots + f_t^{NNm})/m \tag{5.33}$$

where Cf is the forecast combination, $f_t^{NN}$is the Neural Network forecast at time t and m is the number of forecasts.

5.5.11 Naïve Forecast

Naïve forecasts are the most basic and cos-effective forecasting models which provide a benchmark against more complex models. This technique is widely used in empirical finance, especially for financial time series which have patterns that are difficult to predict. In this method, forecasts are calculated based on the last observed value. Mathematically, for time t, the value of observation in time $t-1$ are considered the best forecast:

$$\hat{y}_t = y_{t-1} \tag{5.34}$$

5.5.12 The Moving Average Convergence Divergence Indicator (MACD)

The MACD is a technical indicator that is designed by Gerald Appel in the late 1970s to reveal changes in the strength, momentum, and trend of stock prices. The MACD is chosen as one of the benchmark models because if an individual technical indicator outperforms the integration of a technical indicator and ANN model, then ANN system would be inefficient. The standard MACD is calculated by subtracting the 26 period Exponential Moving Average (EMA) from the 12 period EMA as mathematically expressed below:

$$MACD = 12\, period\ EMA - 26\, period\ EMA \tag{5.35}$$

$$Signal\ Line = 9\, period\ EMA\ of\ the\ MACD \tag{5.36}$$

The signal line is developed by T.Aspray in 1986 to measure the signed distance between MACD line and together they form of MACD histogram. Aspray advises to use MACD (12,26,9) as the system become more responsive. The trading signals are created by the shift between MACD and signal line. When the MACD falls below the signal line, it is a bearish signal which indicates that it may be time to sell. Conversely, when the MACD rises above the signal line, the indicator gives a bullish signal, which suggests that the price of the asset is likely to experience upward momentum.

5.5.13 GARCH Family Models

There are more than 330 GARCH-type models in the existing literature which some of the important ones are discussed under the "Empirical Literature" title in Chapter 2. Therefore, for compactness, the following models are selected models as benchmark models which are namely, GARCH (Bollerslev, 1986), GARCH-M (Engle et al., 1987), EGARCH (Nelson, 1991), PGARCH (Ding et al., 1993) and TGARCH (Zakoian, 1994). The return specification is given by:

$$r_t = \mu + \varepsilon_t \tag{5.37}$$

where μ is the constant mean and $\varepsilon_t = h_t z_t$ refers the returns of residual with 0 mean and 1 variance *(i.i.d.)*.
The conditional variance specifications of the chosen models are as follow:

$$\text{GARCH: } h_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta \, \mathrm{h}_{t-1}^2 \tag{5.38}$$

$$\text{EGARCH: } \ln\left(h_t^2\right) = a_0 + \beta_1 \ln(h_{t-1}^2) + a_1 \left\{ \left| \frac{\varepsilon_{t-1}}{h_{t-1}} \right| - \sqrt{\frac{2}{\pi}} \right\} - \gamma \frac{\varepsilon_{t-1}}{h_{t-1}} \tag{5.39}$$

where h_t^2 is the time-dependent conditional variance and ε_t is the returns of residual. α_0, a_1, β and γ are the parameters estimated using the maximum likelihood method.

5.6 Data and Methodology

5.6.1 Data

In this section, the selected time series data and related statistical and preliminary analysis will be introduced. The same dataset in the previous chapters has been used to evaluate predictions and make healthy comparison between models. Closing price data from the selected indices is converted to the return series by taking the logarithmic differences. The descriptive statistics includes the related quantitative features from the collected dataset. And the statistical analysis gives further information about underlying patterns and trends including; the Mann-Kendall Test for monotonic trend, the Jarque-Bera test for normality and the Augmented Dickey-Fuller test for stationarity.

5.6.2 Markets and Preliminary Analysis

The overall sample period covers 24 years in total as mentioned in Chapter 3 in detail. Table 5.1 and Table 5.2 below report the selected markets & indices, and sample sizes & out-of-sample forecasting periods for each market, respectively.

Table 5.1: Markets and Indices

Market	Index	Index Code
Japan	The Nikkei 225 Index	NIKKEI
Singapore	The Straits Times Index	STI
Hong Kong	The Hang Seng Index	HANG SENG
Malaysia	The Kuala Lumpur Composite Index	KLCI
Indonesia	The Jakarta Composite Index	JCI
Thailand	The SET Index	SET
China	The Shanghai Composite Index	SSE
Taiwan	The Taiwan Capitalization Weighted Stock Index	TAIEX
South Korea	The KOSPI Index	KOSPI
The Philippines	The PSE Index	PSE

Table 5.2: Sample sizes and Out-of-sample forecasting period for daily return series in selected markets

Country	Estimation Period	Estimation Size	Forecast Period	Forecast Size	Full Sample Size
Japan	12/09/1994 - 8/11/2006	2874	8/14/2006 - 5/02/2018	2876	5750
Singapore	8/31/1999 - 12/30/2008	2344	12/31/2008 - 5/02/2018	2346	4690
Hong Kong	1/10/1995 - 8/29/2006	2874	8/30/2006 - 5/03/2018	2877	5751
Malaysia	1/10/1995 - 9/04/2006	2871	9/05/2006 - 4/30/2018	2869	5740
Indonesia	1/11/1995 - 8/25/2006	2847	8/28/2006 - 4/26/2018	2841	5688
Thailand	1/11/1995 - 8/24/2006	2855	8/25/2006 - 4/25/2018	2848	5703
China	1/10/1995 - 9/11/2006	2828	9/12/2006 - 5/03/2018	2829	5657
Taiwan	1/11/1995 - 3/23/2006	2997	3/24/2006 - 5/02/2018	2895	5892
South Korea	1/10/1995 - 5/02/2006	2970	5/03/2006 - 5/02/2018	2973	5943
Philippines	1/11/1995 - 7/17/2006	2875	7/18/2006 - 5/02/2018	2853	5728

Table 5.3 shows the key descriptive statistics of total data sample for each index. The mean fluctuates between 0.004651 and 0.044841 for daily returns. Indonesia outperforms other markets while Thailand stock market performs worst. The return distribution is not symmetrical, and the series have either positive or negative skewness. Positive skewness appears when the median has smaller value than the mean, while negative skewness occurs when the median has greater value than the mean. Eastman and Lucey (2008) suggest that in the event of negative skewness, most returns will be higher than average return, therefore market participants would prefer to invest in negatively skewed equities. According to the Table 5.3, half of the markets present negative skewness, while the other half indicate positive skewness. In a similar way to the concept of skewness, kurtosis indicates sharp events and can be interpreted as a gauge of greatest point in both ways. The kurtosis in a normal distribution is three. A positive kurtosis with the value of greater than three refers to leptokurtosis. Emenike and Aleke (2012) suggest that high kurtosis values indicate big shocks in the time series with either type of sign. As is clear from the table, the values of kurtosis are positive and greater than three in all selected return series which demonstrate leptokurtosis. China has the highest maximum value, while Singapore and Taiwan have the lowest maximum values. The greatest single-day hike has been viewed in China's SSE with 26.99277% and the biggest drop has been occurred in Malaysia's KLCI with -24.15339%. Singapore's STI and Taiwan's TAIEX Indices have the smallest gap between minimum and maximum values in daily frequency with -8.695982% & 7.531083% and, -6.975741% & 6.52462% respectively. This result indicates lowest volatility compared to others. To sum up, Asian stock markets are likely to show high volatility in the return series, especially countries like China and Thailand.

Table 5.3: Summary of descriptive statistics for daily return series

	NIKKEI	STRAITS TIMES INDEX	HANG SENG INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SET INDEX	SSE INDEX	TAIEX	KOSPI	PSE INDEX
Mean	0.0294	0.0105	0.024194	0.012354	0.044841	0.004651	0.028739	0.015257	0.015445	0.015835
Median	0.030928	0.02846	0.0511	0.025455	0.090305	0.015914	0.065357	0.043451	0.050211	0.021669
Maximum	13.23458	7.531083	17.2471	20.81737	13.12768	11.34953	26.99277	6.52462	11.28435	16.1776
Minimum	-12.11103	-8.695982	-14.73468	-24.15339	-12.73214	-16.06325	-17.90509	-6.975741	-12.8047	-13.08869
Std. Dev.	1.504108	1.141326	1.60473	1.267938	1.52564	1.526721	1.761533	1.36745	1.66492	1.393054
Skewness	-0.300663	-0.266133	0.064089	0.502157	-0.19832	0.049086	0.195354	-0.182956	-0.291322	0.162169
Kurtosis	8.540723	8.37642	13.32528	65.37193	11.58383	10.95738	18.86232	5.815682	8.152126	14.21301
Probability	0.000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Observations	5748	4689	5750	5740	5688	5703	5656	5892	5942	5728
Sample	12/09/1994 5/03/2018	8/31/1999 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/11/1995 5/03/2018	1/11/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018	1/10/1995 5/03/2018

Figure A.1 to A.6 in Appendix A indicate the closing prices and returns for each selected market. As reported by the closing prices graphs, there are slumps in all markets during the crisis times of 1997-98 and 2007-08. Although the stock market downturn of 2002 (also called as dot-com crash) hit some markets, there is no sharp declines as in the mentioned crisis above. However, it is clear that a financial crisis in the US directly or indirectly influences the Asian stock markets, and the contagion differs for each market depending on integration with the US market. The return series also reflects high volatility during the crisis, especially in the period of 2007-08. Although the fluctuations around zero, the sign of volatility clustering is clear in all return series.

5.6.3 Mann-Kendall Trend Test

The Mann-Kendall (MK) test is a statistical test to assess whether there is any monotonic upward or downward trend in a time series data. It is a non-parametric (distribution-free) test first proposed by Mann (1945) and further developed by Kendall (1975) and later improved for seasonality feature by Hirsch et al. (1982, 1984). The MK test compares the relative magnitudes of given data instead of the direct values (Gilbert,1987).

In MK test, the null hypothesis H_0 indicates that here is no trend, while the alternative hypothesis H_1 shows that there is a trend in the two-sided test or there is an upward trend (or downward trend) in the one-sided test. For the time series $x_1, x_2 \dots, x_n$ the MK test statistic S formula given as follow:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sign(X_j - X_i) \tag{5.40}$$

where X_j and X_i are sequential data values of the time series data and n is the length of the series. Note that if S > 0 then observations obtained later in time tend to be larger than observations made earlier, while the opposite is true if S < 0.

The indicator function of $(X_j - X_i)$ is given by:

$$sign(X_j - X_i) = \begin{Bmatrix} +1 \; if \; (X_j - X_i) > 0 \\ 0 \quad if \; (X_j - X_i) = 0 \\ -1 \; if \; (X_j - X_i) < 0 \end{Bmatrix} \tag{5.41}$$

The variance of test statistic S is given by:

$$Var(S) = \frac{1}{18}\left[n(n-1)(2n+5) - \sum_{p}^{q} t_p(t_p - 1)(2t_p + 5) \right] \tag{5.42}$$

where t_p is the number of observations in the p^{th}value, and q is the number of tied values. The MK test statistic Z_{MK} as follows:

$$Z_{MK} = \begin{Bmatrix} S-1 \Big/ \sqrt{Var(S)} \; if \;\; S < 0 \\ 0 \; if \; S = 0 \\ S-1 \Big/ \sqrt{Var(S)} \; if \; S > 0 \end{Bmatrix} \tag{5.43}$$

The presence of whether there is a monotonic trend in the series is evaluated by the MK test statistic, Z_{MK}. The positive values of Z_{MK} presents increasing monotonic trend, while the reverse is true for the negative values of Z_{MK}. The null hypothesis is rejected if $|Z_{MK}| > Z_{1-a/2}$ which indicates existence of trend.

The MK test is summarized for the selected indices in the Table 5.4. From the results, as the computed p-value is lower than the significance level (α=0.01), the null hypothesis H_0 is rejected and the alternative hypothesis H_a is accepted. Therefore, there is a presence of monotonic trend in the return series of selected indices.

Table 5.4: Mann-Kendall test results

Mann-Kendall Test										
	NIKKEI	**HSI**	**STI**	**SET**	**KLCI**	**JCI**	**SSE**	**TAIEX**	**KOSPI**	**PSE**
Kendall's tau	-0.042	-0.0714	-0.132	-0.178	-0.215	-0.0922	-0.0829	-0.134	-0.182	-0.0652
S	-693058	-1179449	-1447950	-2898337	-3534679	-1491109	-1325768	-2317424	-3213808	-1069771
Var(S)	2110.1	2112.58	1145.32	2061.34	2101.6	2045.26	2010.94	2273.03	2331.59	2088.74
p-value (Two-tailed)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Alpha(a)	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

5.6.4 Jarque-Bera Test Statistic

The Jarque-Bera test is a goodness-of-fit test for normality whether the data have skewness and kusrtosis (Jarque and Bera, 1980; Bowman and Shenton, 1975). The Jarque-Bera (JB) test is implemented to evaluate whether the selected indices follow a normal distribution. Based on the results from following Table 5.5 of Jarque-Bera test statistic, the normality assumption of null hypotheses is rejected in all selected markets, confirming the non-normal distribution in all series. The level of significance is set to 0.01 (99%) and the corresponding p-value is presented as <0.0001 from the applied computation.

Table 5.5: Jarque-Bera Normality test results

Jarque-Bera Normality Test										
	NIKKEI	**HSI**	**STI**	**SET**	**KLCI**	**JCI**	**SSE**	**TAIEX**	**KOSPI**	**PSE**
JB test statistic	7439.2	2554.6	5702.8	1504.9	9306.6	17500	5933.3	1979.2	6656	3003.3
DF	2	2	2	2	2	2	2	2	2	2
p-value (Two-tailed)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Alpha	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

5.6.5 Testing for Stationarity

Non-stationary behaviours in time series data indicate that parameters such as mean, and variance change over time which makes the data unpredictable. This problem also applies ANN prediction and according to Weigend (2018) non-stationary behaviour may cause negative effect on performance of ANN models. Moreover, Tseng et al. (2002) indicate that seasonal variations also have undesirable implications on Neural Network forecasting. To overcome of non-stationary data which may include cycles, trends or seasonality, the transformation of prices to return series by taking their log-difference is an effective and commonly applied solution. In order to test stationarity of the return series, the Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) has been conducted. The following equation shows the testing procedure for the ADF test regression:

$$\Delta Y_t = a_0 + \beta Y_{t-1} + a_1 \Delta Y_{t-1} + a_2 \Delta Y_{t-2} + \cdots + a_p \Delta Y_{t-p} + \varepsilon_t \tag{5.44}$$

where Y is the dependent variable, a_0 is the constant and p is the lag order of the autoregressive process. Lag length is determined by minimizing the Schwarz information criterion (SIC) until the last lag is statistically significant. The null hypothesis refers Y_t series have unit root, which signifies the data is nonstationary if it is accepted.

Table 5.6 reports the results of selected index returns for daily series. According to the results on the table, the test statistic is smaller than critical values which allows rejecting null hypothesis of unit root (nonstationary) at the significance level (Alpha) of 0.01 (99%) for each series.

Table 5.6: Augmented Dickey-Fuller (ADF) test results

	Augmented Dickey-Fuller (ADF) Test									
	NIKKEI	**HSI**	**STI**	**SET**	**KLCI**	**JCI**	**SSE**	**TAIEX**	**KOSPI**	**PSE**
Tau (Observed Value)	-17.442	-17.446	-16.134	-16.122	-16.751	-15.382	-16.372	-16.844	-16.179	-16.078
Tau (Critical Value)	-3.43131	-3.43131	-3.43156	-3.43132	-3.43131	-3.43132	-3.431326	-3.43129	-3.431271	-3.431314
p-value (One-tailed)	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001	<0.0001
Alpha	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Table 5.7 summarizes the overall descriptive statistics regarding the return series of Asian indices. According to the table below, monotonic trend presence is identified by Mann-Kendall test in all return series. The Jarque-Bera confirms that the series are not normally distributed which confirms skewness and leptokurtic behaviors in varying magnitudes. Finally, the Augmented Dickey Fuller (ADF) test for normality indicates all return series are stationary with the confidence level of 99%.

Table 5.7: Descriptive statistics for daily return series

NIKKEI Daily Index Returns				JCI Daily Index Returns			
Descriptive Statistics	**Confidence Level**	**P-Value**	**Result**	**Descriptive Statistics**	**Confidence Level**	**P-Value**	**Result**
Mann-Kendall	95%	<0.01	Monotonic Trend Presence	Mann-Kendall	95%	<0.01	Monotonic Trend Presence
Jarque-Bera	95%	<0.01	Not Normally Distributed	Jarque-Bera	95%	<0.01	Not Normally Distributed
Dickey-Fuller	95%	<0.01	Stationary	Dickey-Fuller	95%	<0.01	Stationary
HANG SENG Daily Index Returns				SSE Daily Index Returns			
Descriptive Statistics	**Confidence Level**	**P-Value**	**Result**	**Descriptive Statistics**	**Confidence Level**	**P-Value**	**Result**
Mann-Kendall	95%	<0.01	Monotonic Trend Presence	Mann-Kendall	95%	<0.01	Monotonic Trend Presence
Jarque-Bera	95%	<0.01	Not Normally Distributed	Jarque-Bera	95%	<0.01	Not Normally Distributed
Dickey-Fuller	95%	<0.01	Stationary	Dickey-Fuller	95%	<0.01	Stationary
STI Daily Index Returns				TAIEX Daily Index Returns			
Descriptive Statistics	**Confidence Level**	**P-Value**	**Result**	**Descriptive Statistics**	**Confidence Level**	**P-Value**	**Result**
Mann-Kendall	95%	<0.01	Monotonic Trend Presence	Mann-Kendall	95%	<0.01	Monotonic Trend Presence
Jarque-Bera	95%	<0.01	Not Normally Distributed	Jarque-Bera	95%	<0.01	Not Normally Distributed
Dickey-Fuller	95%	<0.01	Stationary	Dickey-Fuller	95%	<0.01	Stationary
SET Daily Index Returns				KOSPI Daily Index Returns			
Descriptive Statistics	**Confidence Level**	**P-Value**	**Result**	**Descriptive Statistics**	**Confidence Level**	**P-Value**	**Result**
Mann-Kendall	95%	<0.01	Monotonic Trend Presence	Mann-Kendall	95%	<0.01	Monotonic Trend Presence
Jarque-Bera	95%	<0.01	Not Normally Distributed	Jarque-Bera	95%	<0.01	Not Normally Distributed
Dickey-Fuller	95%	<0.01	Stationary	Dickey-Fuller	95%	<0.01	Stationary
KLCI Daily Index Returns				PSE Daily Index Returns			
Descriptive Statistics	**Confidence Level**	**P-Value**	**Result**	**Descriptive Statistics**	**Confidence Level**	**P-Value**	**Result**
Mann-Kendall	95%	<0.01	Monotonic Trend Presence	Mann-Kendall	95%	<0.01	Monotonic Trend Presence
Jarque-Bera	95%	<0.01	Not Normally Distributed	Jarque-Bera	95%	<0.01	Not Normally Distributed
Dickey-Fuller	95%	<0.01	Stationary	Dickey-Fuller	95%	<0.01	Stationary

5.7 Methodology

Neural Network models have been utilized on MATLAB and Python software programs. For this research, following Neural Network models have been selected: Multi-Layer Perceptron (MLP), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), Modular

Feedforward Network (MFN), Generalized Feedforward Network (GFN), Radial Basis Function Network (RBFN), Probabilistic Neural Network (PNN).

5.7.1 Hidden Layers

The learning process of a neural network is performed with the layers and the hidden layer(s) plays key role to connect input and output layers as well as providing product for the defined output. Theoretically, single hidden layer with a sufficient neurons is considered capable of approximating any continues function. Practically, single or two hidden layers network is commonly applied and provides good performance (Thomas et al., 2017). Therefore, this study follows the maximum of two hidden layers approach for each NN model.

5.7.2 Epochs

The number of epochs is a hyperparameter that defines the number times that the learning algorithm will work through the entire training dataset (Brownlee, 2018). The default number of 1000 epochs were used for training the data, but early stopping has been applied if there is no improvement after 100 epochs, to prevent overfitting problem (Prechelt, 2012).

5.7.3 Weights

Weights are the parameters in a neural network system that transforms input data within the network’s hidden layers. A weight decides how much influence the input will have on the output. Negative weights reduce the value of an output. The reproduction phase of the models has been performed based on two modes of weight update which are online weighting and batch weighting. In batch mode, changes to the weight matrix are accumulated over an entire presentation of the training data set, while online training updates the weight after presentation of each vector comprising the training set.

5.7.4 Activation Function

Activation function (also known as transfer function) is mathematical equation that determines the output of a neural network by given input or set of inputs. The logic behind the usage of activation function in ANN is to limit the bounds of the output values which can “paralyze” the network and prevent training process. The activation functions can be divided into two groups as linear activation functions and non-linear activation functions. As Hsieh (1995) and Franses and Van Dijk (2000) state the fact that financial markets are non-linear and presence of memory is observed, non-linear activation functions are more suitable for forecasting tasks. There are various types of non-linear transfer functions, but this study adopts the tanh activation function as described below:

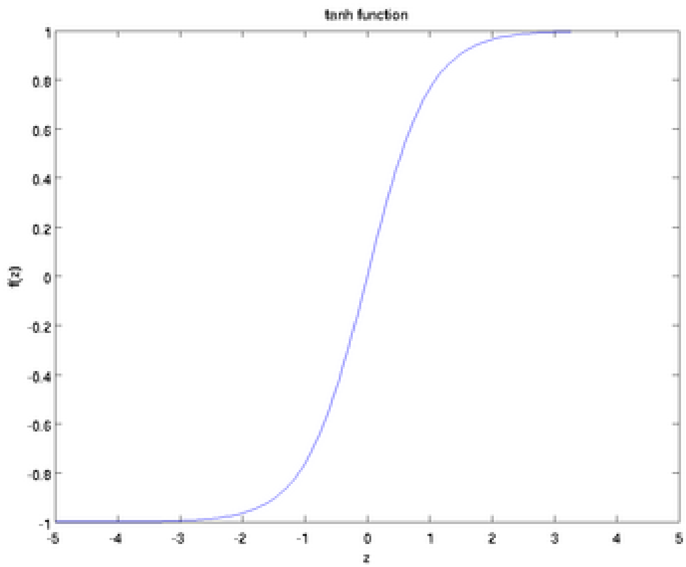
$$y_i(t) = f(x_i(t), w_i) \tag{5.45}$$

where $y_i(t)$ is the output, $x_i(t)$ is the accumulation of input activity from other components and w_i is the weight.

$$\tanh(x) = f\left(x_i, w_,\right) = \begin{Bmatrix} -1 & x_i < -1 \\ 1 & x_i > 1 \\ x_i & else \end{Bmatrix} \tag{5.46}$$

The tanh function ranges from -1 to 1 as shown in the following figure:

Figure 5.13: Hyperbolic Tangent



The tanh function is extensively used in time series forecasting since it delivers robust performance for feedforward neural networks. Although Gomes et al. (2011) and Zhang (2015) evaluate different activation functions in different models such as log-log and Elliott modifications, Karlik and Olgac (2011) and Graves (2012) show that hyperbolic tangent function outperforms all the remaining functions in ANN applications.

5.7.5 Learning Rule

Learning rule in Neural Network is a mathematical method to improve ANN performance via helping neural network to learn from the existing conditions. The Levenberg-Marquardt (LM) algorithm has been conducted in this study which has been designed to work specifically with loss functions. This method has been developed separately by Levenberg (1944) and Marquardt (1963) to provide a numerical solution to the problem of minimizing a non-linear function (Yu and Wilamowski, 2011). It is one of the fastest methods to train network and has stable convergence, therefore it is one of the most suitable higher-order adaptive algorithms in terms of minimizing error functions.

5.7.6 Forecast Evaluation

Great decisions are based on great forecasts. There is wide selection of procedures available in the literature to evaluate the most accurate forecasts. In this study, the most common and important error measures are chosen to evaluate the predictive accuracy of selected volatility models. Nevertheless, there is no consensus about which error function is more suitable to assess the models. Therefore, instead of focusing on a single criterion, five different loss functions are determined for producing forecasts. These loss functions are Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Square Error (RMSE), Quasi-Likelihood (QLIKE) and Mean Squared Error (MSE).

5.7.6.1 Mean Absolute Error (MAE)

MAE measures the average magnitude of the errors in a set of predictions, without considering their direction. It is the average over the test sample of the absolute differences between prediction and actual observation where all individual differences have equal weight. The mean absolute error is given by:

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|\sigma_t^2 - \hat{\sigma}_t^2| \tag{5.47}$$

where n denotes the rank of forecasted data, σ_t^2 is the true volatility series which is obtained by the squared return series and $\hat{\sigma}_t^2$ is the forecasted conditional variance at time t acquired by using GARCH family models.

5.7.6.2 Mean Absolute Percentage Error (MAPE)

MAPE is the sum of the individual absolute errors divided by each period separately. In other words, it is the average of the percentage errors. The advantage of the MAPE is that it is easy to interpret and helpful to compare the performance of the estimated volatility models. The mean absolute percentage error is defined as follows:

$$MAPE = \frac{1}{n}\sum_{t=1}^{n}\frac{|\sigma_t^2 - \hat{\sigma}_t^2|}{\sigma_t^2} \tag{5.48}$$

5.7.6.3 Root Mean Square Error (RMSE)

RMSE is the square root of the average of squared differences between prediction and actual observation. Since the errors are squared before they are averaged, the RMSE gives a relatively high weight to large errors. This means the RMSE is most useful when large errors are particularly undesirable. Its value can only be positive, and a value of zero (almost never achieved in practice) would indicate a perfect fit to the data. In general, a lower RMSE is better than a higher one. However, comparisons across different types of data would be invalid because the measure is dependent on the scale of the numbers used. The following formula is given for the root mean square error:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2} \tag{5.49}$$

5.7.6.4 Quasi-Likelihood Loss Function (QLIKE)

The term quasi-likelihood function was introduced by Robert Wedderburn in 1974 to describe a function that has similar properties to the log-likelihood function. In Qlike loss function, the mean and the variance is specified in the form of a variance function giving the variance as a function of the mean.

$$QLIKE = \frac{1}{n}\sum_{t=1}^{n}\left(\log(\hat{\sigma}_t^2) + \left(\frac{\sigma_t^2}{\hat{\sigma}_t^2}\right)\right) \tag{5.50}$$

Patton and Sheppard (2009), Patton (2011), and Conrad and Kleen (2019) revealed that the squared error loss tends to be more sensitive to extreme observations than QLIKE which provides further motivation for using QLIKE in volatility forecasting applications.

5.7.6.5 Mean Squared Error (MSE)

MSE is another popular accuracy measure in the empirical financial literature developed by Bollerslev et al. (1994) to gauge the forecasting performance of the volatility models. As a distinctive feature, it has the tendency of penalizing large forecast errors compared to other loss functions, thus it is recognized as one of the most appropriate measures in terms of dealing with imperfect volatility proxy (Patton, 2011). The mean squared error is given as follows:

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{5.51}$$

5.7.6.6 Model Confidence Set

Although the given evaluation metrics above allow forecasts to be ranked, it is difficult to determine whether there are any significant distinctions in the values. To draw such conclusions, the present paper implements the Model Confidence Set (MCS) method by Hansen et al. (2011). The procedure follows a sequence of statistic tests which allows to produce a set of “superior” models. The MCS eliminates the worst performing model sequentially based on the equal predictive ability (EPA) till the final set of the MCS find the optimal model by given confidence level. Formally, the procedure starts with the set of alternative candidates forecasting models to be compared, defined by $M_0 = 1,2, \ldots, m_0$. Then to evaluate the performances among selected forecasts, all loss differentials between models are calculated as follow:

$$d_{ij,t} = L_{i,t} - L_{j,t}, \qquad for\ all\ i,j\ \in\ M_0 \tag{5.52}$$

where $d_{ij,t}$ denotes the loss differential between the loss functions of the ith model and jth model at time t. Then for the given set of models the null hypothesis and alternative hypothesis of EPA are formulated as follow:

$$H_{0,M}: E\left(d_{ij,t} = 0\right), \quad \forall i,j = M_0 \tag{5.53}$$

$$H_{A,M}: E\left(d_{ij,t} \neq 0\right), \quad for\ some\ \ i,j = M_0 \tag{5.54}$$

Then the MCS sequential testing procedure starts by testing the null hypothesis of EPA in each stage by given significance level and if it is rejected, the significantly inferior model is eliminated until the first non-rejection occurs. However, in order to decide whether the MCS would further reduce at any step, the null hypothesis of EPA in equation 32 must be estimated at each step of the process. To address this drawback, Hansen et al. (2011) propose the Range Statistic and Semi-quadratic statistic, defined as:

$$T_R = \max_{i,j\,\in\,M_0} \frac{\left|\bar{d}_{i,j}\right|}{\sqrt{\sqrt{\widehat{var}(\bar{d}_{i,j})}}} \quad and \quad T_{SQ} = \sum\nolimits_{i,j\,\in\,M_0} \frac{(\bar{d}_{i,j})^2}{\widehat{var}(\bar{d}_{i,j})} \tag{5.55}$$

where $\bar{d}_{i,j}$ denotes the mean value of $d_{ij,t}$, given by $\bar{d}_{i,j} = {}^{1}\!/_{M} \sum d_{ij,t}$.

5.7.7 Risk Management

5.7.7.1 Value at Risk (VaR) and Expected Shortfall (ES)

Value at Risk (VaR) is a statistical technique that measures and quantifies the level of risk over a specific interval of time. Jorion (1996) defines VaR as the worst expected loss over a target horizon under normal market conditions at a given level of confidence. Due to its simplicity to assess market risk by a certain value and a broad range of applicability, it has become one of the most commonly used risk management metrics by financial institutions. However, some researchers claim that the VaR has several conceptual drawbacks such as disregarding any loss beyond the VaR level which is also called as "tail risk" (Alexander, 2009; Danielsson et al., 2016). To deal with this inherent problem in VaR, Artzner et al. (1999) introduced the Expected Shortfall (ES) which is also called as conditional Value at Risk (CVaR), average value at risk (AVaR), and expected tail loss (ETL). Expected Shortfall is a measure of risk in the field of financial risk management to evaluate the conditional expectation of loss exceeding the Value at Risk level. In another words, where VaR asks the question of "How bad can things get?", expected shortfall asks, "If things go get bad, what is our expected loss?". Therefore, this study adopts both methods for risk management purposes to evaluate the market risk in selected indices.

The VaR equation is defined as follow:

$$VaR = \mu_t + \sigma_t N(\alpha) \tag{5.56}$$

where μ_t is the mean of the logarithmic transformation of daily return series at time *t*, σ_t is the predicted returns volatility, and $N(\alpha)$ is the quantile of the standard normal distribution that corresponds to the VaR probability.

The Expected Shortfall (ES) equation is also given as follow:

$$ES = \mu_t + \sigma_t \frac{f(N(\alpha))}{1-\alpha} \tag{5.57}$$

where μ_t is the mean of the logarithmic transformation of daily return series at time *t*, σ_t is the predicted returns volatility, and $f(N(\alpha))$ is the density function of the α^{th} quantile of the standard normal distribution. For further discussions and the proof of the equations see: Hendricks (1996), Scaillet (2004), Alexander (2009), Hull (2012), Fissler and Ziegel (2016), Taylor (2019).

5.7.7.2. Backtesting

Backtesting measures the accuracy and effectiveness of the Value at Risk (VaR) model. Although the VaR method is widely accepted risk management tool, it is advisable to test the model to verify the obtained results by VaR. Jorion (2002) names backtesting as "reality checks". Moreover, Brown (2008) indicates that "VaR *is only as good as its backtest. When someone shows me a VaR number, I don't ask how it is computed, I ask to see the backtest*" (pp.20). Therefore, to confirm the accountability of the results, three different backtesting methods have been used, namely; Kupiec test, Christoffersen test and Dynamic Quantile (DQ) test.

Kupiec (unconditional coverage) test is a likelihood ratio test (LR_{UC}) proposed by Kupiec (1995) to assess whether the theoretical failure rate of VaR is statistically consistent with the true failure rate. The null hypothesis is tested against the alternative hypothesis whether the observed failure rate significantly differs from the failure rate given by confidence level. The test statistic of the unconditional coverage is given by:

$$LR_{UC} = 2\log\left(1 - N_0/N_1\right)^{N_1-N_0}\left(N_0/N_1\right)^{N_0} - 2\log\left(1-\phi\right)^{N_1-N_0}\phi^{N_0} \qquad (5.58)$$

where $p = E(N_0/N_1)$ is the expected ratio of violations obtained by dividing the number of violations N_0 to forecasting sample size N_1 and, ϕ is the prescribed VaR level. The Kupiec test is asymptomatically distributed $(\sim X^2(1))$ with one degree of freedom under the null hypothesis.

Although the Kupiec test is a widely used technique for backtesting, one of the disadvantages of the unconditional coverage test is focusing only on the number of violations. When the loss in the return of an asset exceeds the expected value of the VaR model, the VaR model breaks for that day. However, it has been observed that these violations occur in clusters. Clustering of violations is something that the risk managers prefer to determine as big losses tend to cause catastrophic incidents compared to single day violations. Thus, the conditional coverage test of

Christoffersen (1998) is proposed to examine not only the frequency of VaR failures but also the time and duration between two consecutive violations. The model adopts the similar theoretical framework as Kupiec's with the extension of separate statistic for the independence of exceptions. The test statistic of the conditional coverage is given by:

$$LR_{CC} = 2\log\left((1-p_{01})^{n_{00}}\, p_{01}^{n_{01}}\left(1-p_{11}\right)^{n_{10}} p_{11}^{n_{11}}\right) \\ -2\log\left((1-p_0)^{n_{00}+n_{10}} {p_0}^{n_{01}+n_{11}}\right) \tag{5.59}$$

where p_{ij} is the expected ratio of violations on state i, while j occurs on the previous period, and n_{ij} is defined as the number of days $for\ (i,j=0,1)$. For the detailed procedure and further information see; Christoffersen (1998), Jorion (2002), Campbell (2005), and Dowd (2006).

In addition to the Kupiec and Christoffersen tests, we use the Dynamic Quantile (DQ) test proposed by Engle and Manganelli (2004). The DQ test is based on a linear regression model to measure whether the current violations are linked to the past violations. The authors define a demeaned process of violation as:

$$Hit_t(a) = I_t(a) - a = \begin{cases} 1-a, & if\ x_t < VaR_t(a), \\ -a, & otherwise. \end{cases} \tag{5.60}$$

where $Hit_t(a)$ is the conditional expectation and if the true return series are less than the VaR quantile $1-a$ and $-a$ otherwise. The sequence assumes that the conditional expectation of $Hit_t(a)$ must be zero at time $t-1$ (see Giot and Laurent, 2004). The designated test statistic for the DQ is given as follow:

$$DQ = \frac{\hat{\psi}' Q' Q \hat{\psi}}{a(1-a)}, \tag{5.61}$$

where Q denotes the matrix of explanatory variables and $\hat{\psi}$ indicates the OLS estimator. The proposed test statistic follows a chi-squared distribution X_q^2, in which $q = rank(X_t)$.

5.8 Empirical Results

Table 5.8 demonstrates the forecasting performance for daily return series based on the calculation of Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Root Mean Squared Error (RMSE), Quasi-Likelihood (QLIKE) and Mean Squared Error (MSE) using the recursive approach. The out-of-sample return forecasts have been obtained by using ten ANN models, and 4 benchmark models are added to evaluate the ANN predictive capability against the conventional forecasting methods. The overall results of forecasting performance inform that the benchmark models are more successful based on MAE criterion on seven of the ten indices, with the only exception of STI, KLCI and JCI indices. The result for the KLCI index is consistent with the study of Yao et al. (1999). According to the MAPE criterion, ANN models are clear winner compared to the benchmark models. Notably, the RNN, RBFN and PNN models provide the lowest MAPE values across multiple indices which indicate their superiority over other forecast models. In terms of the RMSE loss function, the EGARCH model achieves the best results in KLCI and TAIEX indices, whereas the GARCH model performs the worst among all. LSTM model tends to provide more accurate forecast result compared to other models. This contrasts with the work of Selvin et al. (2017), although supports the findings of Chen et al. (2015) and Nelson et al. (2017). The QLIKE and MSE error criteria find substantial support for the prediction power of ANN based models with the only exception of STI, KLCI, and TAIEX indices, for which they provide either mixed results or favour traditional forecasting models. The adaptive and coactive network-based hybrid models of ANFIS and CANFIS indicate the lowest prediction errors specifically in HANG SENG, TAIEX and PSE indices, which support the works of Chang et al. (2009), Boyacioglu and Avci (2010), and Kristjanpoller and Michell (2018).

Table 5.8: Comparison of forecast performance measures for daily return series

NIKKEI INDEX						HANG SENG INDEX					
Model	**MAE**	**MAPE**	**RMSE**	**QLIKE**	**MSE**	**Model**	**MAE**	**MAPE**	**RMSE**	**QLIKE**	**MSE**
LSTM	0.32	6.66	0.46	0.18	**0.21**	LSTM	0.29	7.10	0.44	**0.15**	**0.19**
RNN	0.31	5.69	0.47	0.22	0.22	RNN	0.30	5.44	0.46	NA	0.21
MLP	0.35	6.63	0.51	0.55	0.26	MLP	0.37	9.48	0.54	1.31	0.29
RBFN	0.32	6.56	0.48	0.21	0.23	RBFN	0.34	10.93	0.46	0.45	0.21
ANFIS	0.27	**5.43**	0.51	**0.11**	0.28	ANFIS	0.33	6.76	**0.39**	0.19	0.28
CANFIS	0.33	5.44	0.46	0.13	**0.21**	CANFIS	0.37	6.55	**0.38**	0.22	0.33
PNN	0.40	6.54	0.60	5.74	0.36	PNN	0.39	**5.42**	0.61	6.83	0.37
GFN	0.32	7.06	0.46	0.18	**0.21**	GFN	0.30	7.38	0.45	**0.15**	0.20

MFN	0.32	6.53	**0.45**	0.18	**0.21**
ANN Fc	0.33	6.28	0.49	0.83	0.24
GARCH (1,1)	0.34	10.49	0.69	1.56	0.48
EGARCH (1,1)	**0.25**	10.56	0.69	1.54	0.47
MACD	0.55	13.50	1.27	1.56	0.59
NAIVE	0.41	6.59	0.73	5.71	0.34

MFN	0.34	9.71	0.46	0.16	0.21
ANN Fc	0.34	7.64	0.47	1.18	0.25
GARCH (1,1)	0.26	10.32	0.73	1.46	0.53
EGARCH(1,1)	**0.25**	10.23	0.70	1.46	0.48
MACD	0.91	9.80	1.01	1.91	0.29
NAIVE	0.42	7.81	0.56	6.89	0.38

STRAITS TIMES INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	**0.19**	4.81	0.26	0.33	0.07
RNN	**0.19**	4.82	0.26	0.32	0.07
MLP	0.23	6.66	0.28	**0.26**	0.08
RBFN	**0.19**	**4.34**	0.26	1.66	0.07
ANFIS	0.44	4.57	0.35	0.44	0.13
CANFIS	0.29	5.33	0.28	0.52	0.11
PNN	0.24	4.90	0.35	3.65	0.13
GFN	0.21	6.12	0.27	0.29	0.07
MFN	0.20	5.32	0.26	0.31	0.07
ANN Fc	0.24	5.21	0.29	0.86	0.09
GARCH (1,1)	0.91	9.68	0.20	0.50	**0.04**
EGARCH(1,1)	0.91	9.50	0.20	0.49	**0.04**
MACD	0.80	10.20	0.44	1.94	0.26
NAIVE	0.30	5.94	**0.09**	4.77	0.19

SET INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.37	0.60	0.46	**0.06**	0.21
RNN	0.24	0.80	**0.38**	0.17	**0.15**
MLP	0.31	**0.15**	0.43	0.84	0.18
RBFN	0.25	0.80	**0.38**	0.55	**0.15**
ANFIS	0.24	0.33	0.54	0.47	0.19
CANFIS	0.27	0.28	0.57	0.41	0.22
PNN	0.34	4.51	0.51	3.34	0.26
GFN	0.27	0.60	**0.38**	0.07	**0.15**
MFN	0.26	0.61	**0.38**	0.08	**0.15**
ANN Fc	0.28	0.96	0.45	0.67	0.18
GARCH(1,1)	**0.19**	10.53	0.67	1.21	0.45
EGARCH(1,1)	**0.19**	10.51	0.67	1.15	0.45
MACD	0.55	9.80	0.67	2.03	0.67
NAIVE	0.39	4.50	0.47	3.55	0.34

KUALA LUMPUR COMPOSITE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.18	5.77	0.23	0.54	**0.05**
RNN	0.14	6.11	0.23	0.52	0.05
MLP	0.24	4.53	0.31	0.58	0.09
RBFN	0.21	6.28	0.28	0.32	0.08
ANFIS	0.17	3.33	0.29	0.42	0.09
CANFIS	0.18	3.89	0.37	0.45	0.10
PNN	0.19	4.04	0.29	2.39	0.09
GFN	0.16	6.07	0.23	1.21	**0.05**
MFN	**0.15**	**1.42**	**0.22**	0.84	**0.05**
ANN Fc	0.18	4.60	0.27	0.81	0.07
GARCH(1,1)	0.68	10.00	0.23	0.06	**0.05**
EGARCH(1,1)	0.67	10.05	**0.22**	**0.05**	**0.05**
MACD	0.44	10.21	0.57	1.92	2.40
NAIVE	0.27	4.42	0.66	3.04	0.22

JAKARTA COMPOSITE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.29	6.37	**0.40**	**0.01**	**0.16**
RNN	0.30	6.68	0.41	**0.01**	0.17
MLP	0.33	6.09	0.47	0.80	0.22
RBFN	**0.27**	4.35	**0.40**	1.06	**0.16**
ANFIS	0.37	7.43	0.57	0.26	0.24
CANFIS	0.48	8.55	0.41	0.18	0.23
PNN	0.35	3.95	0.54	7.65	0.29
GFN	0.28	6.23	**0.40**	**0.01**	**0.16**
MFN	0.29	6.60	0.41	0.02	0.17
ANN Fc	0.33	6.25	0.45	1.11	0.20
GARCH(1,1)	0.29	10.94	0.42	0.72	0.24
EGARCH(1,1)	0.29	10.99	0.42	0.76	0.23
MACD	0.37	10.75	0.93	2.03	6.62
NAIVE	0.38	**3.59**	0.80	2.64	0.35

SSE INDEX

Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.40	6.50	0.53	0.29	0.28
RNN	0.40	6.44	0.52	0.27	0.27
MLP	0.40	4.90	0.58	0.31	0.34
RBFN	0.34	4.29	0.51	0.33	**0.26**
ANFIS	0.37	8.43	0.49	**0.25**	0.29
CANFIS	0.36	7.56	0.57	0.28	**0.26**
PNN	0.45	4.90	0.66	5.36	0.43
GFN	0.34	4.04	0.51	0.30	**0.26**
MFN	0.38	5.91	0.52	**0.25**	0.27
ANN Fc	0.38	5.89	0.54	0.85	0.30

TAIEX INDEX

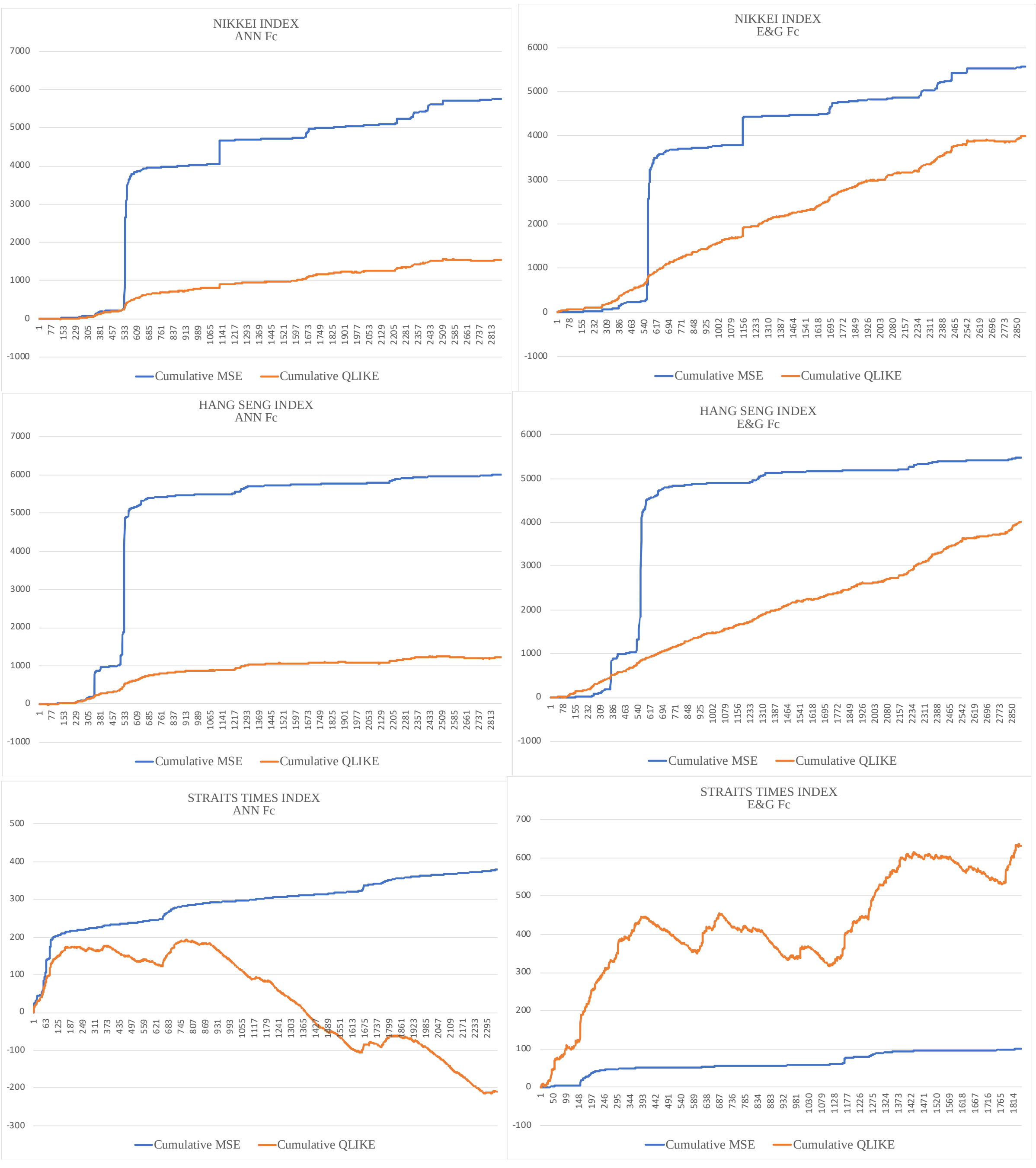
Model	MAE	MAPE	RMSE	QLIKE	MSE
LSTM	0.25	4.89	0.34	0.11	0.12
RNN	0.26	5.17	0.35	0.08	0.12
MLP	0.30	6.44	0.38	**0.01**	0.15
RBFN	0.25	4.52	0.35	0.54	0.12
ANFIS	0.36	4.77	**0.31**	0.29	0.12
CANFIS	0.48	6.49	0.37	0.43	**0.10**
PNN	0.33	**4.34**	0.47	8.15	0.22
GFN	0.26	5.37	0.35	0.09	0.12
MFN	0.26	5.53	0.35	0.08	0.12
ANN Fc	0.31	5.28	0.36	1.09	0.13

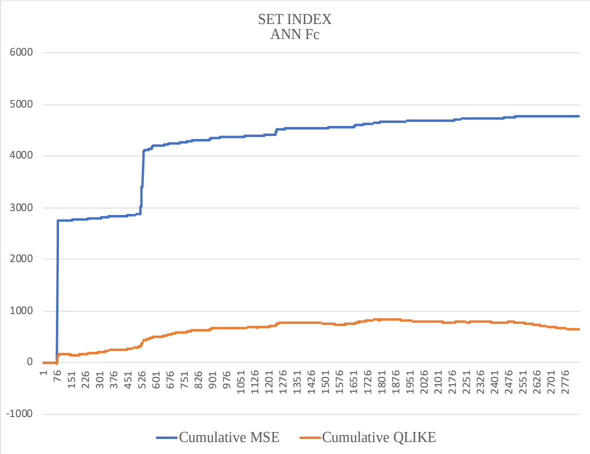
GARCH(1,1)	0.34	10.47	0.69	1.70	0.48	GARCH(1,1)	**0.16**	9.98	0.32	1.03	**0.10**
EGARCH(1,1)	**0.33**	10.52	0.69	1.69	0.48	EGARCH(1,1)	**0.16**	9.84	**0.31**	1.02	**0.10**
MACD	1.12	**1.29**	0.97	1.74	1.33	MACD	0.64	10.25	0.68	1.75	0.17
NAIVE	0.47	7.51	**0.36**	6.64	0.52	NAIVE	0.39	5.89	0.71	4.09	0.30
			KOSPI INDEX						**PSE INDEX**		
Model	**MAE**	**MAPE**	**RMSE**	**QLIKE**	**MSE**	**Model**	**MAE**	**MAPE**	**RMSE**	**QLIKE**	**MSE**
LSTM	0.24	9.12	0.36	**0.03**	**0.13**	LSTM	0.25	9.53	0.37	**0.01**	**0.13**
RNN	0.28	5.97	0.38	0.07	0.14	RNN	0.27	10.27	0.38	0.03	0.14
MLP	0.27	12.97	0.40	1.23	0.16	MLP	0.27	9.80	0.40	0.07	0.16
RBFN	0.39	6.14	0.46	0.07	0.21	RBFN	0.27	5.44	0.41	0.03	0.17
ANFIS	0.76	9.76	0.56	0.28	0.31	ANFIS	**0.18**	5.54	0.18	0.07	0.19
CANFIS	0.63	10.19	0.74	0.44	0.34	CANFIS	0.19	5.61	**0.12**	0.09	**0.13**
PNN	0.34	7.23	0.50	0.14	0.25	PNN	0.34	8.41	0.50	0.06	0.25
GFN	0.26	6.24	0.37	0.09	0.14	GFN	0.26	10.11	0.37	**0.01**	0.14
MFN	0.25	6.49	0.36	0.10	**0.13**	MFN	0.28	11.81	0.38	0.03	0.15
ANN Fc	0.38	8.23	0.46	0.27	0.20	ANN Fc	0.26	8.50	0.35	0.04	0.16
GARCH(1,1)	**0.18**	10.06	0.49	1.01	0.24	GARCH(1,1)	**0.18**	9.82	0.51	1.24	0.26
EGARCH(1,1)	**0.18**	10.09	0.48	1.00	0.23	EGARCH(1,1)	**0.18**	9.73	0.50	1.22	0.25
MACD	0.73	10.20	1.44	1.70	0.24	MACD	0.41	10.42	0.88	1.63	0.24
NAIVE	0.45	**4.62**	**0.35**	3.71	0.43	NAIVE	0.36	**5.42**	**0.12**	4.47	0.30

The comparative predictive performance of standard NN, neuro-fuzzy and deep learning models indicate robust results compared to conventional methods for more occasions than the reverse. More specifically, the LSTM provides superior forecasts for six of the ten markets based on the MSE criterion, which justifies its favored role in long term time series predictions given its memory cell properties (Kim and Kang, 2019). Other deep learning models, such as RNN, MLP and RBFN, are superior in three, three and four occasions respectively. In addition to the findings of Yap et al. (2021) on using deep learning models for predicting short-term movements and market trends in Asian tiger countries, the present results show that deep learning models are preferred in forecasting a wider range of markets. Furthermore, neuro-fuzzy models are favored specifically for the NIKKEI, HANG SENG, SSE, TAIEX and PSE indices, although clearly underperforming for the remaining markets. Although Atsalakis et al. (2016) state that Neuro-fuzzy models are more preferred for turbulent times and shorter-term predictions given their rapid learning capabilities, these results show that neuro-fuzzy models also offer promising results over longer term periods. GFN, MFN and PNN models indicate outperformance in seven, five and two occasions respectively. Notably, the MFN is clearly preferred for KLCI index where four out of five losses indicate preference. The GFN model reports lowest errors based on RMSE, QLIKE and MSE for JCI index. The PNN model is the weakest among all ANN models where it is only preferable based on MAPE criterion for TAIEX and HANG SENG indices. This result supports the view of Chen et al. (2003) for Taiex index where PNN also produces enhanced predictive power compared to parametric benchmark. However, as indicated by Wang and Wu (2017), the overall weaker performance of the PNN could be the result of its high computational complexity in the standard architecture which causes difficulties in the estimation of parameters. Yet, all prediction models display strong forecasts with less than 1% error almost for all indices which indicate their robust predictive capacity. Furthermore, obtained results challenge the weak form of the EMH, by demonstrating that when using historical data, accurate predictions of stock price trends are achievable.

Figure 5.14 below shows the comparison of ANN forecasts and GARCH-based forecast in terms of cumulative MSE and QLIKE error functions for each index to give a better picture of the overall out-of-sample estimation period. According to the graphs, there are big jumps during the 2007-2008 crisis in almost all markets which is reflected by the MSE loss function more significantly compared to the QLIKE error criterion, except for the GARCH-based combination for STI and KLCI indices. It can be said that when the volatility increases during the turbulent times, huge swings occur in the stock markets and the forecasting models are not able to catch these movements, especially based on the cumulative MSE function. However, in terms of the cumulative QLIKE, both ANN-based models and GARCH-based models reflect smaller errors either in chaotic or calm times and perform well. Another notable point is on the Shanghai Composite Index which indicates large increase in volatility during 2015-2016 Chinese Stock Market turbulence, yet it seems to be specific on the Chinese market as other markets don't show similar movements in terms of volatility, especially TAIEX and HSI indices which is claimed highly connected by Huo and Ahmed (2017). Furthermore, the KLCI index implies two different stories in terms of the cumulative QLIKE function. ANN-based forecasts turn negative after the crisis while the GARCH-based forecasts keep climbing. This is due to the different evaluation of the prediction models, so it seems that ANN models overestimate the actual value of the period, while GARCH-based models underestimates the actual values. The similar scenario can also be seen in STI index.

Figure 5.14: Comparison of Cumulative Forecasting Performance Between ANN-based Models and GARCH-based Models

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ANN Fc
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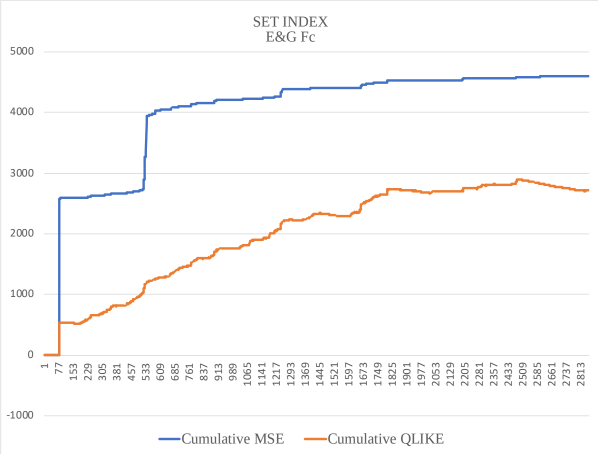
5000
4000
3000
2000
1000
0
-1000
Cumulative MSE
Cumulative QLIKE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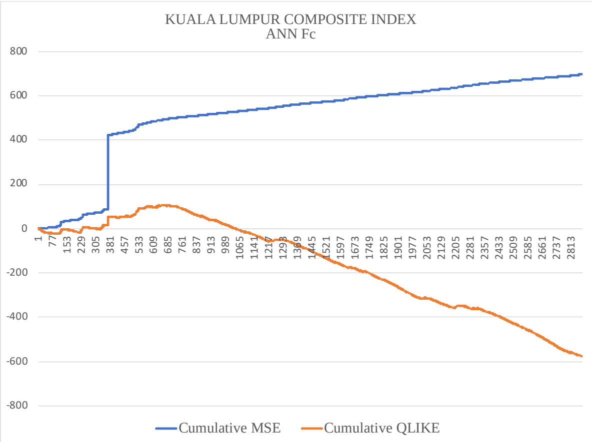
Cumulative MSE
Cumulative QLIKE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ANN Fc
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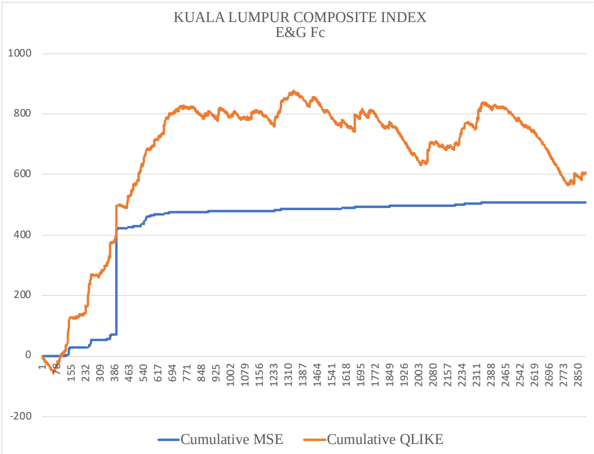
400
200
0
-200
-400
-600
-800
Cumulative MSE
Cumulative QLIKE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E&G Fc
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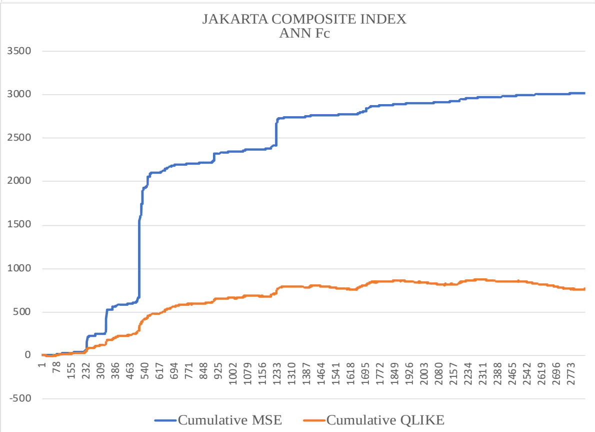
-200
Cumulative MSE
Cumulative QLIKE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ANN Fc
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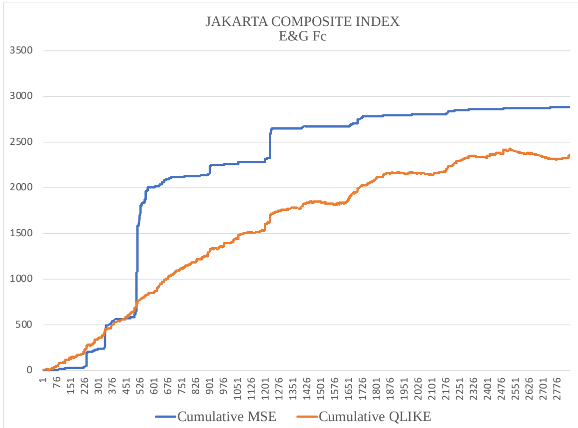
2500
2000
1500
1000
500
0
-500
Cumulative MSE
Cumulative QLIKE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E&G Fc
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2500
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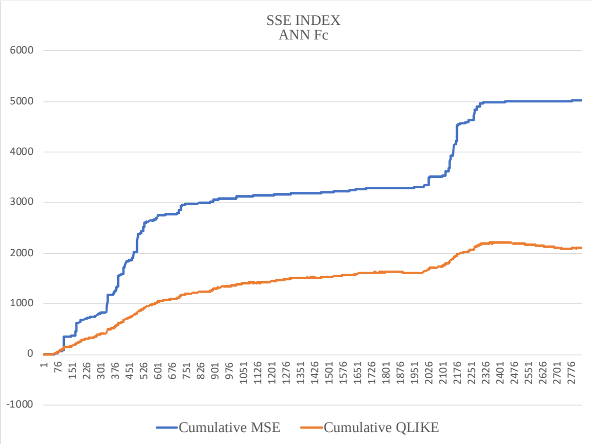
1500
1000
500
0
Cumulative MSE
Cumulative QLIKE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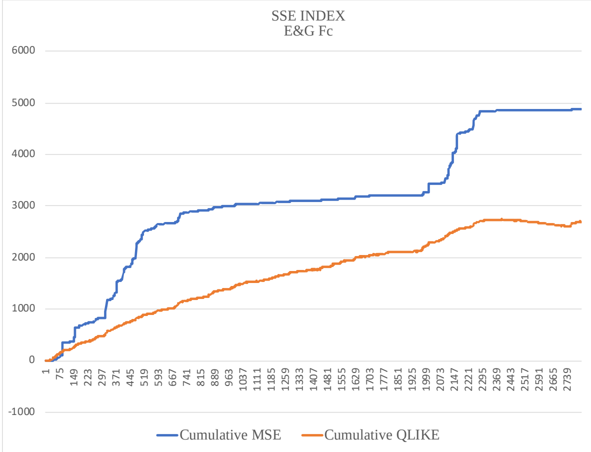
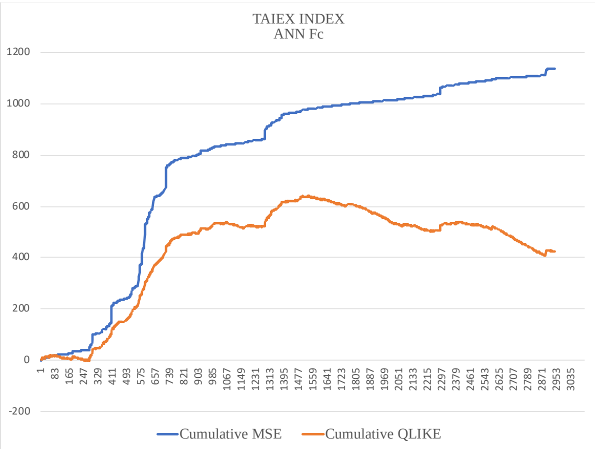
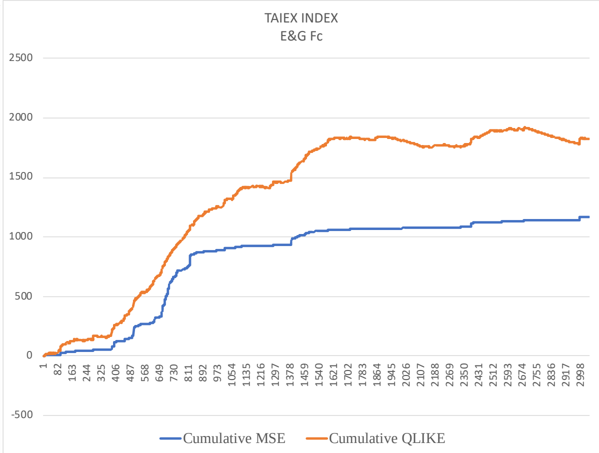
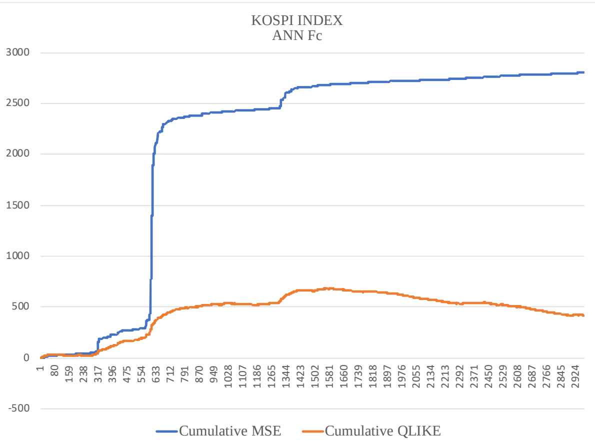
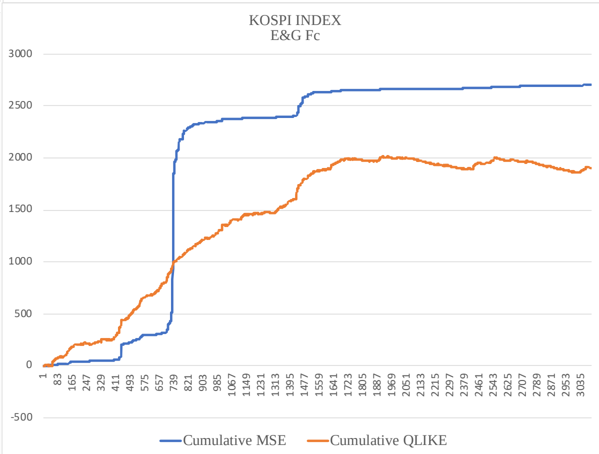
ANN Fc
Cumulative MSE
Cumulative QLIKE

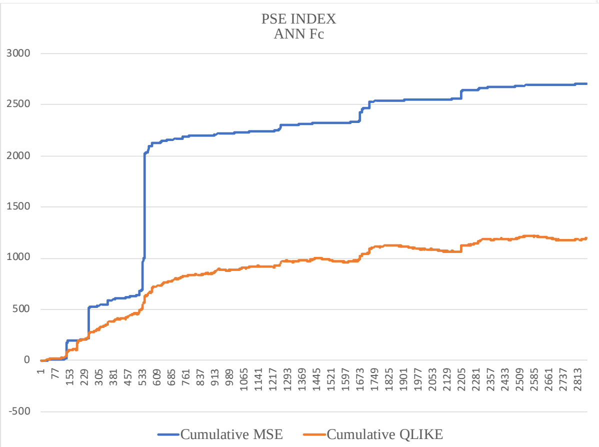

SSE INDEX
E&G Fc
Cumulative MSE
Cumulative QLIKE

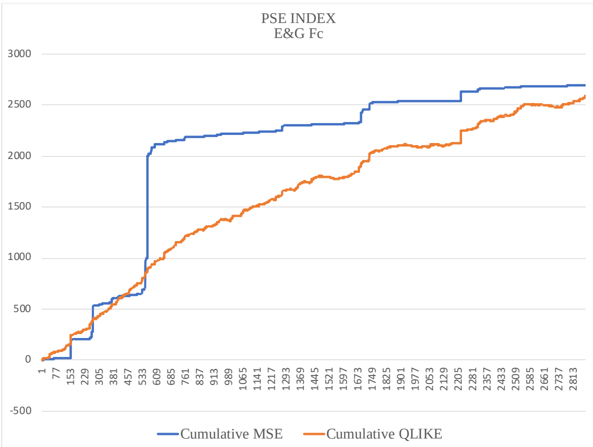

TAIEX INDEX
ANN Fc
Cumulative MSE
Cumulative QLIKE


TAIEX INDEX
E&G Fc
Cumulative MSE
Cumulative QLIKE


KOSPI INDEX
ANN Fc
Cumulative MSE
Cumulative QLIKE


KOSPI INDEX
E&G Fc
Cumulative MSE
Cumulative QLIKE


PSE INDEX
ANN Fc
Cumulative MSE
Cumulative QLIKE


PSE INDEX
E&G Fc
Cumulative MSE
Cumulative QLIKE

Following the studies of Hansen et al. (2011), Wang et al. (2016), and Liu et al. (2017), we also consider Model Confidence Set (MCS) test with the confidence level of 75% which allow us to compare the given model set in MCS framework with a p-value larger than 0.25. Table 5.9 exhibits the MCS test for both MSE and QLIKE metrics based on the out-of-sample forecasting results. The bold value in the table denotes the optimal model chosen by MCS, while the test also considers number of other models with EPA at the given confidence level. The corresponding results of the MCS test indicate the ANN class of models are significantly better than the benchmark models. Specifically, LSTM model is preferred in five occasions based on the MSE criterion and three occasions based on the QLIKE loss function. On the other hand, the QLIKE loss function supports the superiority of MFN model in five markets, while traditional methods are eliminated in most cases. In summary, the MCS test results confirm the superiority of ANN models over the benchmark models of GARCH, EGARCH, MACD and Naïve models.

Table 5.9: The Model Confidence Set test results for individual forecasts given the MSE and QLIKE loss functions

	NIKKEI INDEX	HANG SENG INDEX	STRAITS TIMES INDEX	SET INDEX	KUALA LUMPUR COMPOSITE INDEX	JAKARTA COMPOSITE INDEX	SSE INDEX	TAIEX INDEX	KOSPI INDEX	PSE INDEX
					MSE					
LSTM	0.9480	**1.0000**	**1.0000**	0.0010	**1.0000**	0.0000	0.0488	0.1366	**1.0000**	**1.0000**
RNN	**1.0000**	0.1180	0.0000	0.3564	0.0000	0.0000	0.0000	0.0000	0.0368	0.0000
MLP	0.4280	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
RBFN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0636	0.0000
ANFIS	0.0000	0.7749	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.9654	0.0000	0.0000
CANFIS	0.6689	0.0000	0.0000	0.0000	0.8959	0.0000	0.0000	0.0000	0.0000	0.0443
PNN	0.0184	0.0798	0.0000	0.2074	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000
GFN	0.9990	0.3014	0.0000	**1.0000**	0.0000	0.0000	**1.0000**	0.8248	0.0032	0.0000
MFN	0.5490	0.0000	0.0114	0.0000	0.0000	0.0000	0.0000	0.5430	0.0000	0.0000
ANN Fc	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH(1,1)	0.2872	0.0000	0.0000	0.0000	0.0000	0.0000	0.3966	0.0000	0.5450	0.0000
EGARCH(1,1)	0.4280	0.0000	0.9887	0.0000	0.0000	0.0000	0.2432	0.0000	0.9458	0.0000
MACD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NAIVE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
					QLIKE					
LSTM	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000	**1.0000**	**1.0000**	0.0000	0.0000
RNN	0.0000	0.0000	0.7320	0.0000	0.0000	0.0000	0.0000	0.0000	0.4932	0.0000
MLP	0.8800	0.0000	0.0000	0.0000	0.3349	0.0000	0.0000	0.0000	0.0000	0.0000
RBFN	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
ANFIS	0.7339	0.0000	0.0000	0.0000	0.0000	0.2957	0.0000	0.0000	0.0000	0.5639

CANFIS	0.0000	0.0000	0.2740	0.0000	0.0000	0.0000	0.0000	0.3354	0.0000	0.0000
PNN	0.0000	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000	0.0000
GFN	0.0000	0.0000	0.0000	0.0000	**1.0000**	0.0000	0.0000	0.0000	0.0000	0.0000
MFN	**1.0000**	**1.0000**	0.0000	**1.0000**	0.0000	0.0000	0.0000	0.0000	**1.0000**	**1.0000**
ANN Fc	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
GARCH(1,1)	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.5530	0.0000	0.0000	0.0000
EGARCH(1,1)	0.0000	0.2239	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
MACD	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
NAIVE	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Notes: The table reports the MCS test on both MSE and QLIKE loss functions. The confidence level is set at $\alpha = 0.2$. The forecasting models with Equal Predictive Ability (EPA) at 75% level is highlighted in the table.

Table 5.10 below presents the daily VaR and Expected Shortfall statistics as well as the corresponding test results. Examining the table, the lowest average VaR failure rate at the 1% level is mainly achieved by the hybrid models of ANFIS and CANFIS, while the benchmark models of GARCH and EGARCH report the lowest values in KLCI and SET indices. The PNN model provides the preferred average failure rate for KOSPI index, while the RBFN and PNN models are preferred for the SSE index. In contrast, the LSTM, RNN and MLP models fail to provide minimum VaR rates for any of the selected indices and for which they tend to underestimate potential risks. The detailed VaR plots can be found for each model and market in the Appendix C section from Figure C.11 to C.20.

As recently proposed by Basel Committee in 2017, there is a move regarding quantitative risk measures from VaR to ES (Expected Shortfall). In forecasting ES, the MLP model is preferred at 1% and 5% levels for the SSE, PSE, STI and HANG SENG indices. Furthermore, the RBFN, MFN and PNN models are preferred in both confidence levels for NIKKEI, KLCI and KOSPI indices. Accordingly, it can be inferred that the ANN models are the most suitable across all competing models in terms of Expected Shortfall at all selected confidence levels. The accuracy and reliability of the VaR forecasts are also tested as proposed by Basel I and Basel II . Based on the testing results of Kupiec, Christoffersen and DQ, the results report that none of the models reject the null hypothesis of expected VaR violation (Kupiec’s unconditional coverage test), the independence exceptions of VaR (Christoffersen’s conditional coverage test), and violations of VaR occurred correlated (Dynamic Quantile).

Overall, the results highlight the accuracy of the ANN class of models for volatility forecasting both in terms of statistical measures and economic, VaR and ES, metrics across a range of Asian stock markets. Notably, while there are exceptions, the results, similar to Zhang et al. (1998) and Cao and Wang (2020), suggests that the class of ANN models outperforms traditional forecasting methods across statistical and economic measures.

Table 5.10: Summary of risk management analysis and backtesting results for daily return series

NIKKEI INDEX							HANG SENG INDEX						
	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)		Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0289	ALL	ALL	ALL	0.2503	0.2660	LSTM	0.0290	ALL	ALL	ALL	0.1619	0.1899
RNN	0.0287	ALL	ALL	ALL	0.1923	0.2216	RNN	0.0290	ALL	ALL	ALL	0.1085	0.1463
MLP	0.0290	ALL	ALL	ALL	0.0266	0.1105	MLP	0.0303	ALL	ALL	ALL	**-0.5117**	**-0.2608**
RBFN	0.0271	ALL	ALL	ALL	**-0.0367**	**0.0058**	RBFN	0.0288	ALL	ALL	ALL	0.0511	0.1019
ANFIS	0.0211	ALL	ALL	ALL	0.0313	0.0424	ANFIS	**0.0254**	ALL	ALL	ALL	0.0448	0.0822
CANFIS	**0.0124**	ALL	ALL	ALL	0.0114	0.0193	CANFIS	0.0258	ALL	ALL	ALL	0.0535	0.0998
PNN	0.0271	ALL	ALL	ALL	**-0.0367**	0.0058	PNN	0.0288	ALL	ALL	ALL	0.0511	0.1019
GFN	0.0290	ALL	ALL	ALL	0.2278	0.2594	GFN	0.0294	ALL	ALL	ALL	0.1444	0.1817
MFN	0.0308	ALL	ALL	ALL	0.2748	0.3143	MFN	0.0308	ALL	ALL	ALL	0.2386	0.2724
GARCH(1,1)	0.0269	ALL	ALL	ALL	0.0916	0.0983	GARCH(1,1)	0.0313	ALL	ALL	ALL	0.0568	0.0634
EGARCH(1,1)	0.0262	ALL	ALL	ALL	0.0783	0.0900	EGARCH(1,1)	0.0314	ALL	ALL	ALL	0.0241	0.0293
STRAITS TIMES INDEX							SET INDEX						
	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)		Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0277	ALL	ALL	ALL	0.2526	0.2618	LSTM	0.0291	ALL	ALL	ALL	0.3235	0.3341
RNN	0.0279	ALL	ALL	ALL	0.1608	0.1854	RNN	0.0293	ALL	ALL	ALL	0.1908	0.2216
MLP	0.0265	ALL	ALL	ALL	**-0.0213**	**0.0269**	MLP	0.0301	ALL	ALL	ALL	**-0.1459**	0.0803
RBFN	0.0276	ALL	ALL	ALL	0.1051	0.1358	RBFN	0.0291	ALL	ALL	ALL	0.1702	0.2003
ANFIS	0.0277	ALL	ALL	ALL	0.1148	0.1225	ANFIS	**0.0258**	ALL	ALL	ALL	0.1445	0.1839
CANFIS	0.0270	ALL	ALL	ALL	0.1053	0.1090	CANFIS	0.0270	ALL	ALL	ALL	0.1735	0.2998
PNN	0.0276	ALL	ALL	ALL	0.1051	0.1358	PNN	0.0291	ALL	ALL	ALL	0.1702	0.2003
GFN	0.0270	ALL	ALL	ALL	0.1467	0.1660	GFN	0.0284	ALL	ALL	ALL	0.2142	0.2328
MFN	0.0272	ALL	ALL	ALL	0.1078	0.1360	MFN	0.0297	ALL	ALL	ALL	0.2528	0.2770
GARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0352	0.0384	GARCH(1,1)	**0.0258**	ALL	ALL	ALL	0.0698	**0.0753**
EGARCH(1,1)	0.0242	ALL	ALL	ALL	0.0313	0.0349	EGARCH(1,1)	**0.0258**	ALL	ALL	ALL	0.0669	0.0759
KUALA LUMPUR COMPOSITE INDEX							JAKARTA COMPOSITE INDEX						
	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)		Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0256	ALL	ALL	ALL	0.0534	0.0668	LSTM	0.0282	ALL	ALL	ALL	0.2712	0.2811
RNN	0.0256	ALL	ALL	ALL	-0.0282	0.0091	RNN	0.0287	ALL	ALL	ALL	0.1276	0.1646
MLP	0.0288	ALL	ALL	ALL	0.0423	0.1834	MLP	0.0288	ALL	ALL	ALL	**-0.0162**	0.1190
RBFN	0.0270	ALL	ALL	ALL	0.0321	0.0880	RBFN	0.0297	ALL	ALL	ALL	0.1536	0.2131
ANFIS	0.0263	ALL	ALL	ALL	0.0422	0.0624	ANFIS	0.0255	ALL	ALL	ALL	0.2213	0.2464
CANFIS	0.0275	ALL	ALL	ALL	0.0375	0.0524	CANFIS	**0.0249**	ALL	ALL	ALL	0.1745	0.1930
PNN	0.0270	ALL	ALL	ALL	0.0321	0.0880	PNN	0.0297	ALL	ALL	ALL	0.1536	0.2131
GFN	0.0280	ALL	ALL	ALL	0.2437	0.2574	GFN	0.0289	ALL	ALL	ALL	0.1979	0.2298
MFN	0.0246	ALL	ALL	ALL	**-0.1234**	**-0.0736**	MFN	0.0286	ALL	ALL	ALL	0.2169	0.2427
GARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0255	0.0280	GARCH(1,1)	0.0266	ALL	ALL	ALL	0.0687	0.0735
EGARCH(1,1)	**0.0241**	ALL	ALL	ALL	0.0205	0.0243	EGARCH(1,1)	0.0265	ALL	ALL	ALL	0.0503	**0.0595**
SSE INDEX							TAIEX INDEX						
	Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)		Avg.FR (1%)	Sig. LRcc	Sig. LRuc	Sig. DQ Test	ES (1%)	ES (5%)
LSTM	0.0320	ALL	ALL	ALL	0.5068	0.5175	LSTM	0.0287	ALL	ALL	ALL	0.2679	0.2827
RNN	0.0280	ALL	ALL	ALL	0.0475	0.0866	RNN	0.0286	ALL	ALL	ALL	0.2473	0.2686
MLP	0.0295	ALL	ALL	ALL	**-0.5657**	**-0.3355**	MLP	0.0283	ALL	ALL	ALL	0.0608	0.1483

RBFN	**0.0264**	ALL	ALL	ALL	-0.1772	-0.1306	**RBFN**	0.0278	ALL	ALL	ALL	**0.0484**	0.0895
ANFIS	0.0284	ALL	ALL	ALL	0.1945	0.2675	**ANFIS**	**0.0228**	ALL	ALL	ALL	0.1124	0.1639
CANFIS	0.0293	ALL	ALL	ALL	0.1424	0.1505	**CANFIS**	0.0247	ALL	ALL	ALL	0.1336	0.1469
PNN	**0.0264**	ALL	ALL	ALL	-0.1772	-0.1306	**PNN**	0.0278	ALL	ALL	ALL	**0.0484**	0.0895
GFN	0.0286	ALL	ALL	ALL	0.1222	0.1504	**GFN**	0.0285	ALL	ALL	ALL	0.1938	0.2184
MFN	0.0275	ALL	ALL	ALL	-0.0416	0.0011	**MFN**	0.0276	ALL	ALL	ALL	0.1582	0.1846
GARCH(1,1)	0.0282	ALL	ALL	ALL	0.0875	0.0930	**GARCH(1,1)**	0.0254	ALL	ALL	ALL	0.0927	0.0980
EGARCH(1,1)	0.0286	ALL	ALL	ALL	0.0817	0.0924	**EGARCH(1,1)**	0.0253	ALL	ALL	ALL	0.0770	**0.0846**
			KOSPI INDEX							**PSE INDEX**			
	Avg.FR (1%)	**Sig. LRcc**	**Sig. LRuc**	**Sig. DQ Test**	**ES (1%)**	**ES (5%)**		**Avg.FR (1%)**	**Sig. LRcc**	**Sig. LRuc**	**Sig. DQ Test**	**ES (1%)**	**ES (5%)**
LSTM	0.0283	ALL	ALL	ALL	0.1768	0.1915	**LSTM**	0.0284	ALL	ALL	ALL	0.2154	0.2363
RNN	0.0282	ALL	ALL	ALL	0.2137	0.2343	**RNN**	0.0298	ALL	ALL	ALL	0.2344	0.2892
MLP	0.0288	ALL	ALL	ALL	-0.0790	0.0801	**MLP**	0.0296	ALL	ALL	ALL	**-0.3932**	**-0.1490**
RBFN	0.0280	ALL	ALL	ALL	0.1519	0.1794	**RBFN**	0.0254	ALL	ALL	ALL	-0.1084	-0.0704
ANFIS	0.0274	ALL	ALL	ALL	0.0327	0.0744	**ANFIS**	0.0249	ALL	ALL	ALL	-0.0233	-0.0361
CANFIS	0.0269	ALL	ALL	ALL	0.0459	0.0844	**CANFIS**	**0.0244**	ALL	ALL	ALL	-0.0124	-0.0487
PNN	**0.0150**	ALL	ALL	ALL	**-1.9910**	**-1.9910**	**PNN**	0.0254	ALL	ALL	ALL	-0.1084	-0.0704
GFN	0.0292	ALL	ALL	ALL	0.1974	0.2260	**GFN**	0.0270	ALL	ALL	ALL	0.0539	0.1022
MFN	0.0298	ALL	ALL	ALL	0.2767	0.2995	**MFN**	0.0301	ALL	ALL	ALL	0.3178	0.3458
GARCH(1,1)	0.0261	ALL	ALL	ALL	0.0772	0.0825	**GARCH(1,1)**	0.0271	ALL	ALL	ALL	0.0653	0.0722
EGARCH(1,1)	0.0260	ALL	ALL	ALL	0.0683	0.0807	**EGARCH(1,1)**	0.0259	ALL	ALL	ALL	0.0440	0.0580

Notes: Avg.FR indicates the failure rate of VaR at 1% significance level. LRcc and LRuc show the significance of the conditional (Christoffersen) and unconditional (Kupiec) coverage tests at 1%level of significance, respectively. Sig. DQ Test denotes the significance of the Dynamic Quantile and ES shows the Expected Shortfall at 1% and 5% confidence levels for the selected index.

Figures from C.1 to C.10 in Appendix C illustrate the out-of-sample prediction accuracy of the ANN models for each selected index. According to the graphs, ANN models have strong capacity to catch movements, especially during tranquil times. However, when the volatility increases during the turmoil, such as in the 2008 financial crisis, the return series tend to spike and exhibit strong volatility skew and kurtosis which disrupts the prediction accuracy of the models. However, from the related figures, it can be said that PNN model indicates stronger discriminatory power compared to other Neural Network models, while the LSTM performance remains weak against the big shocks. At this point, it is imperative to stress that a non-anticipated event in the global financial markets may come at a much higher cost for the economy compared to a false alarm. Therefore, it is crucial for supervisory purposes to achieve the maximum possible accuracy in imminent crisis via developed Machine Learning methods for economic and financial crises.

5.9 Conclusion and Future Work

Stock market forecasting is highly important for both practitioners and policymakers since the in-depth comprehension of financial market movements may substantially facilitate administration strategy selection and the development of required plans in case of financial turbulences. This study evaluates different Machine Learning methods to forecast the volatility of ten Asian stock market indices, with the results compared against benchmark models. The empirical results of the ANN models are promising. Out-of-sample forecast evaluation results show that ANN models are superior in each index compared to the benchmark models of GARCH and EGARCH which were the superior accurate prediction models according to Abdalla and Winker (2012) and Lim and Sek (2013). Specifically, the predictive performance of deep learning models is superior in high volatile periods due to the feature of capturing long-range dependencies. Moreover, Neuro Fuzzy models of ANFIS and CANFIS outperforms EGARCH model by considering the asymmetry and long memory properties, thereby offering new exiting capabilities in Asian markets. Overall, the results show that neural network prediction models exhibit improved forecasting accuracy across both statistical and economic based metrics and offer new insights for market participants, academics, and policymakers.

The novel contribution of this paper to the field of empirical finance and existing literature is three-fold. First and foremost, this study explores all key relevant machine learning models to address the problem of financial volatility forecasting. Previous studies tend to evaluate small sets of Neural Network methods. Using the wider range of ANN architectures has different advantages. For example, in stock market prediction exercises, the recurrent ANNs are recommended due to their memory component features that increase prediction accuracy. Therefore, this thesis evaluated seven different ANN architectures as well as a combination forecast. Second, comprehensive performance measures for model evaluation are utilized, namely, both a range of statistical measures (RMSE, MAE, MAPE, MSE, QLIKE, and MCS) and economic based ones (VaR and ES). Third, a wide range of Asian markets are studied in order to have an in-depth examination for an extended set of volatility models across markets that are less studied.

A potential extension of this study could explore a more diverse set of ANN architectures. For example, according to Partaourides and Chatzis (2017), further regularizations methods may increase the capacity of the machine learning systems. Moreover, hidden layers can be extended over two, more data frequencies can be added, and alternative input variables and activation functions can be studied. The value of such novel developments remains to be examined in future research endeavors.

CHAPTER 6

Volatility Spillovers and Contagion During the Major Crises: An Early Warning Approach Based on Deep Learning Model

Abstract

This chapter provides in depth analysis on the volatility transmission channels of ten Asian markets as well as the US market. In order to do that, DCC, GARCH-BEKK, and Diebold-Yilmaz spillover index methodologies are employed for two pre-crisis periods and three major crisis episodes. Furthermore, an Early Warning System (EWS) is introduced by integrating DCC correlations with state-of-the-art Deep Learning (DL) model. The empirical findings of the study demonstrate that the climb in external shock transmissions has long lasting impacts in domestic markets due to contagion effect during the crisis periods. In addition, it is revealed that the heavier magnitude of financial stress transmits among Asian countries via Hong Kong stock market, offering key information for investors and financial regulators in terms of diversification benefits and macroeconomic stability in the region. Furthermore, it is revealed that the degree of volatility spillovers among advanced and emerging equity markets is less compared to the pure spillovers between advanced markets or emerging markets, offering window of opportunity for international market participants in terms of portfolio diversification and risk management applications. On the other hand, the experimental analysis of Long short-term memory (LSTM) network finds evidence of contagion risk. The proposed model successfully verifies bursts in volatility spillovers and generates signals with high accuracy before the 12-month period of crisis, providing supplementary information that contributes to the decision-making process of practitioners, as well as offering indicative evidence that facilitate the assessment of market vulnerability to policy-makers. Finally, the effectiveness and reliability of the LSTM model is confirmed with RMSE and MSE loss functions to avoid false signals.

6.1 Introduction

Volatility is one of the fundamental indicators of risk measures in financial markets. Estimating volatility at the individual equity level, the broad market level or the worldwide level has substantial significance for market participants, financial organizations, and policymakers. One of the biggest challenges of predicting accurate volatility is the growing interconnectedness of financial markets with the globalization and advancements on information technology which increases the contagion of shocks across countries and aggravates the impact of crises. Following the stock market crash of 1987, the debate has been heated among researchers and policy makers regarding the joint and dramatic turmoil in the international financial markets which are located in the different regions and have different characteristics. But more specifically, starting from the early 1990s, the frequency of financial crises has increased, and drastic movements are observed in volatility not only in the originator country, but also in the regional and inter-regional markets. Although the early studies concerning volatility transmission dated back to the aftermath of 1997-98 Asian financial crisis[2], financial contagion and volatility spillovers across different types of stock markets have become a major area of interest in the last two decades (Forbes and Rigobon, 2002; Corsetti et al., 2005; Guo et al., 2011; Jin and An, 2016; Mohti et al., 2019; Okorie and Lin, 2021).

Historically, individual and institutional investors were willing to extend their investments by considering foreign emerging markets for taking advantage of portfolio diversification and enhanced risk-return trade off. The rationale behind this diversification was primarily due to the reduced interconnectedness between developed and emerging markets as well as the protection aptitude of big drawdowns during the possible financial crisis (Bouslama and Ouda, 2014; Thomas et al., 2021). However, a series of financial crises with growing devastating impacts, such as the Asian crisis of 1997, the global financial crisis of 2008, and the COVID-19 recession of 2020 have shown that all these crises indicate a feature in common which is the transmission of volatility in regional and global level due to the cross-market connections. When these market connections remain steady, the shocks are transmitted through the linkages and the recovery can be achieved by the financial and economic activities within the country. Alternatively, if the market linkages get disrupted after the shocks, the crisis starts to feed itself

[2] See Claessens and Forbes (2001) for the survey of notable articles regarding the contagion effect across countries.

and the country's fundamental economic and financial dynamics would not be enough to contain the impact of the crisis where in that case a wider rescue plan with international intervention would be needed. The latter form of crisis is known as "financial contagion". As a result, after the phenomenon and impacts of financial contagion is broadly known, the risk appetite of market participants is diminished for emerging markets, and growing interest has been observed among investors for developed markets (Berger and Turtle, 2011; Mensi et al., 2017).

The empirical literature regarding financial contagion and volatility spillover is broad and different approaches have been adopted by researchers. For example, Baig and Goldfajn (1999) investigated the evidence of contagion among the equity markets of Indonesia, Thailand, Malaysia, Korea, and the Philippines during the Asian financial crisis using Vector Autoregression (VAR) model and found high degrees of correlation compared to tranquil times. Dungey and Martin (2001) examined the impact of contagion among currency and equity markets of Asia during the crisis period of 1997-98 by using latent factor model which allows to quantify the contribution of contagion in addition to the sign of contagion. On the other hand, Forbes and Rigobon (2002) adopted adjusted heteroscedasticity test to identify contagion effects during the 1987 US stock market crash, 1994 Mexican Peso crisis and 1997 Asian crisis. The empirical results indicate that the high level of interdependence exists yet no volatility and return contagion is observed during these periods. Bae et al. (2003) developed a new model to capture the effects of extreme shocks on return series as well as characterize the determinants of contagion applying multinominal logistic regression model. The findings of the study report that the contagion effect is strongly associated with extreme negative returns compared to extreme positive returns. More recently, contagion effect is studied with wider empirical models such as Copula GARCH (Peng and Ng, 2012; Abbara and Zevallos, 2014; Zorgati et al., 2019), Granger causality (Sohel Azad, 2009; Bekiros, 2014; Abdennadher and Hellara, 2018), Markov switching model (Bekaert and Harvey, 2003; Rotta and Valls Pereira, 2016; Chitkasame and Tansuchat, 2019), Regression analysis (Baur and Schulze, 2005; Caporin et al., 2018) and Asymmetric DCC (Kenourgios et al., 2011; Rajwani and Kumar, 2016).

The financial literature also focused on developing Early Warning Systems (EWS) on the detection of contagion effect. One of the earliest prominent studies was conducted by Kaminsky (1999) where he used various indicators such as, imports, equity prices and noise-to-signal ratio to generate EWS to detect crisis. Narayan et al. (2014) designed a spillover index of shocks from stock returns and mutual fund flows to predict stock returns for Indian market. He et al. (2018) studied the intraday spillovers of Chinese stock market by estimating dynamic correlation using VEC-DCC-GARCH. They applied spillover indicators based on generalized variance decomposition framework to create EWS and the findings imply that the dynamic characteristics of volatility spillover are able to create EWS for potential spillovers between industries. Moreover, some studies developed EWS systems based on Artificial Neural Network models. For example, Oh et al. (2006) proposed an EWS system for the detection of financial crisis in Korean market based on daily financial condition indicator (DFCI). The DFCI monitors the movements in Korean financial markets, and it is constructed on machine learning algorithms with genetic algorithms. Although the model is able to provide efficient EWS, the authors conclude that the performance of the model is highly dependent on appropriate input selections and proper training. Furthermore, Chatzis et al. (2018) examined crash event propagation and transmission channels across international stock markets by implementing Machine Learning systems. The experimental results of the study report that cross contagion effects exist between global stock, bond and currency markets and Neural Network models can be used as an early warning tool. Likewise, Samitas et al. (2020) used network analysis and machine learning algorithms based on Asymmetric Dynamic Conditional Correlation (ADCC) model to create an EWS system among bonds, stocks and CDS of 33 countries. The findings revealed that the effectiveness of EWS system based on machine learning is 98.8% to predict contagion risk.

The wide empirical literature of finance shows that there is a relationship between return and volatility spillovers, specifically in the related studies covering contagion effect, risk management, portfolio allocation and stock market efficiency. The findings in the field of the spread of volatility among financial instruments and markets supported the hypotheses of “meteor shower” and “heat wave” proposed by Engle et al. (1990) and the real-world applications show that the predictability of market returns are influenced by spillover effects (Brzeszczyński and Ibrahim, 2019; Yarovaya et al., 2020). Although, these spillover effects restrain the advantage of international portfolio diversification, information regarding the cross-market spillover channels and the degree of impacts may create a chance to forecast the movements in domestic market by utilizing external news from other markets. Thus, examining the directional and bi-directional channels of spillovers is critical to foresee potential crisis as well as grasping regional and international spread of information which can be used to develop

EWS, help market participants for more profitable portfolio diversification and provide guidance for policy makers.

This chapter contributes to the empirical literature of financial econometrics with volatility transmission channels during three different major crisis events in the last few decades as well as developing an early warning system (EWS) by using one of the most developed deep learning algorithms to predict crisis events based on the obtained transmission channels. In this regard, the Long Short-Term Memory (LSTM) algorithm is combined with DCC model to obtain an accurate system for estimating periods of contagion among Asian and the US markets during crisis events in the financial markets. Specifically, the novel contributions of present paper are:

- In most studies, EWS systems are developed based on return series, while only a few studies consider the volatility spillover effects between markets. To the best of my knowledge, the LSTM model has not been covered in the literature to develop EWS based correlations and transmission channels among developed and emerging stock markets. Moreover, the Dynamic Conditional Correlation (DCC) method is integrated for the first time with an advanced deep learning algorithm to examine the impact of foreign information in a domestic market during major crises.

- In this study, daily data is obtained from eleven different emerging and developed markets which tend to be more responsive compared to lower frequency data. The literature mainly focuses on Eurozone markets or developed economies rather than emerging markets. In this study emerging markets of Asia is covered and analysed, and in this regard, we are able to see the progress of changes in terms of vulnerability of foreign shocks and channels of contagion by examining ties between emerging and developed markets during major events.

- Lastly, this is also the first study regarding comparison of major crises, namely the 1997-98 Asian Financial Crisis, GFC crisis of 2007-08, and COVID-19 crisis of 2020. As the impact of COVID-19 crisis is still unknown for many markets, and the source of crises and the major hubs for transmission channels are different in all events, the present study contributes to the literature by providing comparison of interdependencies and changing intensity of contagion channels between markets for different periods.

The remainder of the chapter is organized as follow: Section 6.2. presents the background and gives brief overview in terms of terminology and related studies. Section 6.3. introduces the data and methodological framework including the machine learning algorithms and contagion specification. Section 6.4 discusses empirical results of the study. Finally, section 6.5 draws the conclusion as well as suggests directions for future studies.

6.2 Background

6.2.1 Defining interdependence, spillovers and contagion

The interdependency between stock markets during turbulent times is one of the main problems for risk managers and policy makers. Many empirical studies in the financial literature analyse market interdependencies, specifically focusing on the significant crises in the near future such as the Asian crisis in 1997-98 (Forbes and Rigobon, 2002; Caporale et al., 2006; Morales et al., 2012; Chow, 2017), the subprime mortgage crisis of 2007-08 (Cheung et al., 2010; Tudor, 2011; Aloui et al., 2011; Dungey and Gajurel, 2014; Jin and An, 2016) and the COVID-19 crisis of 2020-21 (Malik et al., 2021; Okorie and Lin, 2021; Akhtaruzzaman et al., 2021). The growing market interdependencies is a natural consequence of accelerated globalization and developing information technology, therefore it is almost impossible for any country and financial market to completely isolate themselves from external crisis and unexpected shocks. In this context, examining financial contagion and spillovers provide further perspective regarding the international transmission channels of volatility.

The terms of interdependence, spillover and contagion are broadly used in the literature and mostly considered related and used interchangeably in the studies of market linkages. However, between the definitions of these phenomena there are differences as interdependence is represented by the relationship that exists between markets in all periods (Forbes and Rigobon, 2002; Beirne and Gieck, 2014). In other words, if the linkages between markets are continuous and persists during negative and positive external events, it is considered interdependent. On the other hand, the definitions of contagion and spillover concepts differ between studies and there is still no broad consensus among financial researchers regarding the definitions of these terms. Masson (1999) states that contagion as transfer of crises between countries that cannot be justified by certain macroeconomic fundamentals. Forbes and Rigobon (2002) argue that there is contagion effect if higher linkages are observed among a group of markets following a crisis event in one of the countries. Furthermore, Pericoli and Sbracia (2003) approach this from another point of view that focuses on the multiple equilibrium issue between countries and define contagion as "*cross-country comovments of asset prices that cannot be explained by fundamentals"* (p.574). On the other hand, Bekaert et al. (2005) adopt factor pricing framework to define contagion and explain as excess correlation between residuals of the given two-factor model after excluding the country specific economic fundamentals such as risk factor and time-varying volatility. However, Morales and Andreosso-O'Callaghan (2014) claim that the definition of contagion should not only be limited to the financials but also need to cover fundamental elements of the economy. To overcome this debate, The World Bank[3] (2013) proposes three different classifications in terms of the definition of contagion: The broad, restrictive, and very restrictive definition.

Broad Definition

"Contagion is the cross-country transmission of shocks or the general cross-country spillover effects".

Restrictive Definition

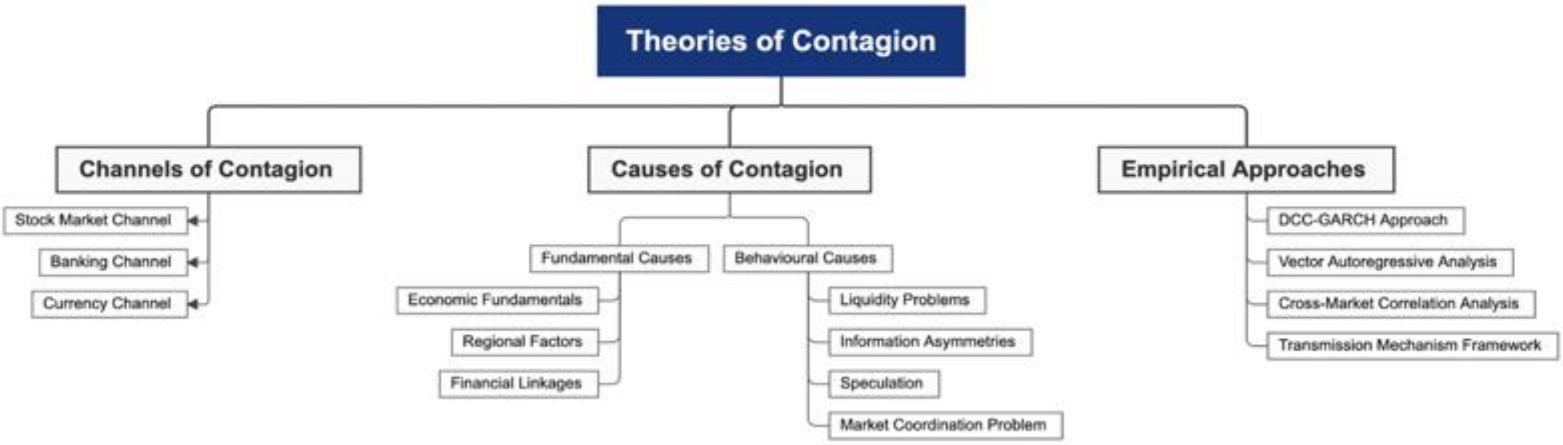
"Contagion is the transmission of shocks to other countries or the cross-country correlation, beyond any fundamental link among the countries and beyond common shocks. This definition is usually referred as excess co-movement, commonly explained by herding behaviour".

Very Restrictive Definition

"Contagion occurs when cross-country correlations increase during "crisis times" relative to correlations during "tranquil times".

[3] The definitions of contagion are obtained from World Bank website: http://go.worldbank.org/JIBDRK3YC0

Figure 6.1: Cognitive Map of Contagion



The figure above presents the cognitive map of different theories regarding contagion. As it is stated, there are various theories about why contagion can occur. A group of studies focused on fundamental causes (Masson, 1998; Corsetti et al., 2000; Van Rijckeghem and Weder, 2003; Forbes, 2002), while the other group of theories focused on the behavioural causes as an underlying theme (Calvo and Mendoza, 2000; Kaminsky et al., 2001; Chang and Majnoni, 2001; Broner et al., 2006). Although the present paper does not examine the fundamental or behavioural causes of contagion, the given theories are particularly valuable in terms of defining contagion framework. The main focus of this chapter is empirical approaches and channels of information mechanisms among financial markets. Therefore, this research adopts the very restrictive definition of World Bank and the framework of Forbes and Rigobon (2002) where contagion is defined as a higher magnitude of volatility and return linkages among a group of markets following a crisis event in one of the countries.

On the other hand, the term “spillover effect” is associated with interdependence and risk, and it is used as information transmission which includes volatility and return series of financial instruments (Diebold and Yilmaz, 2009). Furthermore, Engle et al. (1990) picture a more specific framework to define spillover and explain as the causality in variance among assets and markets. Thus, both definitions are adopted by this study:

Volatility spillover refers to the circumstances when movements in volatility from a foreign market influence the volatility in a domestic market

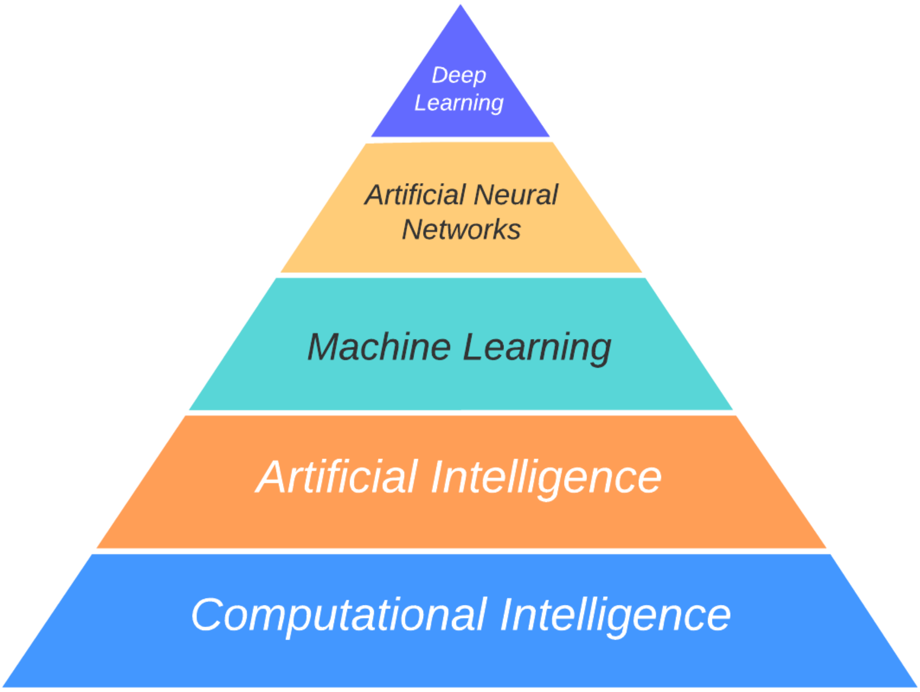
Return spillover refers to the circumstances when movements in return from a foreign market influence the return in a domestic market

Given that the present paper accepts both kinds of spillover effect that can arise either from volatility or return series, the degree of observed spillover effect from one market to another varies over time, and when this degree intensifies and starts to transmit shocks between markets following a crisis event, it is considered a contagion effect.

6.2.2 Computational Intelligence and Deep Learning

Due to its nature, financial markets exhibit highly nonlinear dynamics characteristics which is influenced by various technical and fundamental components, including actions of central banks, economic growth, inflation rates and political developments. Undoubtedly, the interdependencies between these parameters increase the risk of uncertainty, creating a systemic risk (also known as volatility) that is considered as an inherent part of financial system. Although the systemic risk phenomenon challenges decision making process for market participants, it also presents opportunity for those who can accurately assess and effectively manage this risk. In the past few decades, increasing market connectedness and widespread financial crisis show that it is difficult to analyse stock price movements and risk of contagion between markets with traditional statistical methods (Wu, 2020). Therefore, alternative methods have been developed over the years to overcome of the complex nature of financial markets. In this regard, Computational Intelligence (CI) techniques are being introduced as one of the latest interdisciplinary frameworks for the tackling of complex problems in financial markets. CI combines numerical algorithms and mathematical finance, and it is currently employed in various fields from risk management to stock prediction. The range of applications in CI is wide, including Artificial Neural Networks (ANN), Fuzzy Logic, Genetic Algorithms, and Support Vector Machines (SVM), to name a few. Among these various methods, Deep Learning is the youngest and the most sophisticated method among all as it is shown in the following figure.

Figure 6.2: An illustration of the position of Deep Learning comparing with other methods



In general, CI and Artificial Intelligence (AI) mimic cognitive function of human behaviour, such as learning and problem solving, which require explicitly being programmed for machine to behave in certain way in certain situations. On the other hand, Machine Learning (ML) as a subset of CI and AI, is an algorithm that can learn from data which gives an ability to identify patterns and automates model construction. Furthermore, Deep Learning (DL) is a very young field of ML based on ANNs which can calculate large datasets and complex problems with its unique multi-layer neural network architecture. The main advantage of DL is the needlessness of the feature extraction[4] and its capability of self-learning which is considered as an excellent ability to extract relevant information from financial time series to predict price movements and detect the magnitude of market linkages (Cavalcante et al., 2016).

In the last years, DL methods have been used increasingly used in financial market analysis due to their data driven and self-adaptive nature. Gunduz et al. (2017) studied hourly movements of 100 stocks from the Istanbul Stock exchange using Convolutional Neural Network (CNN) model. Number of technical indicators and temporal features have been used

[4] The process of transforming raw data into numerical features that can be processed while preserving the information in the original data set

to train the model and the experimental results showed that the proposed algorithm improves the prediction of stock returns compared to the baseline logistic regression. Maqsood et al. (2020) extended the dataset by adding the US, Hong Kong, Turkey, and Pakistan stock exchanges as well as employing the sentiment analysis from Twitter dataset. 11.42 million tweets were analysed and used as an input for the DL CNN model which show that the major events have impacts on stocks of selected markets, and DL models are able to evaluate large datasets and provide significant improvements to predict patterns of stock movements. On the other hand, Kim and Kang (2019) examined KOSPI 200 index using LSTM, CNN and MLP. The experimental results of the study show that LSTM provide improved forecasting performance compared to CNN and MLP as it works well with sequential data compared to others. Similar results have been obtained by Kim and Won (2018), and Sanboon et al. (2019) using DL models on various datasets. Growing number of studies are being conducted in the financial literature using deep learning models covering wide range of field including exchange rate prediction (Ni et al., 2019; Dautel et al., 2020; Qi et al., 2020; Fisichella and Garolla, 2021; Clavería et al., 2022), stock market forecasting (Chong et al., 2017; Vargas et al., 2017; Hiransha et al., 2018; Shen and Shafiq, 2020; Mohanty et al., 2021; Christy Jeba Malar et al., 2022; Gao et al., 2022), Cryptocurrency analysis (McNally et al., 2018; Karakoyun and Cibikdiken, 2018; Awoke et al., 2021; Jamshed and Dixit, 2022), and energy market (Zhao et al., 2017; Wang et al., 2019; Fan et al., 2019; Assaad and Fayek, 2021).

With reference to the various studies mentioned above, the author agrees that applications of DL algorithms in the field of finance is broad and can be used primarily in modelling and predicting financial data, pricing derivative products, and assessing market sentiment. Long Short-Term Memory (LSTM) network represents one of the most innovative and special kind of DL approaches, and can effectively formulate correlations with learning capabilities. In the methodology section, the author will provide further details on the application of the method.

6.2.3 Literature Review

The globalisation of financial markets has been one of the most important and debated concepts in the financial literature since early 1980s due to the growing economic integration and liberalisations of capital markets. Moreover, thanks to the growing technological advancements in recent years, the international financial markets have become more accessible both for institutional and retail investors which lead to a rapid increase of financial transactions globally and resulted with an expansion of capital flows that the world has not seen before. Although financial globalisation brings large benefits for investors such as portfolio diversification and international asset allocation, the process of financial liberalisation also leads to higher connectedness between domestic and foreign assets and increases the risk of contagion.

Financial crises have received great attention and become a global phenomenon due to the increasing turbulences in emerging and developed markets in the recent years. Although the clear definition of financial crisis remains vague, the literature has clarified some of the fundamentals that form crisis without specifying underlying reasons. For example, Eichengreen and Portes (1987) define financial crisis as: "*A disturbance to financial markets, associated typically with falling asset prices and insolvency amongst debtors and intermediaries, which ramifies through the financial system, disrupting the market's capacity to allocate capital*" (2). Bordo et al. (2001), however, point out the importance of liquidity and describe financial crises as "*episodes of financial-market volatility marked by significant problems of illiquidity and insolvency among financial-market participants and/or by official intervention to contain such consequences*" (55). While Schularic and Taylor (2012) chose to identify crisis by focusing on banking sector as "*events during which a country's banking sector experiences bank runs and sharp increases in default rates, accompanied by large losses of capital that result in public intervention, bankruptcy, or forced merger of financial institutions*" (1). As the different approaches of definitions indicate, the characteristics of financial crises tend to reveal themselves in diverse forms and relying on a single definition may lead to biased results, therefore, each crisis should be studied separately. For example, Leaven and Valencia (2020) identified 151 banking crises, 236 currency crises and 79 sovereign debt crises during the period from 1970 to 2017, excluding the recent novel Covid-19 crisis which had a devastating impact on economies and resulted with a global economic recession. To date, a broad range of studies have focused on revealing causes, timing and impacts of financial crises that break out in different parts of the world. The existing literature classifies crises based on its nature as: currency, banking, and debt crises. Yet, in this section, we will be discussing the three main crises that this chapter focuses on, namely, Asian financial crisis, Global financial crisis (GFC), and the Covid-19 recession, and provide an overview of different views and determinants to explain these crises.

6.2.3.1 1997-98 Asian Financial Crisis

Referred to as one of the major currency crises in the history of the world financial markets, the so-called Asian financial crisis, triggered by the devaluation of Thai baht in July 1997 with a growing contagion effect, spread to neighbouring countries and many other Asian markets which challenged the "Asian economic miracle". The crisis originated in Thailand which had a pegged exchange rate regime with the US dollar, yet it was inconsistent with the fundamentals of the real economy. The country enjoyed rapid economic growth with the other Asian counterparts starting from early 1970s and had significant capital inflows loaned by foreign financial institutions accounting for more than 60% of total inflows. Among these creditors, Japanese commercial banks were the largest lenders of Asia, and due to the real estate collapse in Japan in the 1990s, they started to change their exposure in Southeast Asia by calling their loans back. At the time, Thailand was already suffering with the unsustainable current account deficit, the lack of transparency in monetary system and excessively leveraged financial institutions to the real estate market as well as other chronic political and fiscal problems. Under these pressures, the growing foreign capital outflows triggered the collapse of Thai Baht on July 2, 1997, and the looming financial crisis rapidly spread from Thailand to much of Asia, then to Latin America and Russia, and later to the developed markets, even though there is big dissimilarities between these impacted countries. After the collapse of the Thai baht, the value of most Asian currencies fell 30-85% against the US dollar. This disruption in the financial markets was followed by a period of international stock market depreciation as much as 60%. As a result of the crisis, the International Monetary Fund (IMF) and the World Bank announced a rescue plan for Thailand, followed by Indonesia and Korea later to prevent more severe recession in the region. The crisis showed that the economies in East Asia were more connected to each other than predicted, and the pace of contagion was completely abrupt and devastating.

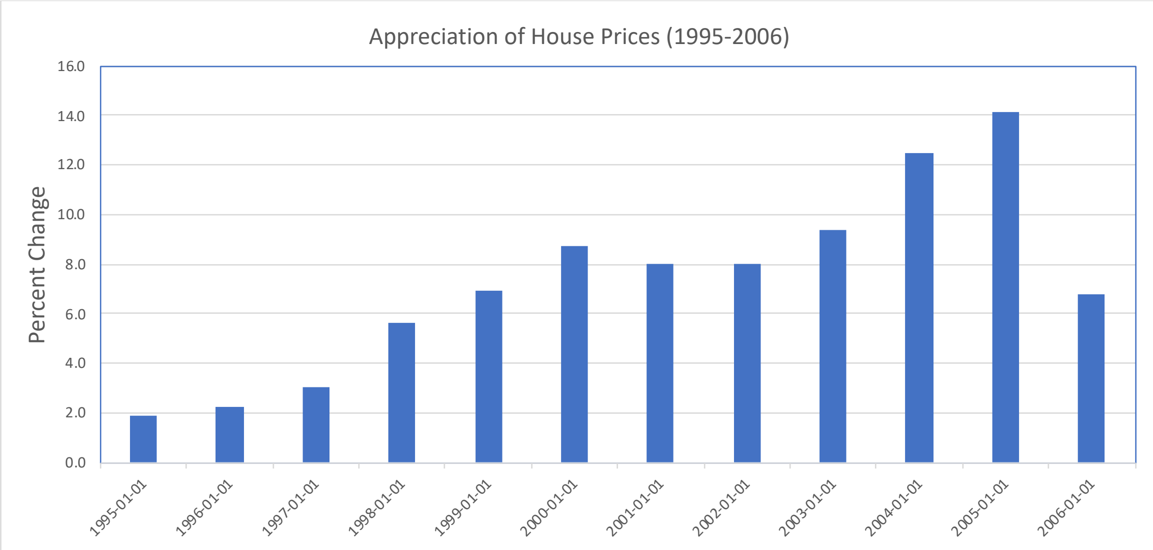
There is controversy on the explanation of the cause of the crisis, and the question of how this crisis spread so quickly from its origin to other countries remains debated. Baig and Goldfajn (1999) studied contagion effects between five countries of Asia during the crisis period, and their findings imply that the correlations in exchange rates and sovereign risk spreads jump during crisis periods as investors tend to react similarly during turbulent times. Yet, the contagion effects among equity markets were found more tentative. The study of Jang and Sul (2002) adopt the Granger-causality test and reveal that the contagion effect is more severe between Asian countries that are more connected economically. On the other hand, Sander and

Kleimeier (2003) investigate the patterns of Asian crisis by using the Granger-causality methodology and their results indicate that the Asian crisis changes contagion patterns between Asia and other related countries compared to pre-crisis and post-crisis period. They conclude with there is no detectable systematic patterns that favour cointegration of the countries which contracts with the study of Jang and Sul (2002). Baur and Schulze (2005) applied the quantile regression model to estimate linear and non-linear linkages and quantify the degree of contagion. The findings of the study indicate that Thailand is the centre of the contagion within the region of Asia, while Hong Kong is the distribution point of contagion to Latin America and Europe but not to the US market. Baur and Fry (2009) focused on different periods of Asian crisis by covering 11 countries, and they found interdependencies during crisis periods rather than volatility contagion. Their findings are also in line with Baur and Schulze (2005) in terms of defining Hong Kong as the main hub of international contagion rather than Thailand. Furthermore, Kim et al. (2013) developed a novel approach by integrating DCCX and MGARCH methods to estimate correlations in Asian economies and they found that the asymmetric spillovers exist between emerging countries of Asia which is later supported by Ahmed et al. (2021).

6.2.3.2 2007-09 Global Financial Crisis

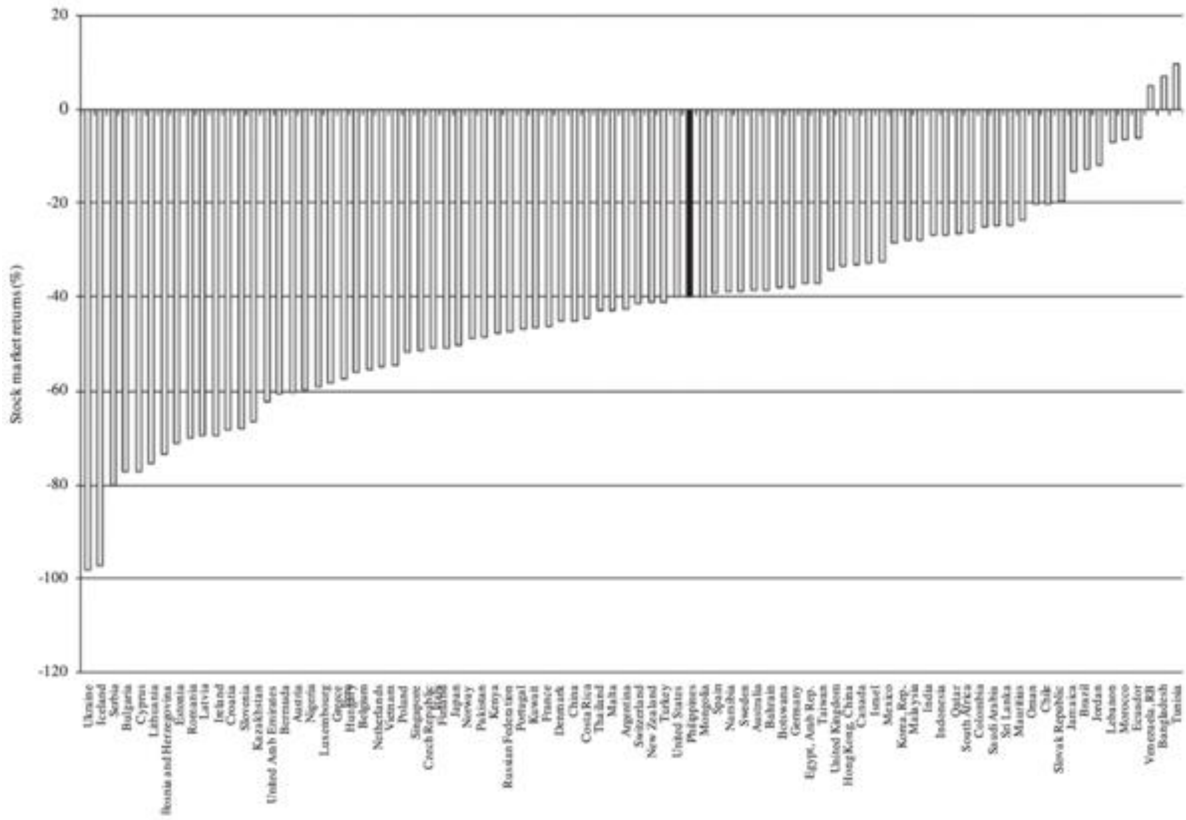
Although Asian countries significantly strengthened the resilience of their economies to financial shocks after the Asian financial crisis, the impact of the global financial crisis (GFC) in 2008 was unexpectedly vigorous. The GFC of 2007-09 is broadly believed by many economists to have been the most catastrophic financial crisis and the biggest economic drop since the Great Depression of 1929-33 (Wang et al.,2017). The US subprime credit crisis started in the summer of 2007, was triggered as a consequence of accumulated factors including, defective credit risk assessments for households by subprime lenders, insufficient financial regulations, worsening quality of US mortgages, excessive private debt levels and inaccurate credit ratings for mortgage-backed securities (Orlowski, 2008; Dell'Ariccia et al., 2012). More specifically, the rapid growth in housing market began after the FED's interest rate cuts in 2001, and it sets the stage for the crisis as appreciation in real house prices accounted for 31.6 % between 2002 and 2006 (51% if not inflation adjusted) as it is shown in Figure 6.3, which is way more than any four-year rates in the past 32 years. These price increases are mostly supported by overseas funds and extraordinarily low interest rates as well as securitizing different types of assets such as mortgage-backed securities and credit default swaps. The securitization of assets enabled subprime lenders to create more loans by pooling debt obligations and savings into packages, and selling these new securities backed by those packages on financial market, so they could rapidly reduce the risk exposure of subprime loans along with compensating the money lent and relend it to new borrowers. This chain of securitisation not only increased the complexities in valuation of assets on balance sheets of these financial institutions, but also created huge linkages among institutions at both national and international levels. When the signs of trouble started to emerge after the drop in housing prices and hike in interest rates in the early 2007, the financial stress and the draining liquidity were already an issue on the Wall St. At the beginning, it seemed to be a distress in a limited scope but following the bankruptcy of Lehman Brothers which was the fourth-largest investment bank in the US, the crisis started to spillover across banks, financial markets, and countries. In the United States, 15 banks failed in 2008, while several others were rescued through government intervention or acquisitions by other banks. The drop in the biggest exchanges of the US between 8-10 October 2008 was 18% for DJIA index and more than 20% for the S&P 500 benchmark index. The spread of the crisis was sharp, and there were significant drops in stock markets of both developed and emerging markets as shown in Figure 6.4.

Figure 6.3: National house price index



Source: S&P/Case-Shiller U.S. National Home Price Index

Figure 6.4: The percentage change of stock market indices for each country from July 2007 to April 2009



Source: Bloomberg

Various studies have been conducted to explain the cause and effects of the crisis over the years, such as Edey (2009) and Hesse and Frank (2009). There is extensive financial literature documenting the causes and impacts of GFC for both emerging and developed markets, such as the studies of Syllignakis and Kouretas (2011), Dungey and Gajurel (2014), Rodríguez (2020), and Paskaleva and Stoykova (2021). Although the worldwide effect of the crisis is substantial, the methodological assessments and the degree of spillover effects on different markets are still limited.[5] Fry et al. (2008) proposed a new model to identify contagion effects

[5] During the GFC, one of the earliest initiatives conducted by the Banque de France in Paris on May 2008 where Dungey (2008) and Idier (2008) presented their works on the matter of contagion effects in financial markets.

via transmission channels of the subprime crisis using the alterations in high order distribution of returns. The findings of the study reveal that the correlation-based tests are not able to detect the new channels of contagion during the crisis periods unlike proposed co-skewness tests. Idier (2008) supported the idea of probability of new contagion channels during the subprime crisis period by adopting Markov switching multifractal model between CAC, DAX, FTSE, and NYSE indices using daily return series. In contrast, Horvath and Petrovski (2013) examined the stock market co-movements in the European markets by using multivariate GARCH models, and the authors stated that there are no empirical findings to support any changes in the degree of stock market integrations caused by the GFC among selected groups of countries. Aloui et al. (2011) show that strong evidence of time-varying dependence and high level of contagion effects exist between BRIC countries and the US during the global financial crisis. Min and Hwang (2012) analysed the process of contagion effects by using the Dynamic Conditional Correlations (DCC) model for the OECD countries and the US from 2006 to 2010. They found strong evidence of increasing contagion during the US financial crisis for the UK, Australia, and Switzerland stock markets, while limited volatility and return contagion in the Japanese Stock Market. Wang (2014) also confirmed that the East Asian stock markets are less sensitive to the negative news originated in the US, while Rapach et al. (2013) found that the US markets have substantial predictive power on other countries but with a lag. Morales and Andreosso-O'Callaghan (2014) examined 58 countries by using various econometric models and surprisingly the empirical results of the study reveal no significant contagion effects originating from the US markets during the subprime crisis period, either in a worldwide or in a regional form. Similarly, Gupta and Guidi (2012) found that correlations increase during the financial crises but return to their initial levels after the crisis. By contrast, the study of Chow et al. (2017) revealed that Asian markets have greater exposure to shocks after the GFC and the surge in spillovers persists after the crisis. Furthermore, Yarovaya et al. (2016) analysed transmission channels across stock markets by implementing range-based volatility estimators and the results revealed that the degree and direction of spillovers differ depending on the method used.

6.2.3.3 Covid-19 Pandemic Crisis

Historically, the world has seen many crises, such as the Great Depression in the 1930s, Black Monday in 1987, the Asian financial crisis in 1997, and the Global Financial Crisis in 2008 where usually the first and the largest impact are observed in the stock markets. Most of these crises were either caused by financial shocks or disruptions in the economies. However, the recent Covid-19 pandemic crisis originated in Hubei province of China in late 2019 and spread across the globe at light-speed, was a health crisis and a total "black swan[6]" event (Morales and Andreosso-O'Callaghan, 2020) in the history of financial markets. At the beginning of the crisis in early 2020, the outbreak of the virus was country-specific, but with the growing number of Covid-19 cases and deaths, and the absence of an effective vaccine, the spread of fear has created an economic shock and has shaken the global financial markets. In March 2020, one of the most turbulent months was experienced in the US financial market where the circuit breakers were triggered four times within two weeks. The meltdown in the US stock market was followed by the Europe and Asia-Pacific indices where UK's FTSE 100, Germany's DAX and Italy's FTSE MIB suffered from one of the biggest single day drops in the history with more than 12% each. A number of Asian countries such as Japan, Singapore and Hong Kong saw significant drops as well in their benchmark indices in the most extensive financial and economic disruption worldwide since the Great Depression of the 1930s. According to the IMF data, more than $16 trillion was wiped out from global stock markets within 33 days which lead to a worldwide recession. A growing number of countries adopted strict quarantine policies and nationwide lockdowns starting from mid-February 2020 which disrupted economic activities enormously. Many industries were affected by strict confinements in developed and emerging countries and stopping activities in these industries also triggered another shock in energy markets. The reduction of oil demand due to the pandemic was also accompanied by a supply shock when OPEC and Russia failed to agree on oil production cuts which induced oil price suffering from a double shock and the price for the US benchmark, West Texas Intermediate (WTI), fell into negative territory (-$37/bbl) for the first time in recorded history. The contagion effects in different asset classes and markets triggered more fears and caused further plunges across the globe where due to the destructive impact of the Covid-19 crisis, most of the economies will not be able to recover their 2019 output levels until 2022 at the earliest, based on the OECD projections.

[6] The term "black swan" was introduced by Taleb (2007) prior to the 2008 subprime crisis which refers to an extremely negative event or occurrence that is impossibly difficult to predict. Black Swan events are characterized by their extreme rarity, severe impact, and the widespread insistence that they were obvious in hindsight.

Following the devastating impact of Covid-19 globally, a growing number of studies examine the topic from various perspectives. Akhtaruzzaman et al. (2021) analysed contagion effects among China and G7 countries by focusing on financial and nonfinancial firms. They used DCC models to estimate financial transmission channels and the results indicate that China and Japan are the main transmitters of spillovers during the Covid-19 crisis period. He et al. (2020) investigated the contagion effects of Covid-19 on stock markets by applying conventional *t*-tests and non-parametric Mann-Whitney tests. They used daily return data from stock markets of eight countries and the findings reveal that there were bidirectional contagion effects among Asian, European, and American stock markets, and Covid-19 does not have negative effect on the selected stock markets. On the other hand, the study of Wang et al. (2020) rejects the idea of no impact of Covid-19 on stock markets as the empirical results of their study show that the pandemic has led massive shocks in international financial markets. They also provide evidence of directional spillover channels between selected markets where Chinese and Japanese financial markets detected as net spillover recipients, while British and American stock markets function as main spillover transmitters during the pandemic in contrast to the results of Akhtaruzzaman et al. (2021). Baker et al. (2020), and Ramelli and Wagner (2020) examined the reaction of stock prices on Covid-19. Bouri et al. (2021) explored extreme return connectedness between different asset classes during the pandemic. Abuzayed et al. (2021) focused on systemic distress risk spillover by using conditional value at risk (CoVaR) and dynamic conditional correlation (DCC) methods and they found that the developed markets in North America and Europe exposed more marginal extreme risk compared to Asian stock markets during the Covid-19 period. Zehri (2021) investigated the inherent correlations among the US and East Asian markets and the findings show that large spillovers exist from the US market, but the China's bourses have more indirect exposure to these shocks rather than direct spillovers. For further studies regarding the impact of pandemic on different sectors, see, Azimli (2020), Salisu and Akanni (2020), Gunay (2020), Yarovaya et al. (2020), Liu et al. (2021), Okorie and Lin (2021), Ghorbel and Jeribi (2021), and Le and Tran (2021).

6.3 Data and Methodology

6.3.1 Data

The data for the present paper are retrieved from Bloomberg data base and covers closing prices of widely accepted indices from ten Asian stock markets, i.e Nikkei 225 Index (NIKKEI) from Japan, Hang Seng Index (HSI) from Hong Kong, Korea Composite Stock Market Index (KOSPI) from South Korea, Taiwan Capitalization Weighted Stock Index (TAIEX) from Taiwan, the Straits Times Index (STI) from Singapore, SSE Composite Index (SSE) from China, PSE Composite Index (PSE) from Philippines, The Stock Exchange of Thailand Index (SET) from Thailand, Kuala Lumpur Composite Index (KLCI) from Malaysia, and Jakarta Stock Exchange Composite Index (JCI) from Indonesia. Moreover, S&P 500 Composite Index (SP500) from the US is also considered to give a broader perspective during different crises periods, as the source for the GFC in 2007-2009 is believed to be the US (Chanˆ et al., 2019). In order to satisfy stationarity, closing price series have been converted to return series by taking the first difference of the log-transformed series using the below formula:

$$R_t = \log\left(P_t/P_{t-1}\right) * 100 \tag{6.1}$$

where R_t denotes the logarithmic return at time t. P_t and P_{t-1} are the closing price of the index at time t and $t-1$ respectively.

The full sample period of the study consists of 4726 return data in total, starting from 03 July 1997 to 09 March 2021. Specifically, the data have been split into five different sub-periods coving both pre-crisis and crisis periods. The Asian crisis period spans from 03 July 1997 to 29 December 1998 with 315 observations. Pre-GFC period covers data between 06 January 1999 and 26 June 2007 with 1675 observations, and the GFC period takes place between 05 July 2007 and 30 July 2009 with 410 return series. Following, Pre-Covid crisis period extends from 31 July 2009 to 10 March 2020 with 2030 observations, and finally Covid crisis period covers the dates between 30 December 2020 and 09 March 2021 with 283 counts. During the data cleansing, one of the major challenges was non-synchronous holidays in different markets which leads computation difficulties and negatively affect the output of the models. To deal with this issue, the return series on these days are taken zero, as zero return indicates the actual return on non-trading days (Yarovaya et al., 2016). In terms of the selection of the different sub-periods, there is still no consensus on the financial literature regarding the dating of a specific crisis period (Kose, 2011). Furthermore, the dating is also not consistent across papers that study different financial market crises, such as Chiang et al. (2007), Laeven and Valencia (2008), Baur and Fry (2009), Syllignakis and Kouretas (2011), Kenourgios and Padhi (2012), Arghyrou and Kontonikas (2012). Therefore, to identify breaking points, this paper considers structural break tests of Bai and Perron (1998, 2003) and, Lee and Strazicich (2013). The structural break tests are applied multiple times to the full period, and as expected presence of multiple breaks are identified which differ from one market to another. Therefore, the identified multiple breaking points are compared with sharp movements in closing prices for each index to capture the common patterns. Then the chosen dates are divided to pre-crisis and crisis periods and used as an input for the selected models.

Table 6.1 presents the descriptive statistics of the daily stock market returns for six different periods. Based on the result of Jarque-Bera test statistic, the normality assumption of null hypotheses is rejected in all selected markets, confirming the non-normal distribution in all series. These results are expected, as returns of equities do not follow normal distribution (Beedles and Simkowitz, 1978). Thus, return distribution is not symmetrical and the series have either positive or negative skewness. Positive skewness appears when the median has smaller value than the mean, while negative skewness occurs when the median has greater value than the mean. Eastman and Lucey (2008) suggest that in the event of negative skewness, most returns will be higher than average return, therefore market participants would prefer to invest in negatively skewed equities.

According to the Table, majority of the markets present negative skewness during the full period, with the only exception of KLCI and SET indices which indicate positive skewness. Furthermore, Asian crisis period and Covid crisis period exhibit similarities in terms of skewness as 7 out of 11 markets (63.6%) have positively skewed returns. On the other hand, GFC period and pre-covid crisis period indicated negatively skewed returns in all markets. In a similar way to the concept of skewness, kurtosis indicates sharp events and can be interpreted as a gauge of greatest point in both ways. The kurtosis in a normal distribution is three. A positive kurtosis refers to leptokurtosis, while negative kurtosis demonstrates platykurtosis. Emenike and Aleke (2012) suggest that high kurtosis values indicate big shocks in the time series with either type of sign. As it is clear from the tables, the values of kurtosis are only positive in all selected return series which demonstrate leptokurtosis, and it ranges between 0.654 (NIKKEI during Covid crisis period) and 40.749 (KLCI during the full sample period).

KLCI has the highest maximum value with 8.799, while SET has the lowest minimum value with -6.976 in daily return series. Malaysia's KLCI Index has the greatest gap between maximum and minimum values with 8.799% and, -6.185% during the Asian crisis period which is also justified by the standard deviation by measuring the average volatility. The value of standard deviation is 1.456% in Malaysia's KLCI Index which is the highest all among others in all periods. Japan's NIKKEI and Hong Kong's HSI Indices have the smallest gap between minimum and maximum values during the Covid crisis period and pre-covid crisis period respectively with -1.766% & 1.333% and, -1.761% & 1.443% respectively. This is also supported by the standard deviation which is 0.514% for NIKKEI and 0.247% for HSI. This result indicates lowest volatility compared to others. To sum up, as is expected stock markets show lower volatility during the pre-crisis period, while volatility rises during all crisis periods.

Table 6.1: Descriptive statistics of selected stock markets for each period

	Mean	Standard Error	Median	Standard Deviation	Sample Variance	Kurtosis	Skewness	Range	Minimum	Maximum	Sum	Count	JB Prob
Entire Sample Period (03/07/1997 - 09/03/2021)													
SP500	0.006	0.008	0.025	0.530	0.281	7.703	-0.505	8.007	-4.113	3.895	30.011	4726	0
NIKKEI	-0.001	0.009	0.014	0.653	0.426	6.000	-0.287	11.007	-5.260	5.748	-4.869	4726	0
HSI	-0.001	0.010	0.016	0.689	0.474	10.048	-0.104	13.889	-6.399	7.490	-6.666	4726	0
JCI	0.015	0.010	0.033	0.671	0.451	8.169	-0.201	10.520	-5.529	4.990	70.877	4726	0
KLCI	0.003	0.008	0.011	0.517	0.268	40.749	1.448	14.984	-6.185	8.799	14.096	4726	0
KOSPI	0.012	0.011	0.031	0.741	0.549	6.071	-0.183	10.272	-5.371	4.901	54.653	4726	0
PSE	0.003	0.009	0.000	0.603	0.364	10.605	-0.335	12.846	-6.220	6.625	13.072	4726	0
SSE	0.013	0.010	0.025	0.667	0.445	4.832	-0.184	8.103	-4.020	4.083	63.757	4726	0
STI	-0.005	0.008	0.006	0.532	0.283	7.114	-0.310	7.820	-3.975	3.844	-25.301	4726	0
TAIEX	0.007	0.009	0.017	0.589	0.347	3.643	-0.183	7.149	-4.315	2.834	34.136	4726	0
SET	0.005	0.010	0.002	0.714	0.509	6.801	0.060	11.905	-6.976	4.929	0.171	4726	0
Asian Crisis Period (03/07/1997-29/12/1998)													
SP500	-0.003	0.032	0.040	0.564	0.318	6.343	-0.803	5.256	-3.089	2.167	-0.790	315	0
NIKKEI	-0.034	0.044	-0.018	0.788	0.621	1.726	0.175	5.914	-2.587	3.327	-10.707	315	0
HSI	-0.055	0.074	-0.008	1.316	1.731	5.269	0.217	13.889	-6.399	7.490	-17.178	315	0
JCI	-0.068	0.075	-0.089	1.325	1.756	2.192	0.012	10.173	-5.529	4.643	-21.577	315	0
KLCI	-0.060	0.082	-0.177	1.456	2.119	7.262	1.150	14.984	-6.185	8.799	-18.995	315	0
KOSPI	-0.057	0.080	-0.040	1.427	2.037	1.052	0.258	9.391	-5.038	4.353	-17.840	315	0
PSE	-0.057	0.060	-0.060	1.070	1.145	1.568	-0.082	7.526	-4.232	3.294	-18.002	315	0
SSE	0.008	0.038	0.020	0.678	0.460	5.542	-0.768	6.538	-3.790	2.747	2.599	315	0
STI	-0.066	0.055	-0.088	0.983	0.966	2.623	0.080	7.820	-3.975	3.844	-20.938	315	0

TAIEX	-0.030	0.041	-0.086	0.726	0.527	1.371	-0.038	5.365	-2.956	2.409	-9.412	315	0
SET	-0.006	0.029	-0.029	0.518	0.268	1.801	0.231	3.905	-2.150	1.749	-2.091	315	0
Pre-GFC Period (06/01/1999 - 29/06/2007)													
SP500	0.003	0.012	0.014	0.488	0.238	2.113	0.142	4.613	-2.192	2.421	5.824	1675	0
NIKKEI	-0.004	0.014	0.004	0.583	0.340	1.472	-0.258	5.632	-3.142	2.491	-6.296	1675	0
HSI	0.017	0.014	0.016	0.582	0.339	2.798	-0.131	6.242	-3.882	2.360	27.697	1675	0
JCI	0.032	0.016	0.029	0.640	0.410	5.597	-0.013	9.739	-4.748	4.990	52.827	1675	0
KLCI	0.015	0.011	0.016	0.443	0.197	5.840	-0.274	5.295	-2.754	2.541	24.528	1675	0
KOSPI	0.030	0.021	0.065	0.840	0.705	2.838	-0.170	9.641	-5.371	4.270	50.302	1675	0
PSE	0.009	0.014	0.000	0.558	0.312	13.742	0.741	10.209	-3.583	6.625	15.475	1675	0
SSE	0.029	0.016	0.019	0.647	0.418	5.254	0.429	8.103	-4.020	4.083	48.306	1675	0
STI	0.009	0.012	0.019	0.508	0.258	3.775	-0.358	6.349	-3.950	2.399	15.358	1675	0
TAIEX	0.002	0.017	-0.001	0.686	0.470	2.859	-0.150	6.996	-4.315	2.680	2.903	1675	0
SET	-0.033	0.022	-0.076	0.887	0.786	3.340	0.587	9.284	-4.355	4.929	-54.808	1675	0
GFC Period (05/07/2007 - 30/07/2009)													
SP500	-0.065	0.046	0.030	0.935	0.874	3.114	-0.717	7.082	-4.113	2.969	-26.777	410	0
NIKKEI	-0.039	0.052	-0.016	1.050	1.103	5.163	-0.115	11.007	-5.260	5.748	-16.129	410	0
HSI	-0.016	0.057	0.066	1.153	1.329	3.073	-0.099	11.135	-5.899	5.237	-6.536	410	0
JCI	0.020	0.046	0.056	0.932	0.869	3.346	-0.258	8.221	-4.910	3.311	8.343	410	0
KLCI	-0.007	0.023	-0.012	0.473	0.224	1.102	-0.038	3.360	-1.598	1.761	-3.030	410	0
KOSPI	0.001	0.047	0.067	0.946	0.894	5.067	-0.553	9.753	-4.852	4.901	0.549	410	0
PSE	-0.019	0.039	-0.015	0.782	0.612	7.210	-0.860	8.749	-5.684	3.064	-7.701	410	0
SSE	0.009	0.052	0.070	1.055	1.114	1.100	-0.004	7.164	-3.241	3.924	3.757	410	0
STI	-0.040	0.040	-0.025	0.819	0.671	1.861	-0.055	7.047	-3.777	3.270	-16.505	410	0
TAIEX	-0.006	0.042	0.053	0.849	0.721	0.730	-0.022	5.386	-2.552	2.834	-2.630	410	0
SET	0.061	0.031	0.044	0.635	0.409	0.801	-0.131	4.535	-2.280	2.359	25.171	410	0
Pre-Covid Crisis Period (31/07/2009 - 10/03/2020)													
SP500	-0.006	0.011	0.012	0.490	0.240	2.045	-0.442	4.380	-2.614	1.767	-11.742	2030	0
NIKKEI	0.009	0.010	0.041	0.460	0.212	7.135	-0.790	7.085	-4.039	3.046	18.607	2030	0
HSI	0.004	0.005	0.014	0.247	0.061	3.431	-0.429	3.204	-1.761	1.443	8.181	2030	0
JCI	0.004	0.009	0.014	0.416	0.173	4.705	-0.621	4.916	-2.788	2.128	8.272	2030	0
KLCI	0.010	0.013	0.026	0.590	0.348	5.710	-0.483	8.202	-4.844	3.358	20.872	2030	0
KOSPI	0.008	0.010	0.023	0.466	0.217	3.814	-0.498	5.447	-3.040	2.407	16.507	2030	0
PSE	0.002	0.013	0.024	0.595	0.354	5.211	-0.761	6.284	-3.850	2.434	3.290	2030	0
SSE	-0.005	0.008	0.006	0.347	0.121	4.171	-0.748	3.902	-2.702	1.200	-11.157	2030	0
STI	0.005	0.009	0.026	0.396	0.157	3.088	-0.586	4.431	-2.494	1.937	10.104	2030	0
TAIEX	0.016	0.009	0.027	0.420	0.176	6.866	-0.808	5.525	-3.431	2.094	32.348	2030	0
SET	0.020	0.013	0.035	0.605	0.366	15.729	-1.104	11.570	-6.976	4.594	39.733	2030	0
Covid Crisis Period (30/12/2020 - 09/03/2021)													
SP500	0.078	0.038	0.077	0.635	0.403	10.474	0.998	6.533	-2.638	3.895	22.065	283	0
NIKKEI	0.038	0.031	0.027	0.514	0.264	0.654	-0.247	3.099	-1.766	1.333	10.844	283	0
HSI	0.009	0.034	0.013	0.579	0.335	1.897	-0.143	4.304	-2.165	2.139	2.430	283	0
JCI	0.042	0.036	0.011	0.606	0.367	9.210	0.830	6.446	-2.232	4.214	11.839	283	0

KLCI	0.026	0.027	0.019	0.452	0.204	7.970	0.382	5.225	-2.347	2.878	7.255	283	0
KOSPI	0.078	0.037	0.080	0.619	0.383	6.913	0.959	5.969	-2.385	3.583	22.143	283	0
PSE	0.021	0.044	0.003	0.732	0.536	18.725	-1.901	8.467	-6.220	2.247	5.903	283	0
SSE	0.011	0.026	0.017	0.441	0.195	2.252	-0.480	3.330	-1.999	1.331	3.074	283	0
STI	0.027	0.032	0.022	0.543	0.294	11.621	-0.722	5.877	-3.317	2.560	7.507	283	0
TAIEX	0.093	0.031	0.081	0.525	0.276	4.145	0.239	4.501	-1.820	2.681	26.285	283	0
SET	-0.016	0.033	0.003	0.569	0.323	2.031	-0.323	4.211	-2.333	1.877	-4.557	283	0

6.3.1.1 Correlation Coefficient Test

One of the most traditional approaches of assessment stock market dependences is the estimation of unconditional correlation coefficient matrix which is also known as Pearson's r. The Pearson product-moment correlation coefficient is a measure of the strength of a linear association between two variables. The coefficient number ranges between -1.0 and 1.0 where a value of 0 indicates that there is no association between the two markets. A value greater than 0 indicates a positive association; that is, as the value of stock index A increases, so does the value of the stock index B. A value less than 0 indicates a negative association; that is, as the value of stock index A increases, the value of the stock index B decreases. This method is often applied by market participants to manage risk exposure, but it is important to note that the method does not provide any information regarding causation (Kim et al., 2020).

The Pearson's correlation coefficient between any two stock markets i and j is calculated as follow:

$$P_{ij,t} = \frac{E_{t-1}\{(R_{i,t}R_{j,t}) - (R_{i,t})(R_{j,t})\}}{\sqrt{E_{t-1}\{(R_{i,t}^2) - (R_{i,t})^2\}}\sqrt{E_{t-1}\{(R_{j,t}^2) - (R_{j,t})^2\}}} \quad (6.2)$$

where R_i and R_j are vectors of return series of stock markets i and j respectively, and P is the Pearson's correlation coefficient.

Table 6.2 reports the cross-correlation matrixes for each selected period. According to the results, there is a notable increase in cross-country correlations during the turbulent periods compared to pre-crises periods. Asian markets are mostly more correlated with each other compared to the correlation with the US stock market which is not surprising due to the regional dynamics. On the other hand, majority of market pairs are positively correlated except for the

SET index which mostly negatively correlated with the other stock markets which can be considered for diversification by international investors to minimise portfolio risk. The top three market pairs in terms of the magnitude of correlations are STI-HSI (Pearson's r of 0.806), STI-KOSPI (Pearson's r of 0.768) during the GFC period, and SSE-SP500 (Pearson's r of 0.759) during the pre-covid crisis period which indicate possibility of contagion during the turbulent times. The lowest correlation coefficient is observed between SSE and KOSPI during the Asian crisis period which is reported as 0.001. It should be also noted that the cross-market correlations are higher in the recent years compared to the earlier periods which is perhaps due to the globalization and increasing financial market integration (Sirimevan et al., 2019; Wu, 2020). In addition, the entire sample period provides broader perspective regarding correlations and indicates some differences compared to the sub-periods. One of the most notable changes is observed in NIKKEI which shows very weak correlations in contrast to pre-crises periods. Specifically, the estimated correlation with the US market is virtually nonexistence suggesting potential for portfolio diversification and risk management strategies exist between equity markets of the US and Japan in the long run. Similarly, Thailand's SET index continues to be a good hedge in the region by negatively cointegrating with the major equity markets. The highest degree of correlation is found between STI-HSI (Pearson's r of 0.656) during the full period confirming the study of Hui (2005). Higher level of long-term correlation between markets increases the contagion risks and limit diversification window for international investors. Therefore, examining short-run correlation coefficients among equity markets is important since diversification benefits and risk exposure significantly change during different sub-periods within the region.

Table 6.2: Correlation coefficient matrix of stock indices for each period

Entire Sample Period (03/07/1997 - 09/03/2021)											
	SP500	***NIKKEI***	***HSI***	***JCI***	***KLCI***	***KOSPI***	***PSE***	***SSE***	***STI***	***TAIEX***	***SET***
SP500	1,000										
NIKKEI	0,000	1,000									
HSI	0,184	0,024	1,000								
JCI	0,113	0,031	0,443	1,000							
KLCI	0,083	0,042	0,423	0,342	1,000						
KOSPI	0,156	0,001	0,492	0,339	0,323	1,000					
PSE	0,052	0,008	0,355	0,357	0,298	0,299	1,000				
SSE	0,041	0,016	0,316	0,160	0,112	0,144	0,128	1,000			
STI	0,190	0,038	0,656	0,471	0,454	0,491	0,365	0,194	1,000		
TAIEX	0,130	0,004	0,455	0,331	0,275	0,461	0,284	0,185	0,448	1,000	

SET	-0,038	0,014	0,002	0,003	0,014	0,002	-0,006	-0,015	-0,008	0,014	1,000

Asian Crisis Period (03/07/1997-29/12/1998)

	SP500	***NIKKEI***	***HSI***	***JCI***	***KLCI***	***KOSPI***	***PSE***	***SSE***	***STI***	***TAIEX***	***SET***
SP500	1.000										
NIKKEI	-0.074	1.000									
HSI	0.227	0.079	1.000								
JCI	0.035	0.161	0.395	1.000							
KLCI	0.215	0.126	0.456	0.355	1.000						
KOSPI	0.189	-0.019	0.226	0.194	0.267	1.000					
PSE	0.193	0.120	0.449	0.376	0.287	0.209	1.000				
SSE	-0.146	0.120	0.052	0.018	0.040	0.001	0.112	1.000			
STI	0.165	0.142	0.591	0.448	0.489	0.197	0.545	0.028	1.000		
TAIEX	0.079	0.056	0.311	0.233	0.292	0.167	0.236	0.080	0.353	1.000	
SET	-0.029	-0.058	0.034	-0.069	-0.034	-0.022	0.017	-0.053	0.025	-0.028	1.000

Pre-GFC Period (06/01/1999 – 29/06/2007)

	SP500	***NIKKEI***	***HSI***	***JCI***	***KLCI***	***KOSPI***	***PSE***	***SSE***	***STI***	***TAIEX***	***SET***
SP500	1.000										
NIKKEI	0.023	1.000									
HSI	-0.045	0.271	1.000								
JCI	0.069	0.274	0.082	1.000							
KLCI	0.023	0.459	0.201	0.203	1.000						
KOSPI	-0.093	-0.050	0.002	-0.027	-0.034	1.000					
PSE	0.030	0.285	0.264	0.181	0.331	0.044	1.000				
SSE	-0.024	-0.023	0.036	-0.029	-0.086	-0.042	-0.029	1.000			
STI	0.081	0.577	0.321	0.326	0.446	-0.029	0.343	-0.018	1.000		
TAIEX	0.087	0.226	0.123	0.064	0.180	-0.053	0.200	0.129	0.211	1.000	
SET	-0.032	0.002	-0.033	-0.012	0.016	-0.077	-0.079	-0.043	-0.056	0.044	1.000

GFC Period (05/07/2007 – 30/07/2009)

	SP500	***NIKKEI***	***HSI***	***JCI***	***KLCI***	***KOSPI***	***PSE***	***SSE***	***STI***	***TAIEX***	***SET***
SP500	1.000										
NIKKEI	-0.042	1.000									
HSI	0.228	0.036	1.000								
JCI	0.251	-0.013	0.677	1.000							
KLCI	0.063	0.087	0.631	0.560	1.000						
KOSPI	0.195	-0.003	0.691	0.585	0.568	1.000					
PSE	0.076	-0.087	0.523	0.471	0.557	0.445	1.000				
SSE	-0.018	0.059	0.502	0.273	0.302	0.322	0.289	1.000			
STI	0.220	0.055	0.806	0.647	0.631	0.768	0.376	0.331	1.000		
TAIEX	0.138	-0.036	0.656	0.546	0.557	0.735	0.510	0.330	0.648	1.000	
SET	-0.052	0.042	-0.056	-0.014	-0.032	-0.066	-0.054	-0.099	-0.073	-0.015	1.000

Pre-Covid Crisis Period (31/07/2009 - 10/03/2020)

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET
SP500	1.000										
NIKKEI	0.591	1.000									
HSI	0.561	0.491	1.000								
JCI	0.611	0.512	0.521	1.000							
KLCI	-0.047	0.043	-0.046	0.063	1.000						
KOSPI	0.341	0.394	0.433	0.354	-0.079	1.000					
PSE	0.528	0.337	0.320	0.332	-0.019	0.205	1.000				
SSE	0.759	0.619	0.538	0.600	0.013	0.325	0.412	1.000			
STI	0.581	0.475	0.476	0.672	0.070	0.322	0.312	0.629	1.000		
TAIEX	0.242	0.153	0.127	0.235	0.056	0.065	0.120	0.282	0.170	1.000	
SET	-0.062	-0.100	0.024	-0.037	-0.053	-0.044	-0.012	-0.043	-0.057	-0.059	1.000

Covid Crisis Period (30/12/2020 - 09/03/2021)

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET
SP500	1.000										
NIKKEI	0.065	1.000									
HSI	0.194	0.014	1.000								
JCI	0.054	0.065	0.408	1.000							
KLCI	-0.065	-0.006	0.444	0.443	1.000						
KOSPI	0.122	0.069	0.658	0.493	0.536	1.000					
PSE	-0.134	0.025	0.219	0.415	0.366	0.343	1.000				
SSE	0.128	0.032	0.616	0.359	0.273	0.426	0.138	1.000			
STI	0.059	0.029	0.584	0.520	0.624	0.658	0.296	0.369	1.000		
TAIEX	0.085	0.051	0.543	0.455	0.476	0.687	0.317	0.450	0.587	1.000	
SET	-0.014	-0.026	0.079	0.070	0.196	0.103	0.073	-0.104	0.105	0.026	1.000

6.3.1.2 Unit Root Test

In order to test stationarity of the return series, the Augmented Dickey-Fuller (ADF) test proposed by Dickey and Fuller (1981) and the Phillips-Perron (PP) test proposed by Phillips and Perron (1988) have been conducted. The following equation shows the testing procedure for the ADF test regression:

$$\Delta Y_t = a_0 + \beta Y_{t-1} + a_1 \Delta Y_{t-1} + a_2 \Delta Y_{t-2} + \cdots + a_p \Delta Y_{t-p} + \varepsilon_t \qquad (6.3)$$

where Y is the dependent variable, a_0 is the constant and p is the lag order of the autoregressive process. Lag length is determined by the Schwarz information criterion (SIC). The null hypothesis refers Y_t series have unit root, which signifies the data is nonstationary if it is accepted.

The PP method provides a non-parametric approach compared to ADF test by considering unspecified autocorrelation and heteroscedasticity in addition to the unit root test. It addresses the issue of serial correlation by modifying the t-test statistic in the non-augmented DF regression so the asymptotic properties of the regression will not be impacted. The test equation is given as follow:

$$\Delta Y_t = \mu + a_t + (p-1)\Delta Y_{t-1} + \varepsilon_t \tag{6.4}$$

Table 6.3 reports the stationarity results of index returns for selected frequencies. According to the results on the table, the test statistic is smaller than the critical values which allows rejecting the null hypothesis of unit root (nonstationary) in both ADF and PP tests at all levels of significance for each series.

Table 6.3: ADF and PP stationary tests for selected periods

	Full Period		**Asian Crisis Period**		**Pre-GFC Period**		**GFC Period**		**Pre-Covid Crisis Period**		**Covid Crisis Period**	
	ADF	*PP*	*ADF*	*PP*	*ADF*	*PP*	*ADF*	*PP*	*ADF*	*PP*	*ADF*	*PP*
SP500	-71.988	-72.006	-6.854	-32.480	-11.764	-15.747	-6.159	-44.507	-13.841	-19.762	-7.741	-24.286
NIKKEI	-71.574	-71.554	-6.807	-31.650	-11.618	-16.175	-6.990	-42.456	-13.072	-17.175	-6.613	-32.415
HSI	-38.923	-69.353	-6.599	-33.410	-12.664	-15.176	-6.351	-39.741	-13.921	-17.652	-7.547	-27.302
JCI	-41.291	-61.293	-8.490	-22.820	-11.054	-14.153	-7.644	-33.116	-13.524	-19.087	-7.691	-27.026
KLCI	-58.382	-58.029	-7.347	-23.890	-11.301	-15.208	-7.683	-34.235	-11.003	-22.230	-6.271	-33.439
KOSPI	-42.113	-66.631	-7.000	-25.010	-12.818	-15.587	-7.666	-35.332	-13.100	-16.324	-8.055	-32.574
PSE	-62.908	-62.858	-7.068	-24.879	-11.402	-14.768	-7.540	-34.644	-11.990	-19.85	-6.396	-30.367
SSE	-67.807	-68.074	-7.063	-31.863	-10.141	-18.005	-7.172	-39.952	-12.836	-20.46	-7.441	-23.219
STI	-49.268	-63.864	-6.908	-22.807	-12.738	-15.45	-6.140	-37.839	-13.641	-18.304	-6.286	-28.764
TAIEX	-66.709	-66.679	-6.180	-30.883	-12.623	-16.024	-7.456	-36.791	-12.830	-20.767	-7.638	-29.495
SET	-44.314	-62.680	-6.779	-22.847	-10.132	-14.588	-6.986	-34.983	-10.939	-20.121	-7.481	-26.647

Notes: Critical values: 1% level is -3.43132; 5% level is -2.86185; 10% level is -2.56698. Test critical values are based on MacKinnon (1996). Prob. is less than 0.001 in all cases.

6.3.2 Methodology

The present section explains the correlation models that used in the investigation of volatility spillovers in the selected markets.

6.3.2.1 The Dynamic Conditional Correlation Method

The dynamic conditional correlation (DCC) model is introduced by Engle (2002) which is the generalized version of constant conditional correlation (CCC) model of Bollerslev (1990) to estimate volatility spillover and dependencies among different time series. The DCC model allows to investigate time-dependent conditional correlations and it is able to examine big correlation matrices. Moreover, the coefficients in the model are independent from the number of correlated series which gives more flexibility compared to earlier models. The methodology can be built by two-step procedure. In the first step, the univariate GARCH (1,1) procedure is followed to obtain the conditional variance of each parameter, while in the second step the conditional correlation estimates is conducted by using the standardized residuals acquired in the first step. Considering this, the mean equations are given as follow:

$$
\begin{aligned}
R_{ft} &= \mu_f + \sum_{l=1}^{n} \alpha_{fl} R_{ft-l} + \sum_{l=1}^{n} \beta_{fl} R_{st-l} + \varepsilon_{ft} \\
R_{st} &= \mu_s + \sum_{l=1}^{n} \alpha_{sl} R_{st-l} + \sum_{l=1}^{n} \beta_{sl} R_{ft-l} + \varepsilon_{st}
\end{aligned}
\qquad (6.5)
$$

where f denotes the first country and s indicates the second country. The mean equations above are used to obtain residual series which will then applied to derive the variance equations as shown in the following equations:

$$
\begin{aligned}
\sigma_{ft}^2 &= \alpha_{f0} + \alpha_{f1} \varepsilon_{ft-1}^2 + \beta_{f1} \sigma_{ft-1}^2 \\
\sigma_{st}^2 &= \alpha_{s0} + \alpha_{s1} \varepsilon_{st-1}^2 + \beta_{s1} \sigma_{st-1}^2
\end{aligned}
\qquad (6.6)
$$

where σ_t^2 denotes conditional variance, α_1 and β_1 indicate ARCH and GARCH terms. The standardized residuals are denoted by ε and α_0 refers the constant term.

Following the data generating process of Engle (2002), the dynamic conditional correlation procedure can be defined as follow:

$$
Q_t = (1 - \alpha - \beta)P + \alpha \varepsilon_{t-1} \varepsilon'_{t-1} + \beta Q_{t-1} \qquad (6.7)
$$

where Q_t represents the covariance matrix with $Q_t = (q_{fs,t})$, $P = E[\varepsilon_t \varepsilon_t']$ and $\alpha + \beta < 1$. A significant ARCH term (α) indicates that the correlations vary appreciably over time henceforth the spillovers exist among the selected markets. The GARCH parameter (β) indicates the persistence of the shock to the correlation therefore the shock at time $t-1$ effects the correlation at time t. Although the correlation is mean reverting as $\alpha + \beta < 1$, it is possible to have a $\alpha + \beta = 1$ which means the conditional correlation is integrated to the order 1. For further details, see; Peseran and Peseran (2007), Hafner and Franses (2009), and Syllignakis and Kouretas (2011).

6.3.2.2 The GARCH-BEKK Model

Another adopted approach by the present study is named by Baba-Engle-Kraft-Kroner (BEKK) model and it was initially introduced by Engle and Kroner (1995). The GARCH-BEKK specification with single lag is defined as follow:

$$H_t = C^{\circ\prime} C^{\circ} + D' \varepsilon_{t-1} \varepsilon_{t-1}' D + G' H_{t-1} G \tag{6.8}$$

where H_t is the variance-covariance matrix, D and G are the $k \times k$ parameter matrices, C° is the constant matrix with lower triangular vector and ε_{t-1} is the lagged residual term. The restriction applies to constant matrix C° to be the lower triangular, while the parameter matrices have no restrictions. As the present study focuses on potential spillover effects between each selected markets, the central point is to obtain estimated parameters of D and G matrices. Specifically, we would like to see the linkages among variances of selected markets which is demonstrated by the off-diagonal coefficients of matrix G. Moreover, the coefficients estimated by matrix D provides the innovations on volatility. In other words, the off-diagonal elements of D and G matrices deliver details about "news effect" and "spillover effect", respectively (Kim et al., 2013). In this regard, the significance of D and G can be used to assess the degree of shocks and spillover between selected markets (Li and Majerowska, 2008). Thus, the BEKK model with the bivariate system is utilized and the equation is given as follow:

$$\begin{aligned} H_t = C^{\circ\prime} C^{\circ} &+ \begin{pmatrix} d_{11} & d_{21} \\ d_{12} & d_{22} \end{pmatrix} \begin{pmatrix} \varepsilon_{1,t-1}^2 & \varepsilon_{1,t-1}\varepsilon_{2,t-1} \\ \varepsilon_{2,t-1}\varepsilon_{1,t-1} & \varepsilon_{2,t-1}^2 \end{pmatrix} \begin{pmatrix} d_{11} & d_{12} \\ d_{21} & d_{22} \end{pmatrix} \\ &+ \begin{pmatrix} g_{11} & g_{21} \\ g_{12} & g_{22} \end{pmatrix} H_{t-1} \begin{pmatrix} g_{11} & g_{12} \\ g_{21} & g_{22} \end{pmatrix} \end{aligned} \tag{6.9}$$

Specifically, the expanded form of conditional variance elements can be written as:

$$h_{11,t} = d_{11}^2\varepsilon_{1,t-1}^2 + d_{21}^2\varepsilon_{2,t-1}^2 + 2d_{11}d_{21}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + g_{11}^2h_{11,t-1}^2 + g_{21}^2h_{22,t-1}^2 + 2g_{11}g_{22}h_{12,t-1}$$

$$h_{22,t} = d_{12}^2\varepsilon_{1,t-1}^2 + d_{22}^2\varepsilon_{2,t-1}^2 + 2d_{12}d_{22}\varepsilon_{1,t-1}\varepsilon_{2,t-1} + g_{12}^2h_{11,t-1}^2 + g_{22}^2h_{22,t-1}^2 + 2g_{11}g_{22}h_{21,t-1} \tag{6.10}$$

where $h_{ij,t}$ indicates $(i,j)^{th}$ element of H_t which is the conditional variance, $\varepsilon_{i,t}$ refers to the $(i)^{th}$ element of error term ε_t. Specifically, in the first equation d_{12} and g_{21}, and in the second equation d_{21} and g_{12} are in the focus in terms of their significance as they provide the information about spillover effects between markets. It also should be noted that, the signs of the estimated coefficients here is not important as the conditional variance is determined by their squared value. The BEKK model is estimated by maximising the quasi-likelihood method under the assumption of conditional normality.

6.3.2.3 The Diebold and Yilmaz Spillover Index

The Diebold and Yilmaz (2009) methodological framework is one of the most common and popular spillover models in the current literature. By adopting the forecast error variance decompositions from the VAR model, it allows assessing news and shocks across different markets by enabling bidirectional connections among parameters in a single spillover index. However, one of the main issues in the Diebold and Yilmaz (2009) model is that the structure is built on the Cholesky decomposition which is highly sensitive to the variable ordering. To overcome of this deficiency, Diebold and Yilmaz (2012) improved the model to make the forecast error variance decompositions invariant to the ordering of the variables by adopting the generalized impulse response approach of Koop et al. (1996) and Pesaran and Shin (1998). Therefore, in this study, the revised version of Diebold and Yilmaz (2012) framework is adopted to examine volatility spillovers across the markets.

Consider a covariance stationary p-th order, N-variable VAR:

$$R_t = \mu_0 + \sum_{p=1}^{p} \emptyset_p R_{t-p} + \varepsilon_t \tag{6.11}$$

where R_t is a vector of N-variables, implying the volatilities of returns from stock markets at time t, $\emptyset_p$ indicates NxN coefficient matrix and ε_t is an $Nx1$ independent and identically distributed vector of disturbances with covariance matrix Σ.

One of the fundamental parts of the method is the moving average representation of the VAR which is given by:

$$R_t = \mu_0 + \sum_{i=0}^{\infty} K_i \varepsilon_{t-i} \tag{6.12}$$

where the NxN coefficient matrix of K_i is defined by:

$$K_i = \emptyset_1 K_{i-1} + \emptyset_2 K_{i-2} + \cdots + \emptyset_p K_{i-p} \tag{6.13}$$

where K_0 represents the identity matrix of NxN with $K_i = 0\ for\ i < 0$.

The given framework of Diebold and Yilmaz (2012) with the generalized VAR specification of Koop et al. (1996) and Pesaran and Shin (1998) enables to produce variance decompositions without relying on the ordering of the variables. According to this method, the H-step ahead error variance for $H = 1,2,\ldots,\infty$ obtained from forecasting the ith parameter that are due to innovations from the jth parameter for $i,j = 1,\ldots N;\ and\ i \neq j$, is defined as:

$$\Psi_{ij}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} (d_i' K_h \delta d_j)^2}{\sum_{h=0}^{H-1} (d_i' K_h \delta K_h' d_i)} \tag{6.14}$$

where δ is the estimated variance matrix of the vector ε, σ_{jj} is the estimated standard deviation of the error term ε for the jth element, and d_i is the the selection vector with the ith element unity and zero otherwise. Under the generalized decomposition, the sums of forecast error variance contributions are not equal to 1: $\sum_{j=1}^{N} \Psi_{ij}(H) \neq 1$. Therefore, each entry of the of the variance decomposition matrix needs to be normalized by its row sum as follow:

$$\tilde{\Psi}_{ij}(H) = \frac{\Psi_{ij}(H)}{\sum_{j=1}^{N} \Psi_{ij}(H)} \tag{6.15}$$

with $\sum_{j=1}^{N}\widetilde{\Psi}_{ij}(H)=1$ and $\sum_{i,j=1}^{N}\widetilde{\Psi}_{ij}(H)=N$ by construction where it allows normalizing the contributions of spillover from shocks. We can then calculate the total volatility spillover index as follow:

$$TS(H)=\frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\Psi}_{ij}(H)}{\sum_{i,j=1}^{N}\widetilde{\Psi}_{ij}(H)}\times 100=\frac{\sum_{i,j=1,i\neq j}^{N}\widetilde{\Psi}_{ij}(H)}{N}\times 100 \qquad (6.16)$$

which allows to measure average contribution of spillover from volatility shocks to other variables. In other words, the total spillover index states the degree of shocks to volatility spillover between the markets. On the other hand, this method is very adjustable as the variance decompositions are invariant to the ordering of the parameters. Therefore, Diebold and Yilmaz (2012) further introduced the directional spillover concept by using the normalized factors of the generalized variance decomposition matrix. The size of the directional spillover received by market i from other markets j can be measured using the equation 6.17, as follow:

$$DS_{i\leftarrow j}(H)=\frac{\sum_{j=1,i\neq j}^{N}\widetilde{\Psi}_{ij}(H)}{\sum_{j=1}^{N}\widetilde{\Psi}_{ij}(H)}\times 100=\frac{\sum_{j=1,i\neq j}^{N}\widetilde{\Psi}_{ij}(H)}{N}\times 100 \qquad (6.17)$$

Conversely, the size of the directional spillover transmitted by market i to all other markets j is given in the equation 6.18, as follow:

$$DS_{i\rightarrow j}(H)=\frac{\sum_{j=1,i\neq j}^{N}\widetilde{\Psi}_{ji}(H)}{\sum_{j=1}^{N}\widetilde{\Psi}_{ij}(H)}\times 100=\frac{\sum_{j=1,i\neq j}^{N}\widetilde{\Psi}_{ji}(H)}{N}\times 100 \qquad (6.18)$$

The difference between the aggregate volatility shocks transmitted to market i, and those gross volatility shocks received by all other markets indicates the net volatility spillover which can be computed as follow:

$$NS_{i}(H)=DS_{i\rightarrow j}(H)-DS_{i\leftarrow j}(H) \qquad (6.19)$$

In other words, the above equation reflects whether a market (country) is a receiver or transmitter of volatility shocks. Furthermore, the net pairwise volatility spillover can be calculated as follow:

$$NPS_{ij}(H)=\left(\frac{\widetilde{\Psi}_{ji}(H)}{\sum_{i,z=1}^{N}\widetilde{\Psi}_{iz}(H)}-\frac{\widetilde{\Psi}_{ij}(H)}{\sum_{j,z=1}^{N}\widetilde{\Psi}_{jz}(H)}\right)\times 100=\frac{\widetilde{\Psi}_{ji}(H)-\widetilde{\Psi}_{ij}(H)}{N}\times 100 \qquad (6.20)$$

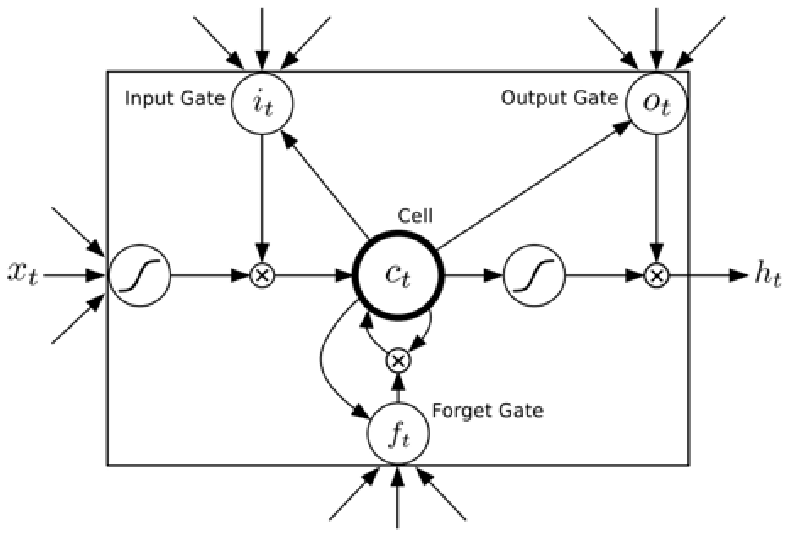
which is basically the difference between total volatility shocks sent by market i to market j and those received by market i from market j.

We implement the total spillover index in this study to examine interdependence and spillover activity across the selected markets for different crisis and non-crisis periods as well as presenting the degree of contributions from each market to all remaining markets.

6.3.2.4 Early Warning System Via Long Short-Term Memory Model

LSTMs are a specialized category of Recurrent Neural Network (RNN) based deep learning models. LSTM algorithm has a unique feature of learning the order dependence among sequenced elements which provides significant advantage in time series analysis. The LSTM model was first introduced by Hochreiter and Schmidhuber (1997) and recently improved by Graves (2013) to overcome of the vanishing and exploding gradient[7] disappearance issue in RNN algorithm which leads long term dependence problems. LSTM network consists of a memory cell which enables to store information over time and the flow of data is controlled by special gating units; namely, input gates, forget gates, and the output gates. These gates allow LSTM cells to learn the important parts of the sequence and forget the less important ones. Therefore, it can identify complexities and non-linearities in times series data which offers a key advantage especially during the turbulent times in stock markets. The structure of a memory cell in LSTM unit is shown in the Figure 6.5.

Figure 6.5: The structure of a memory cell in LSTM unit



[7] Exploding gradients are a problem when large error gradients accumulate and result in very large updates to neural network model weights during training.

In figure 6.5, x_t refers the input data at time t, c_t is the vector of the memory cell and h_t denotes the output vector of the LSTM cell. The estimation procedure of LSTM network is defined as follow:

Step 1: Estimation of the candidate memory cell

In this step, the value of the memory cell $\tilde{C}_t$ is predicted.

$$\tilde{C}_t = \tanh\left[W_c\ (h_{t-1}, x_t) + b_c\right] \tag{6.21}$$

where W_c is the weight matrix, h_{t-1} is the output vector of the LSTM cell at the previous time, and b_c is the bias vector.

Step 2: Estimation of the input gate

The vector of the input gate i_t is determined at this stage where it controls the new information in the current state of the network.

$$i_t = \sigma\left[W_i\ (h_{t-1}, x_t) + b_i\right] \tag{6.22}$$

where σ is the sigmoid activation function, W_i is the weight matrix, and b_i is the bias vector.

Step 3: Estimation of the forget gate

In step three, the value of the forget gate f_t is computed where it evaluates the relevancy of past information and remembers only the relevant information at the current slot while discarding (temporarily) irrelevant data.

$$f_t = \sigma\left[W_f\ (h_{t-1}, x_t) + b_f\right] \tag{6.23}$$

where W_f is the weight matrix, and b_f is the bias vector.

Step 4: Estimation of the current state of the memory cell

Given the values of the input gate, the forget gate and the candidate memory cell in the previous steps, we can now compute the current value of the memory cell c_t:

$$c_t = f_t * c_{t-1} + i_t * \tilde{C}_t \tag{6.24}$$

where c_{t-1} is the previous state of memory cell and "$*$ " refers the dot product which indicates the operation of the artificial neural network.

Step 5: Estimation of the output gate

In this stage, the value of the output gate o_t is calculated where it produces the output from the network at the current slot.

$$o_t = \sigma \left[W_o \left(h_{t-1}, x_t\right) + b_o\right] \qquad (6.25)$$

where W_o is the weight matrix, and b_o is the bias vector.

Step 6: Estimation of the output of the LSTM unit

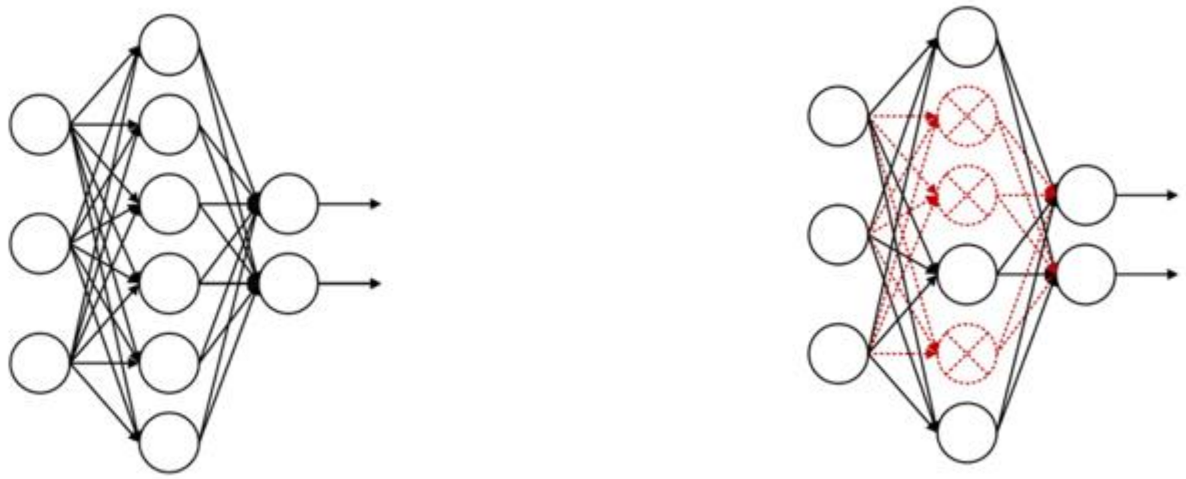
In the final stage, the predicted output of the LSTM unit h_t is produced.

$$h_t = \ o_t * \tanh\left(c_t\right) \qquad (6.26)$$

The internal process of a neuron is performed using the three control gates and memory cell which allowed the LSTM model to efficiently store, read and update long period of data.

One of the main issues during the training is over-fitting. To improve the expressive capability of the model, the dropout method proposed by Srivastava et al. (2014) is applied. Dropout refers to a technique that discards neurons temporarily from the neural network during the training of LSTM which helps preventing complex co-adaptations on training data. The dropout operation is performed by dropping the neurons in each stage for inputs, outputs and given layers with the dropout rate of P, and during the dropout training the coefficient $(1 - p)$ *N is utilized to scale down the neuron activations. This process improves model averaging and helps to enhance generalization ability of the network. The neural network structure of LSTM is shown without (left figure) and with (right figure) dropout in the figure 6.6.

Figure 6.6: The flow chart of LSTM model without and with dropout



Model Construction

In this stage, the optimal LSTM model is constructed for the present study. First, the Dynamic Conditional Correlation (DCC) model of Engle (2002) is conducted for each selected periods on bivariate basis to extract the correlations. Then obtained correlations are transferred to LSTM model for training and test. To build the model, one input layer, two hidden layers consist of LSTM blocks with sufficient neurons and a single output layer is chosen. The sigmoid activation function is adopted for the calculation of the input and output doors, while tangent activation function is used for vector creating in cell state. For the hyperparameter process 1000 epochs are chosen for training the data, but early stopping has been applied if there is no improvement after 100 epochs, to prevent overfitting problem (Prechelt, 2012). The reproduction phase of the model has been performed based on batch weighting which accumulates changes in the weight matrix over an entire presentation of the training data set. The weights are updated by the ADM optimization algorithm. Then in the final stage, based on the results received during the trials, the early warning system is created using the sigma method of Sevim et al. (2014). The signals are triggered in various sigma levels, and in case of false alarms, the given signals are verified by using the evaluation metrics of Root Mean Square Error (RMSE) and Mean Squared Error (MSE) by applying the following equations:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2} \tag{6.27}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(\sigma_t^2 - \hat{\sigma}_t^2)^2 \tag{6.28}$$

where n denotes the rank of forecasted data, σ_t^2 is the actual series which is obtained by the DCC model and $\hat{\sigma}_t^2$ is the predicted correlations at time t acquired by using the LSTM model.

6.4 Empirical Results

This section presents the empirical findings of the overall chapter and examines interdependence of selected financial markets by applying three different methods. First, the paper investigates transmission mechanisms in tranquil times and compares two pre-crisis periods which are the Pre-GFC and Pre-Covid Crisis periods. Next, we compare the three major crises periods, namely, the Asian Crisis in 1997-98, the Global Financial Crisis (GFC) in 2007-08, and the Covid Crisis in 2020 as the main focus of this study. Furthermore, we extend the financial crises analysis by developing an Early Warning System (EWS) based on a deep learning LSTM model and predict the dynamic correlation patterns between markets which is one of the main contributions of the present chapter. Finally, we assess the identified correlations and determine thresholds for "excessive spillover" by using the sigma model and test the given contagion risk by following the MSE and RMSE error criterion.

6.4.1 Subsample analysis: Comparison of pre-crisis periods

Table 6.4 presents the estimated results of Dynamic Conditional Correlation (DCC) method for each pre-crisis periods. In the DCC method, the estimated parameter *alpha1* indicates the ARCH term, which shows the impact of news from previous periods to the current conditional correlation. On the other hand, the coefficient *beta1* refers to the GARCH term, which represents the long-run magnitude of persistence in the conditional correlation.

According to the results, the obtained conditional correlations are positive in almost all markets for each period, except for the stock markets of the US and Japan during the pre-GFC, and Malaysia during the Pre-CC period. The estimates of *alpha1* and *beta1* report significance in 1% level in most cases which reveal the time-varying variance and covariance process, thus confirming the non-constant conditional correlations. The joint DCC parameters of *a1* and *b1* are summed to 0.8862 for pre-GFC, and 0.9228 for Pre-CC period which are close to one in both cases suggesting the correlation structure is considerably persistent. The persistence of correlations is higher in Pre-CC period compared to pre-GFC, where similar results are obtained in individual cases as well. The sum of the *alpha1* and *beta1* parameters are lower than unity in all selected markets, which indicates mean reverting correlation process. In other words, if the conditional correlations between two equity markets increase following a negative event in one of the countries, it will again return to the long-run unconditional correlation path. Overall, this is an expected outcome as two tranquil periods are compared which also confirms that the DCC model is accurately defined and able to capture correlation structure among the markets for selected periods.

Table 6.4: Comparison of DCC estimates

	Pre-GFC Period					**Pre-CC Period**			
	Estimate	Std. Error	t value	Prob.		Estimate	Std. Error	t value	Prob.
[SnP_500].mu	-0.0085	0.0342	-0.2498	0.8027	[SnP_500].mu	0.0476	0.0200	2.3803	0.0173
[SnP_500].omega	0.0179	0.0108	1.6498	0.0990	[SnP_500].omega	0.0155	0.0088	1.7698	0.0768
[SnP_500].alpha1	0.1066	0.0298	3.5775	0.0003	[SnP_500].alpha1	0.4161	0.1440	2.8897	0.0039
[SnP_500].beta1	0.8695	0.0364	23.8723	0.0000	[SnP_500].beta1	0.5829	0.1025	5.6880	0.0000
[NIKKEI].mu	-0.0572	0.0408	-1.3996	0.1616	[NIKKEI].mu	0.0343	0.0249	1.3768	0.1686
[NIKKEI].omega	0.0351	0.0180	1.9530	0.0508	[NIKKEI].omega	0.0103	0.0065	1.5887	0.1121
[NIKKEI].alpha1	0.1410	0.0455	3.1016	0.0019	[NIKKEI].alpha1	0.1340	0.0463	2.8902	0.0039
[NIKKEI].beta1	0.8242	0.0454	18.1581	0.0000	[NIKKEI].beta1	0.8367	0.0535	15.6492	0.0000
[HSI].mu	0.0232	0.0441	0.5263	0.5987	[HSI].mu	0.0258	0.0287	0.8993	0.3685
[HSI].omega	0.0476	0.0348	1.3648	0.1723	[HSI].omega	0.0212	0.0353	0.6026	0.5468
[HSI].alpha1	0.1616	0.0640	2.5263	0.0115	[HSI].alpha1	0.0370	0.0617	0.5987	0.0494
[HSI].beta1	0.8079	0.0779	10.3715	0.0000	[HSI].beta1	0.8686	0.1986	4.3744	0.0000
[JCI].mu	0.0486	0.0397	1.2229	0.2214	[JCI].mu	0.0140	0.0186	0.7520	0.4520
[JCI].omega	0.0640	0.0500	1.2793	0.2008	[JCI].omega	0.0146	0.0066	2.2293	0.0258
[JCI].alpha1	0.1900	0.0744	2.5530	0.0107	[JCI].alpha1	0.1893	0.0832	2.2742	0.0230
[JCI].beta1	0.7492	0.1234	6.0704	0.0000	[JCI].beta1	0.7196	0.0832	8.6510	0.0000
[KLCI].mu	0.0045	0.0235	0.1913	0.8483	[KLCI].mu	-0.0154	0.0136	-1.1349	0.2564
[KLCI].omega	0.0321	0.0149	2.1593	0.0308	[KLCI].omega	0.0007	0.0013	0.5419	0.5879
[KLCI].alpha1	0.1113	0.0368	3.0270	0.0025	[KLCI].alpha1	0.0607	0.0273	2.2213	0.0263
[KLCI].beta1	0.7447	0.0825	9.0239	0.0000	[KLCI].beta1	0.9383	0.0185	50.8292	0.0000
[KOSPI].mu	0.0145	0.0373	0.3899	0.6966	[KOSPI].mu	0.0279	0.0241	1.1599	0.2461
[KOSPI].omega	0.0144	0.0092	1.5675	0.1170	[KOSPI].omega	0.0423	0.0232	1.8279	0.0676
[KOSPI].alpha1	0.0808	0.0264	3.0562	0.0022	[KOSPI].alpha1	0.1808	0.1327	1.3619	0.0732
[KOSPI].beta1	0.9017	0.0245	36.8293	0.0000	[KOSPI].beta1	0.5858	0.2152	2.7223	0.0065
[PSE].mu	0.0033	0.0341	0.0978	0.9221	[PSE].mu	0.0022	0.0253	0.0866	0.9310
[PSE].omega	0.0341	0.0240	1.4189	0.1559	[PSE].omega	0.0047	0.0043	1.0930	0.2744
[PSE].alpha1	0.1223	0.0634	1.9298	0.0536	[PSE].alpha1	0.0822	0.0412	1.9934	0.0462

[PSE].beta1	0.8239	0.0822	10.0169	0.0000	[PSE].beta1	0.9077	0.0285	31.8358	0.0000
[SSE].mu	0.0622	0.0538	1.1548	0.2482	[SSE].mu	0.0238	0.0278	0.8543	0.3929
[SSE].omega	0.0175	0.0204	0.8554	0.3923	[SSE].omega	0.0082	0.0063	1.3122	0.1894
[SSE].alpha1	0.0597	0.0308	1.9361	0.0529	[SSE].alpha1	0.1120	0.0619	1.8103	0.0703
[SSE].beta1	0.9257	0.0400	23.1514	0.0000	[SSE].beta1	0.8686	0.0508	17.0945	0.0000
[STI].mu	-0.0128	0.0339	-0.3777	0.7056	[STI].mu	0.0217	0.0175	1.2416	0.2144
[STI].omega	0.0291	0.0211	1.3779	0.1682	[STI].omega	0.0054	0.0056	0.9617	0.3362
[STI].alpha1	0.1394	0.0576	2.4201	0.0155	[STI].alpha1	0.1864	0.1030	1.8090	0.0704
[STI].beta1	0.8211	0.0759	10.8130	0.0000	[STI].beta1	0.8018	0.1064	7.5352	0.0000
[TAIEX].mu	0.0061	0.0377	0.1617	0.8715	[TAIEX].mu	0.0329	0.0207	1.5890	0.1121
[TAIEX].omega	0.0190	0.0113	1.6793	0.0931	[TAIEX].omega	0.0075	0.0133	0.5607	0.5750
[TAIEX].alpha1	0.0786	0.0247	3.1747	0.0015	[TAIEX].alpha1	0.0747	0.0773	0.9666	0.0338
[TAIEX].beta1	0.8961	0.0258	34.7737	0.0000	[TAIEX].beta1	0.8641	0.1786	4.8388	0.0000
[SET].mu	0.0024	0.0137	0.1146	0.7957	[SET].mu	0.0719	0.0310	2.8834	0.0721
[SET].omega	0.0270	0.0250	1.7003	0.0756	[SET].omega	0.0032	0.0492	0.4950	0.4550
[SET].alpha1	0.0456	0.0135	3.2874	0.0022	[SET].alpha1	0.0351	0.0566	0.5771	0.0407
[SET].beta1	0.9301	0.0233	19.4565	0.0000	[SET].beta1	0.9491	0.1133	8.8198	0.0000
[Joint]dcca1	0.0172	0.0043	1.6824	0.0025	[Joint]dcca1	0.0108	0.0015	5.0103	0.0022
[Joint]dccb1	0.8690	0.0423	20.5234	0.0000	[Joint]dccb1	0.9120	0.0816	11.1810	0.0000

To further assess the time variation of the volatility spillover across selected markets, the bivariate GARCH-BEKK method is employed. The below tables from 6.5 to 6.8 report the estimation results of GARCH-BEKK models for each tranquil period. The estimated coefficient α_{ij} represents the ARCH term, indicating "news surprises" among equity markets. Furthermore, the estimated GARCH term parameter, β_{ij}, depicts the persistence of innovations between markets (Kim et al., 2013). These two coefficients indicate the volatility spillovers among the equity markets as well as highlighting the persistence of shocks between each other. Both the "news effect" and "volatility spillover" effect helps us to analyse possible transmission mechanisms either within the region of Asia or with the US. In all given tables below, the p-values are indicated in parentheses under each one of the estimated parameters, while the significance level is denoted with asterisks. Finally, it should be noted that, the correct readings of tables are from rows to columns. For example, the news effects of SP500 to the remaining equity markets can be followed in the first row. In other words, the markets in the rows indicate the "source" of spillover, while the recipients of the shocks are reported in the columns.

According to the empirical results, similar characteristics of financial stress have been evidenced during both pre-crisis periods. Specifically, the role of USA and Hong Kong is strong in terms of the volatility transmission channels, where they both contribute to the volatility of remaining stock markets with a great extent. However, the emerging markets of Asia are somehow more immune to these news shocks and volatility spillover effects such as Thailand and China. Statistical significance of coefficients is limited in both periods, mostly in 10% level. A two-way relationship between selected equity markets is also observed in both periods where China and Korea are leading in terms of interdependencies with the rest of the countries. Past news about shocks in the equity markets of Japan and Hong Kong positively affect the current conditional volatility of the remaining markets, while previous news for Singapore and Taiwan has a negative impact on the current volatility on the rest of the markets. Besides, the current conditional volatility of one market depends not only on its own past volatility but also past volatility of the other market, confirming interdependencies among each other.

Table 6.5: GARCH-BEKK results for α_{ij}: Pre-GFC Period

α_{ij}	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET
SP500		-0.138*** (0.001	0.284 (0.052)	0.051** (0.007)	-0.179*** (0.002)	0.048 (0.275)	0.125 (0.501)	-0.082* (0.024)	0.048 (0.275)	-0.029 (0.200)	0.023 (0.004)
NIKKEI	0.095 (0.415)		-0.048 (0.615)	-0.047 (0.704)	-0.133*** (0.001)	0.030 (0.545)	0.358** (0.005)	-0.004 (0.823)	0.030 (0.545)	-0.040** (0.008)	-0.370 (0.496)
HSI	0.142 (0.363)	0.047 (0.453)		0.229*** (0.001)	0.186** (0.006)	-0.019 (0.728)	-0.207 (0.196)	-0.136 (0.043)	-0.019 (0.728)	0.020 (0.633)	0.021 (0.798)
JCI	0.024 (0.313)	-0.092 (0.652)	-0.465** (0.001)		-0.179*** (0.002)	-0.164* (0.286)	0.284 (0.052)	-0.500 (0.120)	-0.164* (0.286)	0.168 (0.128)	0.044** (0.003)
KLCI	0.047 (0.453)	0.153 (0.121)	0.001 (0.982)	0.022 (0.913)		0.086 (0.063)	-0.048 (0.615)	-0.024 (0.662)	-0.040 (0.090)	-0.018 (0.527)	-0.106* (0.027)
KOSPI	-0.092 (0.652)	-0.024 (0.662)	0.008 (0.451)	0.036 (0.472)	0.048 (0.275)		0.171 (0.161)	-0.024 (0.662)	0.020 (0.865)	0.003 (0.647)	-0.090 (0.526)
PSE	0.153 (0.121)	-0.220 (0.089)	0.027** (0.003)	0.266*** (0.001)	0.030 (0.545)	0.422* (0.003)		-0.024 (0.662)	0.024 (0.628)	-0.107* (0.302)	-0.113** (0.004)
SSE	-0.024 (0.662)	0.293 (0.220)	0.039* (0.015)	0.260*** (0.002)	-0.019 (0.728)	0.021* (0.014)	0.368** (0.002)		0.048 (0.275)	-0.019 (0.550)	0.125 (0.293)
STI	-0.220 (0.089)	-0.194 (0.215)	-0.157 (0.183)	0.207*** (0.009)	-0.164* (0.286)	0.391** (0.002)	-0.021 (0.517)	-0.035 (0.174)		-0.020 (0.889)	0.023 (0.004)
TAIEX	0.293 (0.220)	0.021** (0.001)	0.015 (0.463)	0.344*** (0.001)	-0.040 (0.090)	-0.405** (0.001)	-0.344 (0.075)	-0.091 (0.090)	0.078 (0.470)		-0.370 (0.496)
SET	-0.194 (0.215)	0.047 (0.453)	-0.031 (0.430)	0.022 (0.913)	0.020 (0.865)	0.402*** (0.001)	0.012 (0.765)	-0.021 (0.517)	0.078 (0.470)	0.008 (0.451)	

Notes: This table presents the "news surprises" with estimated parameters from bivariate GARCH-BEKK method. P-values are denoted within parentheses. *, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.6: GARCH-BEKK results for β_{ij}: Pre-GFC Period

β_{ij}	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET
SP500		-0.029 (0.509)	0.037*** (0.000)	-0.020 (0.970)	-0.022 (0.635)	0.024 (0.962)	-0.041** (0.980)	0.008 (0.925)	-0.065** (0.001)	-0.025 (0.501)	0.018** (0.004)
NIKKEI	0.255 (0.053)		0.142 (0.363)	0.024 (0.302)	-0.010 (0.477)	0.072 (0.466)	-0.047 (0.704)	0.171 (0.166)	0.001 (0.982)	0.008** (0.005)	0.055 (0.077)
HSI	0.004** (0.005)	0.084 (0.052)		-0.021 (0.644)	-0.083 (0.499)	0.067 (0.554)	0.229*** (0.001)	0.255 (0.053)	0.008 (0.451)	-0.027 (0.196)	0.010 (0.482)
JCI	-0.041 (0.294)	-0.048 (0.615)	0.027 (0.673)		-0.082 (0.196)	0.061 (0.380)	-0.179*** (0.002)	0.004** (0.005)	-0.027** (0.003)	0.089 (0.522)	0.015 (0.710)

KLCI	0.011 (0.883)	0.171 (0.161)	-0.082 (0.332)	0.017 (0.885)		-0.086 (0.063)	-0.133*** (0.001)	-0.041 (0.294)	0.029* (0.015)	-0.041 (0.615)	-0.017 (0.861)
KOSPI	0.255 (0.053)	0.034 (0.052)	-0.025 (0.421)	0.046 (0.978)	-0.026*** (0.005)		0.186** (0.006)	0.011 (0.883)	-0.057 (0.183)	-0.071 (0.161)	-0.019 (0.120)
PSE	-0.041 (0.615)	-0.078 (0.216)	-0.064 (0.692)	-0.130* (0.092)	-0.036*** (0.001)	-0.062 (0.419)		0.024 (0.313)	0.015 (0.463)	0.096 (0.282)	-0.015 (0.463)
SSE	-0.071 (0.161)	-0.021 (0.191)	-0.060 (0.978)	-0.028 (0.105)	0.031 (0.488)	-0.044 (0.186)	0.024 (0.305)		-0.310 (0.430)	-0.024 (0.322)	-0.143 (0.871)
STI	0.096 (0.282)	-0.018 (0.229)	0.160 (0.320)	0.173* (0.023)	-0.013 (0.975)	0.138** (0.008)	0.015 (0.341)	0.079 (0.376)		0.021 (0.282)	0.089** (0.001)
TAIEX	-0.024 (0.322)	-0.014 (0.330)	-0.054 (0.605)	0.045 (0.462)	-0.469*** (0.001)	0.062* (0.017)	0.024 (0.355)	-0.084 (0.322)	0.044* (0.960)		-0.001 (0.950)
SET	-0.041 (0.615)	-0.031 (0.924)	0.021** (0.001)	-0.041 (0.237)	0.095** (0.004)	0.002 (0.628)	0.002*** (0.003)	-0.018 (0.356)	-0.011 (0.125)	-0.027 (0.484)	

Notes: This table presents the "volatility spillover" from bivariate GARCH-BEKK method. P-values are denoted within parentheses.

*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.7: GARCH-BEKK results for α_{ij}: Pre-CC Period

α_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		-0.138*** (0.001	0.284 (0.052)	0.051** (0.007)	-0.179*** (0.002)	0.048 (0.275)	0.125 (0.501)	-0.082* (0.024)	0.048 (0.275)	-0.029 (0.200)	0.023 (0.004)
NIKKEI	0.095 (0.415)		-0.048 (0.615)	-0.047 (0.704)	-0.133*** (0.001)	0.030 (0.545)	0.358** (0.005)	-0.004 (0.823)	0.030 (0.545)	-0.040** (0.008)	-0.370 (0.496)
HSI	0.142 (0.363)	0.047 (0.453)		0.229*** (0.001)	0.186** (0.006)	-0.019 (0.728)	-0.207 (0.196)	-0.136 (0.043)	-0.019 (0.728)	0.020 (0.633)	0.021 (0.798)
JCI	0.024 (0.313)	-0.092 (0.652)	-0.465** (0.001)		-0.179*** (0.002)	-0.164* (0.286)	0.284 (0.052)	-0.500 (0.120)	-0.164* (0.286)	0.168 (0.128)	0.044** (0.003)
KLCI	0.047 (0.453)	0.153 (0.121)	0.001 (0.982)	0.022 (0.913)		0.086 (0.063)	-0.048 (0.615)	-0.024 (0.662)	-0.040 (0.090)	-0.018 (0.527)	-0.106* (0.027)
KOSPI	-0.092 (0.652)	-0.024 (0.662)	0.008 (0.451)	0.036 (0.472)	0.048 (0.275)		0.171 (0.161)	-0.024 (0.662)	0.020 (0.865)	0.003 (0.647)	-0.090 (0.526)
PSE	0.153 (0.121)	-0.220 (0.089)	0.027** (0.003)	0.266*** (0.001)	0.030 (0.545)	0.422* (0.003)		-0.024 (0.662)	0.024 (0.628)	-0.107* (0.302)	-0.113** (0.004)
SSE	-0.024 (0.662)	0.293 (0.220)	0.039* (0.015)	0.260*** (0.002)	-0.019 (0.728)	0.021* (0.014)	0.368** (0.002)		0.048 (0.275)	-0.019 (0.550)	0.125 (0.293)
STI	-0.220 (0.089)	-0.194 (0.215)	-0.157 (0.183)	0.207*** (0.009)	-0.164* (0.286)	0.391** (0.002)	-0.021 (0.517)	-0.035 (0.174)		-0.020 (0.889)	0.023 (0.004)
TAIEX	0.293 (0.220)	0.021** (0.001)	0.015 (0.463)	0.344*** (0.001)	-0.040 (0.090)	-0.405** (0.001)	-0.344 (0.075)	-0.091 (0.090)	0.078 (0.470)		-0.370 (0.496)
SET	-0.194 (0.215)	0.047 (0.453)	-0.031 (0.430)	0.022 (0.913)	0.020 (0.865)	0.402*** (0.001)	0.012 (0.765)	-0.021 (0.517)	0.078 (0.470)	0.008 (0.451)	

Notes: This table presents the "news surprises" with estimated parameters from bivariate GARCH-BEKK method. P-values are denoted within parentheses.

*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.8: GARCH-BEKK results for β_{ij}: Pre-CC Period

β_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		-0.029 (0.509)	0.037*** (0.000)	-0.020 (0.970)	-0.022 (0.635)	0.024 (0.962)	-0.041** (0.980)	0.008 (0.925)	-0.065** (0.001)	-0.025 (0.501)	0.018** (0.004)
NIKKEI	0.006 (0.911)		0.142 (0.363)	0.024 (0.302)	-0.010 (0.477)	0.072 (0.466)	-0.047 (0.704)	0.171 (0.166)	0.001 (0.982)	0.008** (0.005)	0.055 (0.077)
HSI	-0.001 (0.847)	0.023 (0.259)		-0.021 (0.644)	-0.083 (0.499)	0.067 (0.554)	0.229*** (0.001)	0.255 (0.053)	0.008 (0.451)	-0.027 (0.196)	0.010 (0.482)
JCI	0.067** (0.002)	-0.083** (0.001)	0.027 (0.673)		-0.082 (0.196)	0.061 (0.380)	-0.179*** (0.002)	0.004** (0.005)	-0.027** (0.003)	0.089 (0.522)	0.015 (0.710)
KLCI	0.033 (0.176)	0.016 (0.403)	-0.082 (0.332)	0.017 (0.885)		-0.086 (0.063)	-0.133*** (0.001)	-0.041 (0.294)	0.029* (0.015)	-0.041 (0.615)	-0.017 (0.861)

KOSPI	0.007 (0.820)	0.012 (0.994)	-0.025 (0.421)	0.046 (0.978)	-0.026*** (0.005)		0.186** (0.006)	0.011 (0.883)	-0.057 (0.183)	-0.071 (0.161)	-0.019 (0.120)
PSE	-0.013 (0.992)	-0.078 (0.216)	-0.064 (0.692)	-0.130* (0.092)	-0.036*** (0.001)	-0.062 (0.419)		0.024 (0.313)	0.015 (0.463)	0.096 (0.282)	-0.015 (0.463)
SSE	0.099 (0.688)	-0.044 (0.191)	-0.060 (0.978)	-0.028 (0.105)	0.031 (0.488)	-0.044 (0.186)	0.024 (0.305)		-0.310 (0.430)	-0.024 (0.322)	-0.143 (0.871)
STI	-0.028 (0.670)	-0.026 (0.229)	0.160 (0.320)	0.173* (0.023)	-0.013 (0.975)	0.138** (0.008)	0.015 (0.341)	0.079 (0.376)		0.021 (0.282)	0.089** (0.001)
TAIEX	-0.062 (0.987)	0.024 (0.330)	-0.054 (0.605)	0.045 (0.462)	-0.469*** (0.001)	0.062* (0.017)	0.024 (0.355)	-0.084 (0.322)	0.044* (0.960)		-0.001 (0.950)
SET	0.016 (0.772)	0.031 (0.824)	0.021** (0.001)	-0.041 (0.237)	0.095** (0.004)	0.002 (0.628)	0.002*** (0.003)	-0.018 (0.356)	-0.011 (0.125)	-0.027 (0.484)	

Notes: This table presents the “volatility spillover” from bivariate GARCH-BEKK method. P-values are denoted within parentheses.
*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

The in-depth analysis of volatility transmission channels across stock indices is conducted by applying the Diebold and Yilmaz (2012) framework in the Table 6.9 and Table 6.10. According to the empirical results in the given tables, the estimated Total Spillover Index is 19.033% during pre-GFC period, while the magnitude of the total volatility spillovers during Pre-CC period is slightly higher with 22.025% which supports the earlier findings of DCC model. In terms of the *contribution to others (spillovers),* the Hong Kong Stock Market is the most influential during the pre-GFC period with 2.736% which corroborates the earlier findings of Chow (2017). It is an expected outcome since Hong Kong is considered as international financial hub of Asia with significantly larger equity market capitalization to GDP ratio compared to other Asian countries. On the other hand, USA records the highest outward volatility spillover with 9.894% during the Pre-CC period which is in line with the study of Rapach et al. (2013). Taiwan is surprisingly the major contributor of spillover among Asian markets during the Pre-CC period which is consistent with the findings of Yarovaya et al. (2016). The outward spillover contribution from Thailand has the lowest degree for both selected periods which indicates it is the least influential among all.

The *contribution from others* column presents the sensitivity degree of external shocks for each market. Based on the outcome of Table 6.9 and Table 6.10, Hong Kong and Singapore have the highest sensitivity to inward volatility spillover during the pre-GFC period with 4.410% and 3.796% respectively. Similarly, the impact of volatility spillovers from all foreign markets to a domestic market have the largest reported values for China and Singapore during the Pre-CC period with 3.822% and 3.928% respectively. It should be noted that China was one of the least sensitive countries to external shocks during the pre-GFC period, while it has become one of the most sensitive during the Pre-CC. One of the reasons behind this dramatic change is that the Chinese market was shielded by restrictions for international market participants in early stages, while it became more accessible for foreign investors in recent years as revealed by Fernández et al.'s (2016) de-jure measure of equity market liberalizations. On the other hand, Thailand is one of the least vulnerable countries to external news in both periods with Korea during the Pre-GFC period and Malaysia during the Pre-CC period.

Turning to cross-country spillovers, the obtained record in tables below indicate that the USA is one of the leading volatility transmitters in both periods followed by Hong Kong in first pre-crisis period and Taiwan in second pre-crisis period. Furthermore, the volatility spillover amongst mature markets is positive and larger which indicates stronger cross-market interdependence and financial linkages amid these markets. Nevertheless, the cross-market volatility spillovers between emerging markets of Asia are trivial in most cases or even virtually non-existent. These findings are in line with the work of IMF (2016) that developed financial markets are more prone to high level of integrations with each other compared to emerging markets.

Overall, the Asian markets tend to receive volatility transfer from the intra-regional and inter-regional level prior to the crises. The reported values of pairwise volatility spillovers also indicate growing interconnectedness between markets which increase the exposure of portfolio risk for market participants. However, the degree of volatility spillovers among advanced and emerging equity markets is less compared to the solely spillovers between advanced market or emerging markets, offering a window of opportunity for international market participants in terms of portfolio diversification and risk management.

Table 6.9: Comparison of DY framework across markets: Pre-GFC period

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET	C. from others
SP500	7.881	0.978	0.024	0.007	0.061	0.000	0.037	0.036	0.040	0.021	0.006	1.210
NIKKEI	0.688	7.809	0.240	0.057	0.189	0.002	0.021	0.009	0.035	0.037	0.004	1.282
HSI	2.909	0.532	4.681	0.089	0.183	0.083	0.116	0.119	0.129	0.244	0.007	4.410
JCI	0.385	0.106	0.131	7.973	0.139	0.056	0.173	0.025	0.059	0.026	0.018	1.118
KLCI	1.538	0.066	0.066	0.196	6.930	0.002	0.034	0.039	0.129	0.081	0.010	2.161
KOSPI	0.157	0.039	0.100	0.045	0.009	8.624	0.063	0.037	0.006	0.006	0.006	0.467
PSE	0.324	0.034	0.208	0.698	0.048	0.018	7.521	0.019	0.182	0.037	0.001	1.570
SSE	0.284	0.226	0.097	0.047	0.026	0.001	0.001	8.285	0.014	0.045	0.064	0.806
STI	1.040	0.067	0.539	1.058	0.222	0.134	0.564	0.054	5.294	0.105	0.012	3.796
TAIEX	0.796	0.073	0.315	0.018	0.227	0.037	0.046	0.040	0.193	7.326	0.021	1.765
SET	0.078	0.008	0.016	0.037	0.005	0.080	0.102	0.083	0.032	0.007	8.643	0.448
C. to others (spillover)	8.198	2.129	1.736	2.254	1.111	0.413	1.156	0.462	0.818	0.608	0.148	19.033%

C. to others including own	16.078	9.939	6.417	10.227	8.040	9.037	8.677	8.747	6.113	7.934	8.791	

Notes: C.from others – Directional spillovers from all market *j* to market *i* ; C. to others (spillover) – Directional spillovers from market *i* to all markets *j* C. to others including own – Directional spillovers from market *i* to all markets *j* including its own contribution. Remaining columns indicate net pairwise (*i*,*j*)-th spillovers between markets. Total Volatility spillover index is given in the lower right corner.

Table 6.10: Comparison of DY framework across markets: Pre-CC period

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET	C. from others
SP500	8.082	0.015	0.031	0.043	0.000	0.001	0.022	0.058	0.019	0.818	0.001	1.009
NIKKEI	1.241	7.601	0.021	0.059	0.002	0.007	0.001	0.004	0.012	0.141	0.002	1.490
HSI	1.055	0.641	7.059	0.101	0.011	0.030	0.013	0.001	0.077	0.102	0.001	2.032
JCI	2.171	0.627	0.131	5.680	0.002	0.020	0.001	0.021	0.080	0.353	0.005	3.411
KLCI	0.009	0.002	0.002	0.001	9.065	0.003	0.000	0.001	0.000	0.001	0.008	0.026
KOSPI	0.458	1.118	0.289	0.116	0.002	6.989	0.005	0.004	0.004	0.104	0.002	2.102
PSE	0.780	0.021	0.005	0.096	0.011	0.093	8.036	0.001	0.005	0.043	0.000	1.055
SSE	1.584	0.545	0.703	0.218	0.002	0.042	0.021	5.269	0.051	0.653	0.002	3.822
STI	2.102	0.218	0.116	0.805	0.003	0.016	0.030	0.057	5.163	0.582	0.000	3.928
TAIEX	0.491	0.357	0.557	0.287	0.001	0.130	0.007	1.156	0.137	5.966	0.002	3.125
SET	0.002	0.011	0.001	0.002	0.003	0.001	0.000	0.002	0.002	0.001	9.066	0.025
C. to others (spillover)	9.894	3.554	1.856	1.727	0.038	0.342	0.101	1.306	0.387	2.797	0.023	22.025%
C. to others including own	17.976	11.156	8.916	7.407	9.103	7.331	8.136	6.575	5.550	8.763	9.089	

Notes: C.from others – Directional spillovers from all market *j* to market *i* ; C. to others (spillover) – Directional spillovers from market *i* to all markets *j* C. to others including own – Directional spillovers from market *i* to all markets *j* including its own contribution. Remaining columns indicate net pairwise (*i*,*j*)-th spillovers between markets. Total Volatility spillover index is given in the lower right corner.

6.4.2 Subsample analysis: Comparison of Crisis periods

One of the major contributions of the present chapter to the empirical finance literature is the analysis of volatility transmission channels across equity markets during the different crisis periods. In examining this phenomenon, the Asian Crisis, the GFC, and the Covid Crisis periods are separately covered in this section and in-depth investigation of information transfer channels is conducted and compared in intra- and inter-regional levels as well as in cross-market context. As the interpretation of the rows and columns within the tables are provided and explained in the previous section, the same logical perspective applies when interpreting given tables in the present section.

Results in Table 6.11 reports the correlation dynamics based on the DCC model. Based on the obtained empirical values, the conditional correlation relationship is positive in most of the selected markets for each period. However, there are some exceptions such as Malaysia during the Asian crisis period, USA, Japan, Singapore, and Thailand during the GFC period, and the

Philippines, Singapore, and Thailand during the Covid Crisis period. Moreover, the coefficients of *alpha1* and *beta1* reports significance in 10% level in most cases which reveal the time-varying variance and covariance process, thereby confirming the non-constant conditional correlations. The joint DCC parameters of *a1* and *b1* are summed to 0.9140 for the Asian crisis period, 0.8762 for the GFC period, and 0.5506 during the Covid Crisis period suggesting the correlation structure is considerably persistent. On the other hand, the ARCH parameter is the strongest during the Covid Crisis period (0.0284), while it is the weakest during the Asian crisis period (0.0021) which indicates shocks are remarkably stronger in the recent periods compared to earlier crises. However, there is a different story for individual cases as the magnitude of crisis impacts and exposure to shocks vary for each market. Furthermore, the GARCH parameter is significantly lower during the Covid Crisis period compared to earlier crises which exhibits the degree of reduced volatility. The sum of the *alpha1* and *beta1* parameters are lower than unity in all selected markets, which implies the existence of dynamic conditional correlations. In other words, if the conditional correlations between two equity markets increase following a negative event in one of the countries, it will again return to the long-run unconditional correlation path. Overall, the empirical DCC findings of present study are in line with Gupta and Guidi (2012) where they analyse the time varying co-movements of Asian markets, and we can confirm the existence of correlations over time and the presence of contagion effect during different crisis periods among selected markets.

Table 6.11: Comparison of DCC estimates

Asian Crisis Period					**GFC Period**					**Covid Crisis Period**				
	Estimate	Std. Error	t value	Prob.		Estimate	Std. Error	t value	Prob.		Estimate	Std. Error	t value	Prob.
[SnP_500].mu	0.0476	0.0200	2.3803	0.0173	[SnP_500].mu	-0.0085	0.0342	-0.2498	0.8027	[SnP_500].mu	0.0497	0.0242	2.0556	0.0398
[SnP_500].omega	0.0155	0.0088	1.7698	0.0768	[SnP_500].omega	0.0179	0.0108	1.6498	0.0990	[SnP_500].omega	0.0170	0.0109	1.5590	0.1190
[SnP_500].alpha1	0.4161	0.1440	2.8897	0.0039	[SnP_500].alpha1	0.1066	0.0298	3.5775	0.0003	[SnP_500].alpha1	0.2273	0.1282	1.7729	0.0763
[SnP_500].beta1	0.5829	0.1025	5.6880	0.0000	[SnP_500].beta1	0.8695	0.0364	23.8723	0.0000	[SnP_500].beta1	0.7124	0.1161	6.1387	0.0000
[NIKKEI].mu	0.0343	0.0249	1.3768	0.1686	[NIKKEI].mu	-0.0572	0.0408	-1.3996	0.1616	[NIKKEI].mu	0.0382	0.0306	1.2480	0.2120
[NIKKEI].omega	0.0103	0.0065	1.5887	0.1121	[NIKKEI].omega	0.0351	0.0180	1.9530	0.0508	[NIKKEI].omega	0.0002	0.0026	0.0932	0.9257
[NIKKEI].alpha1	0.1340	0.0463	2.8902	0.0039	[NIKKEI].alpha1	0.1410	0.0455	3.1016	0.0019	[NIKKEI].alpha1	0.0000	0.0093	0.0000	1.0000
[NIKKEI].beta1	0.8367	0.0535	15.6492	0.0000	[NIKKEI].beta1	0.8242	0.0454	18.1581	0.0000	[NIKKEI].beta1	0.9990	0.0005	21.1043	0.0000
[HSI].mu	0.0258	0.0287	0.8993	0.3685	[HSI].mu	0.0232	0.0441	0.5263	0.5987	[HSI].mu	0.0043	0.0325	0.1308	0.8960
[HSI].omega	0.0212	0.0353	0.6026	0.5468	[HSI].omega	0.0476	0.0348	1.3648	0.1723	[HSI].omega	0.0210	0.0258	0.8122	0.4167
[HSI].alpha1	0.0370	0.0617	0.5987	0.5494	[HSI].alpha1	0.1616	0.0640	2.5263	0.0115	[HSI].alpha1	0.0767	0.0426	1.7996	0.0719
[HSI].beta1	0.8686	0.1986	4.3744	0.0000	[HSI].beta1	0.8079	0.0779	10.3715	0.0000	[HSI].beta1	0.8509	0.1170	7.2711	0.0000
[JCI].mu	0.0140	0.0186	0.7520	0.4520	[JCI].mu	0.0486	0.0397	1.2229	0.2214	[JCI].mu	0.0450	0.0301	1.4927	0.1355
[JCI].omega	0.0146	0.0066	2.2293	0.0258	[JCI].omega	0.0640	0.0500	1.2793	0.2008	[JCI].omega	0.0390	0.0179	2.1759	0.0296

[JCI].alpha1	0.1893	0.0832	2.2742	0.0230	[JCI].alpha1	0.1900	0.0744	2.5530	0.0107	[JCI].alpha1	0.1855	0.1003	1.8498	0.0643
[JCI].beta1	0.7196	0.0832	8.6510	0.0000	[JCI].beta1	0.7492	0.1234	6.0704	0.0000	[JCI].beta1	0.6788	0.1096	6.1913	0.0000
[KLCI].mu	-0.0154	0.0136	-1.1349	0.2564	[KLCI].mu	0.0045	0.0235	0.1913	0.8483	[KLCI].mu	0.0010	0.0247	0.0419	0.9666
[KLCI].omega	0.0007	0.0013	0.5419	0.5879	[KLCI].omega	0.0321	0.0149	2.1593	0.0308	[KLCI].omega	0.0202	0.0135	1.4928	0.1355
[KLCI].alpha1	0.0607	0.0273	2.2213	0.0263	[KLCI].alpha1	0.1113	0.0368	3.0270	0.0025	[KLCI].alpha1	0.1070	0.0608	1.7600	0.0784
[KLCI].beta1	0.9383	0.0185	50.8292	0.0000	[KLCI].beta1	0.7447	0.0825	9.0239	0.0000	[KLCI].beta1	0.7524	0.1227	6.1301	0.0000
[KOSPI].mu	0.0279	0.0241	1.1599	0.2461	[KOSPI].mu	0.0145	0.0373	0.3899	0.6966	[KOSPI].mu	0.0566	0.0258	2.1949	0.0282
[KOSPI].omega	0.0423	0.0232	1.8279	0.0676	[KOSPI].omega	0.0144	0.0092	1.5675	0.1170	[KOSPI].omega	0.0347	0.0252	1.3759	0.1689
[KOSPI].alpha1	0.1808	0.1327	1.3619	0.1732	[KOSPI].alpha1	0.0808	0.0264	3.0562	0.0022	[KOSPI].alpha1	0.2592	0.1203	2.1547	0.0312
[KOSPI].beta1	0.5858	0.2152	2.7223	0.0065	[KOSPI].beta1	0.9017	0.0245	36.8293	0.0000	[KOSPI].beta1	0.6311	0.1622	3.8901	0.0001
[PSE].mu	0.0022	0.0253	0.0866	0.9310	[PSE].mu	0.0033	0.0341	0.0978	0.9221	[PSE].mu	-0.0106	0.0473	-0.2253	0.8218
[PSE].omega	0.0047	0.0043	1.0930	0.2744	[PSE].omega	0.0341	0.0240	1.4189	0.1559	[PSE].omega	0.0125	0.0093	1.3446	0.1787
[PSE].alpha1	0.0822	0.0412	1.9934	0.0462	[PSE].alpha1	0.1223	0.0634	1.9298	0.0536	[PSE].alpha1	0.0393	0.0384	1.0237	0.3060
[PSE].beta1	0.9077	0.0285	31.8358	0.0000	[PSE].beta1	0.8239	0.0822	10.0169	0.0000	[PSE].beta1	0.9180	0.0601	15.2628	0.0000
[SSE].mu	0.0238	0.0278	0.8543	0.3929	[SSE].mu	0.0622	0.0538	1.1548	0.2482	[SSE].mu	0.0237	0.0222	1.0655	0.2867
[SSE].omega	0.0082	0.0063	1.3122	0.1894	[SSE].omega	0.0175	0.0204	0.8554	0.3923	[SSE].omega	0.0247	0.0129	1.9073	0.0565
[SSE].alpha1	0.1120	0.0619	1.8103	0.0703	[SSE].alpha1	0.0597	0.0308	1.9361	0.0529	[SSE].alpha1	0.1555	0.0709	2.1923	0.0284
[SSE].beta1	0.8686	0.0508	17.0945	0.0000	[SSE].beta1	0.9257	0.0400	23.1514	0.0000	[SSE].beta1	0.7153	0.1012	7.0703	0.0000
[STI].mu	0.0217	0.0175	1.2416	0.2144	[STI].mu	-0.0128	0.0339	-0.3777	0.7056	[STI].mu	-0.0001	0.0220	-0.0045	0.9964
[STI].omega	0.0054	0.0056	0.9617	0.3362	[STI].omega	0.0291	0.0211	1.3779	0.1682	[STI].omega	0.0277	0.0122	2.2771	0.0228
[STI].alpha1	0.1864	0.1030	1.8090	0.0704	[STI].alpha1	0.1394	0.0576	2.4201	0.0155	[STI].alpha1	0.2369	0.0880	2.6912	0.0071
[STI].beta1	0.8018	0.1064	7.5352	0.0000	[STI].beta1	0.8211	0.0759	10.8130	0.0000	[STI].beta1	0.5971	0.1103	5.4148	0.0000
[TAIEX].mu	0.0329	0.0207	1.5890	0.1121	[TAIEX].mu	0.0061	0.0377	0.1617	0.8715	[TAIEX].mu	0.1040	0.0282	3.6859	0.0002
[TAIEX].omega	0.0075	0.0133	0.5607	0.5750	[TAIEX].omega	0.0190	0.0113	1.6793	0.0931	[TAIEX].omega	0.0855	0.0338	2.5294	0.0114
[TAIEX].alpha1	0.0747	0.0773	0.9666	0.3338	[TAIEX].alpha1	0.0786	0.0247	3.1747	0.0015	[TAIEX].alpha1	0.2281	0.0845	2.6996	0.0069
[TAIEX].beta1	0.8641	0.1786	4.8388	0.0000	[TAIEX].beta1	0.8961	0.0258	34.7737	0.0000	[TAIEX].beta1	0.4020	0.1673	2.4024	0.0163
[SET].mu	0.0724	0.0137	0.1146	0.3937	[SET].mu	-0.0419	0.0310	1.8374	0.0721	[SET].mu	-0.0829	0.0420	3.8834	0.9657
[SET].omega	0.0270	0.0150	0.7003	0.0756	[SET].omega	0.0242	0.0328	1.4950	0.4550	[SET].omega	0.0922	0.0792	2.2309	0.4550
[SET].alpha1	0.0456	0.0135	3.2874	0.0022	[SET].alpha1	0.0549	0.0566	0.5771	0.0404	[SET].alpha1	0.0374	0.0566	0.5771	0.0011
[SET].beta1	0.7151	0.0123	19.4565	0.0000	[SET].beta1	0.8891	0.0693	8.8198	0.0000	[SET].beta1	0.4918	0.0911	8.8198	0.0000
[Joint]dcca1	0.0021	0.0013	0.0103	0.0518	[Joint]dcca1	0.0072	0.0043	1.6824	0.0325	[Joint]dcca1	0.0284	0.0138	2.0599	0.0394
[Joint]dccb1	0.9120	0.0816	11.1810	0.0000	[Joint]dccb1	0.8690	0.0423	20.5234	0.0000	[Joint]dccb1	0.5222	0.1956	2.6698	0.0076

The following six tables from 6.12 to 6.17 present the results from bivariate GARCH-BEKK model for pairs of each stock market. The news surprises based on α_{ij} coefficient, which is presented in tables 6.12, 6.14, and 6.16. Additionally, volatility transmission channels are represented by coefficient β_{ij} in tables 6.13, 6.15, and 6.17 for each crisis period. As highlighted in the previous section, these two parameters show volatility spillovers among equity markets of selected countries, and also indicate persistence of the impact of news shocks between markets. The p-values in the tables below are indicated in parentheses under each one of the estimated parameters, while the significance level is denoted with asterisks. It is important to note that, the correct interpretation of tables is from rows to columns. As an example, the news effects of NIKKEI to the remaining equity markets can be followed in the second row. In other words, the markets in the rows show the “source” of spillover, while the recipients of the shocks are given in the columns.

The behaviour of volatility spillovers during the Asian financial crisis can be seen in tables 6.12 and 6.13. According to the estimated results, the presence of strong volatility spillover channels was identified. Specifically, countries that transmit increased spillovers during the Asian financial crisis are also the most severely impacted ones. Specifically, Indonesia and Hong Kong indicate sizeable news and volatility spillover effects to the rest of the region. It is also interesting to notice that Indonesia and Hong Kong are main recipients of volatility shocks during this period as well as the Philippines. On the other hand, Japan and USA seem to be very immune to the external shocks together with China. However, the case of China is different due to the restrictions on foreign capital movements as mentioned in the earlier section. Moreover, there is significant bi-directional volatility spillover among some cross-market pairs, such as Japan and Malaysia, Singapore, and Thailand as well as China and Hong Kong. The impact of USA on the continent of Asia is rather limited in terms of shock and volatility spillovers, indicating minimal financial risk propagation during the crisis. Finally, most of the parameters are significant in various levels, suggesting long lasting financial distress among pairs. It should also be mentioned that the financial linkages are stronger between the equity markets of Southeast Asia compared to the stock markets of Far East Asia.

Table 6.12: GARCH-BEKK results for α_{ij}: Asian Crisis Period

α_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		0.020	-0.054	0.065	0.039	-0.083**	0.046	0.020**	0.201	0.190***	0.034
		(0.691)	(0.156)	(0.090)	(0.195)	(0.003)	(0.241)	(0.713)	(0.002)	(0.000)	(0.169)
NIKKEI	0.02		0.275***	0.006	0.037	0.020	-0.144***	0.151	0.03	-0.203	0.067*
	(0.715)		(0.003)	(0.888)	(0.414)	(0.579)	(0.061)	(0.088)	(0.965)	(0.105)	(0.439)
HSI	-0.500	-0.087		0.202**	0.213**	0.104	0.336***	0.204	0.376	0.013	0.093
	(0.212)	(0.728)		(0.004)	(0.007)	(0.553)	(0.005)	(0.062)	(0.278)	(0.922)	(0.230)
JCI	-0.437***	-0.141	0.297		-0.070	0.243***	0.138	0.231	0.245	-0.189	-0.210
	(0.017)	(0.562)	(0.008)		(0.281)	(0.005)	(0.332)	(0.080)	(0.050)	(0.164)	(0.309)
KLCI	0.016	0.289**	-0.097	0.151*		0.061	-0.076	0.300*	0.059*	-0.104	0.041**
	(0.950)	(0.021)	(0.196)	(0.044)		(0.515)	(0.390)	(0.044)	(0.429)	(0.465)	(0.498)
KOSPI	-0.500	0.020	-0.218	0.304**	0.186		0.139	0.020	0.442*	0.178	0.013
	(0.004)	(0.858)	(0.116)	(0.002)	(0.079)		(0.130)	(0.865)	(0.022)	(0.293)	(0.794)
PSE	-0.320**	-0.009	0.312***	0.236***	-0.106**	-0.066		0.270*	0.500***	-0.238**	-0.286*
	(0.003)	(0.909)	(0.001)	(0.002)	(0.039)	(0.428)		(0.010)	(0.001)	(0.009)	(0.003)
SSE	0.020	0.146*	-0.161***	0.019	0.031	0.020	0.093		0.026	0.187**	0.219
	(0.796)	(0.001)	(0.004)	(0.610)	(0.306)	(0.501)	(0.513)		(0.543)	(0.005)	(0.157)
STI	-0.272**	-0.095	0.217	-0.061	0.057	-0.081	0.053	0.089		-0.207*	0.185**
	(0.009)	(0.379)	(0.068)	(0.205)	(0.343)	(0.092)	(0.452)	(0.365)		(0.012)	(0.080)

TAIEX	-0.328**	-0.013	0.057	0.060	0.117*	0.021	-0.285***	0.223**	0.190***		-0.205*
	(0.003)	(0.864)	(0.377)	(0.921)	(0.019)	(0.593)	(0.003)	(0.003)	(0.005)		(0.012)
SET	-0.120*	0.193*	-0.237*	0.193	0.304**	-0.036	0.257	0.068*	0.191	0.006	
	(0.004)	(0.001)	(0.010)	(0.003)	(0.005)	(0.627)	(0.147)	(0.407)	(0.316)	(0.922)	

Notes: This table presents the "news surprises" with estimated parameters from bivariate GARCH-BEKK method. P-values are denoted within parentheses.

*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.13: GARCH-BEKK results for β_{ij}: Asian Crisis Period

β_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		0.010	0.286***	-0.058	-0.049*	-0.029	-0.138*	0.010	0.021	-0.041	0.011
		(0.300)	(0.001)	(0.218)	(0.031)	(0.786)	(0.014)	(0.355)	(0.746)	(0.720)	(0.469)
NIKKEI	0.010		-0.089	0.007	-0.219**	0.010	0.500*	-0.145	0.037	0.010	0.012*
	(0.500)		(0.438)	(0.948)	(0.005)	(0.196)	(0.012)	(0.474)	(0.687)	(0.973)	(0.839)
HSI	0.500	0.380		-0.502**	0.121*	0.437***	0.358***	-0.477	-0.343	-0.321***	0.023
	(0.412)	(0.346)		(0.001)	(0.039)	(0.001)	(0.001)	(0.057)	(0.003)	(0.001)	(0.004)
JCI	0.232**	0.223	-0.597***		0.375**	-0.543*	-0.180	-0.198	0.500**	-0.137	-0.370
	(0.003)	(0.946)	(0.008)		(0.001)	(0.005)	(0.520)	(0.280)	(0.005)	(0.159)	(0.496)
KLCI	-0.048	0.175	0.072	-0.151		0.013	-0.261	-0.354	-0.026*	0.076	0.021
	(0.345)	(0.334)	(0.574)	(0.004)		(0.712)	(0.090)	(0.253)	(0.573)	(0.469)	(0.798)
KOSPI	0.394	0.010	-0.518***	-0.239*	-0.109		-0.060	0.010	0.117	-0.500	0.044**
	(0.001)	(0.566)	(0.006)	(0.002)	(0.451)		(0.388)	(0.567)	(0.450)	(0.001)	(0.003)
PSE	0.072	0.457***	-0.333***	-0.500***	0.299**	0.026		-0.003	0.306*	0.391**	-0.106*
	(0.781)	(0.001)	(0.001)	(0.002)	(0.001)	(0.425)		(0.992)	(0.018)	(0.001)	(0.027)
SSE	0.010	-0.43**	0.145	-0.199	-0.048	0.010	-0.250**		-0.043	-0.379	-0.090
	(0.461)	(0.0012)	(0.810)	(0.309)	(0.365)	(0.130)	(0.001)		(0.543)	(0.138)	(0.526)
STI	0.166	0.449**	-0.067	0.147	-0.037	0.166	0.234	-0.067		0.147	-0.113**
	(0.379)	(0.001)	(0.766)	(0.281)	(0.428)	(0.379)	(0.226)	(0.766)		(0.281)	(0.004)
TAIEX	0.094	-0.013	-0.084	0.068	0.058	-0.041***	--0.098*	-0.120**	-0.120**		0.125
	(0.525)	(0.864)	(0.790)	(0.407)	(0.260)	(0.001)	(0.014)	(0.005)	(0.004)		(0.293)
SET	-0.360*	0.289*	-0.137	-0.026	0.005**	-0.108	-0.149**	0.087	0.011	0.043	
	(0.001)	(0.019)	(0.004)	(0573)	(0.005)	(0.634)	(0.001)	(0.377)	(0.016)	(0.279)	

Notes: This table presents the "volatility spillover" from bivariate GARCH-BEKK method. P-values are denoted within parentheses.

*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Next, we investigated the cross-market linkages during the GFC period which is considered one of the most significant financial shocks in the post-war period (Edey, 2009). The picture during the GFC period is different compared to the Asian crisis, since the epicentre of the crisis is USA which is the biggest economy and main financial hub of the world. According to tables 6.14 and 6.15, USA is the biggest contributor of the financial distress as expected, and the most affected countries are the emerging markets of Asia, especially Malaysia, the Philippines and Singapore. Similar vulnerability is also detected in Taiwan, yet with a lower magnitude compared to the aforementioned markets. It is very interesting to note that Japan, Hong Kong, and China are the least impacted ones. Two-way volatility spillover effect is found between some markets, including USA and Taiwan, Korea and Indonesia, and Singapore and Hong Kong. Moreover, co-movements between Singapore and Indonesia are rather weak, signifying reduced risk for international portfolio managers. The findings of the GFC period are mostly in line with the study of Hesse and Frank (2009) in terms of interdependencies within the region.

Table 6.14: GARCH-BEKK results for α_{ij}: GFC Period

α_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		0.120 (0.681)	0.088 (0.053)	0.075 (0.003)	0.492*** (0.001)	0.087 (0.111)	-0.022 (0.768)	0.048 (0.275)	0.133 (0.077)	0.162** (0.001)	0.014* (0.029)
NIKKEI	0.092 (0.739)		-0.012 (0.726)	0.002 (0.739)	-0.049 (0.749)	-0.011 (0.817)	0.020 (0.787)	0.030 (0.545)	0.018 (0.720)	0.020 (0.766)	0.017* (0.289)
HSI	0.500** (0.004)	-0.055 (0.247)		0.007*** (0.940)	0.087 (0.749)	-0.364*** (0.001)	0.294* (0.014)	-0.019 (0.728)	0.200* (0.047)	-0.078 (0.372)	-0.058 (0.404)
JCI	-0.345*** (0.007)	0.020 (0.677)	-0.109 (0.103)		-0.091 (0.577)	0.161 (0.089)	-0.266* (0.010)	-0.164* (0.286)	0.097 (0.294)	-0.001 (0.984)	0.040 (0.739)
KLCI	0.050 (0.225)	-0.029 (0.200)	0.030 (0.420)	0.179*** (0.001)		0.145* (0.030)	0.216*** (0.086)	-0.040 (0.090)	0.149** (0.005)	-0.104 (0.140)	0.327** (0.005)
KOSPI	-0.374*** (0.004)	-0.040** (0.008)	0.226 (0.016)	0.304** (0.002)	0.186 (0.079)		0.139 (0.130)	0.020 (0.865)	0.442* (0.022)	0.178 (0.293)	0.013 (0.794)
PSE	0.442*** (0.001)	0.020 (0.633)	0.140* (0.014)	0.169* (0.010)	0.381*** (0.001)	-0.213* (0.164)		0.024 (0.628)	-0.486 (0.001)	0.183** (0.001)	0.445 (0.012)
SSE	0.001 (0.263)	0.168 (0.128)	0.065 (0.408)	0.001* (0.009)	0.329* (0.004)	-0.175 (0.160)	0.500* (0.012)		-0.169 (0.187)	0.020** (0.760)	-0.079 (0.351)
STI	-0.212** (0.001)	-0.018 (0.527)	0.078 (0.277)	0.002 (0.970)	0.056 (0.680)	-0.126 (0.202)	0.445*** (0.001)	-0.007 (0.866)		-0.088 (0.393)	-0.161* (0.278)
TAIEX	0.528** (0.002)	0.003 (0.647)	-0.051 (0.458)	0.159*** (0.001)	0.500* (0.019)	-0.240 (0.028)	0.495*** (0.001)	-0.077 (0.338)	-0.161 (0.241)		-0.088* (0.377)
SET	0.463** (0.001)	-0.107* (0.302)	0.215** (0.001)	0.209** (0.003)	0.217** (0.001)	0.064 (0.409)	-0.029 (0.204)	-0.040* (0.165)	0.021 (0.346)	-0.110 (0.155)	

Notes: This table presents the "news surprises" with estimated parameters from bivariate GARCH-BEKK method. P-values are denoted within parentheses. *, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.15: GARCH-BEKK results for β_{ij}: GFC Period

β_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		0.070 (0.312)	0.073*** (0.001)	-0.082 (0.001)	-0.319*** (0.001)	-0.082* (0.024)	-0.353* (0.017)	0.015 (0.002)	-0.479*** (0.001)	0.058 (0.001)	-0.035 (0.568)
NIKKEI	0.030 (0.383)		-0.003 (0.844)	0.001 (0.385)	-0.041 (0.817)	-0.004 (0.823)	0.010 (0.429)	0.038 (0.782)	-0.017 (0.552)	-0.022* (0.003)	-0.003 (0.843)
HSI	0.265*** (0.001)	0.028 (0.411)		0.500 (0.064)	-0.023* (0.001)	-0.136 (0.043)	-0.500 (0.001)	-0.054 (0.895)	0.136 (0.001)	-0.214 (0.456)	0.409** (0.003)
JCI	0.197 (0.079)	0.010 (0.310)	0.500* (0.011)		-0.032 (0.377)	0.170 (0.120)	-0.395*** (0.002)	-0.004** (0.005)	0.027** (0.003)	0.284 (0.052)	0.015 (0.710)
KLCI	-0.302** (0.001)	0.016 (0.298)	-0.008 (0.725)	0.327*** (0.001)		0.001 (0.987)	-0.326*** (0.001)	0.036*** (0.008)	-0.035 (0.174)	-0.416* (0.007)	-0.013 (0.745)
KOSPI	-0.464*** (0.001)	0.024 (0.053)	0.422* (0.003)	0.246*** (0.009)	-0.090 (0.635)		-0.164** (0.003)	-0.070 (0.024)	-0.091 (0.090)	-0.089 (0.581)	0.286* (0.003)
PSE	-0.219* (0.019)	0.010 (0.247)	0.021* (0.014)	0.099** (0.009)	-0.325*** (0.001)	-0.116 (0.064)		0.175 (0.498)	-0.021 (0.517)	0.039 (0.034)	0.183 (0.004)
SSE	-0.002 (0.711)	-0.055 (0.444)	0.391** (0.002)	-0.156** (0.001)	0.368** (0.002)	0.184 (0.267)	0.368** (0.002)		0.170 (0.481)	0.414*** (0.008)	-0.115 (0.284)
STI	0.442** (0.001)	0.004 (0.781)	-0.405** (0.001)	0.050* (0.046)	-0.113 (0.375)	0.061 (0.219)	-0.021 (0.517)	-0.164 (0.251)		-0.171 (0.697)	0.303* (0.036)
TAIEX	0.048 (0.573)	0.010 (0.277)	0.402*** (0.001)	0.010 (0.879)	-0.357*** (0.001)	0.251 (0.102)	-0.344 (0.075)	0.072 (0.600)	0.303* (0.027*)		-0.068 (0.437)
SET	0.035 (0.803)	-0.039 (0.744)	0.041** (0.353)	0.066* (0.056)	0.078 (0.428)	-0.078 (0.628)	0.012 (0.765)	-0.308 (0.226)	-0.171 (0.683)	-0.088 (0.377)	

Notes: This table presents the "volatility spillover" from bivariate GARCH-BEKK method. P-values are denoted within parentheses. *, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Finally, the recent Covid Crisis period is investigated in tables of 6.16 and 6.17. The estimated results are mixed compared to the earlier crisis periods. The main transmitter of news shocks and volatility spillovers is Hong Kong, while the role of China on other markets continue to be limited. The magnitude of financial distress is severely increased for some countries such as Japan and Taiwan which is most probably due to the strict lockdown measures and government policies in these countries (Zehri, 2021). Notably, China is neither a net transmitter nor a net recipient of shocks and spillovers during the crisis period, which is very surprising as the crisis started in China. The effect of financial market of China seems to be minimal which contradicts with the findings of Fu et al. (2021), yet it is in line with the study of Zehri (2021) as the heavier magnitude of financial stress transmits via Hong Kong. Less parameters are statistically significant compared to the earlier crises, which indicate there will be no long-lasting effects. Bi-directional relationships exist between Japan and USA, and Singapore and Thailand, while two-way volatility spillover effect is found between most of the markets such as Korea and Indonesia, Taiwan, and China as well as Malaysia and the Philippines. It should also be mentioned that the financial interlinkages and spillover channels are stronger within the markets of Far East Asia compared to the Southeast Asian economies, implying different crisis characteristics than the Asian crisis period or the GFC period. In general terms, the equity markets of Asia as well as the US are profoundly succumbed to strong volatility spillovers, from both peripheral and core stock markets. The news shocks turn into important and enduring stress transmission, so that it can be said that the financial sector is one of the most volatile and susceptible to increasing financial distress and episode of financial catastrophes.

Table 6.16: GARCH-BEKK results for α_{ij}: Covid Crisis Period

α_{ij}	**SP500**	**NIKKEI**	**HSI**	**JCI**	**KLCI**	**KOSPI**	**PSE**	**SSE**	**STI**	**TAIEX**	**SET**
SP500		-0.074	-0.015	0.176***	0.020	0.097	0.022	-0.034	0.078	-0.076	-0.204*
		(0.241)	(0.787)	(0.006)	(0.932)	(0.284)	(0.913)	(0.654)	(0.315)	(0.720)	(0.019)
NIKKEI	0.054		-0.028	-0.118	0.020	-0.033	0.036	-0.185	0.067	-0.159	0.021
	(0.414)		(0.696)	(0.172)	(0.771)	(0.619)	(0.472)	(0.401)	(0.332)	(0.081)	(0.855)
HSI	-0.350***	0.207		0.397***	0.144	0.094	0.266***	-0.287	0.212	-0.015	-0.035
	(0.006)	(0.164)		(0.001)	(0.464)	(0.369)	(0.001)	(0.072)	(0.129)	(0.836)	(0.664)
JCI	-0.492***	0.147	0.004		0.422***	0.439***	0.260***	0.156*	0.238	0.178*	0.389***
	(0.007)	(0.178)	(0.954)		(0.002)	(0.001)	(0.002)	(0.049)	(0.119)	(0.014)	(0.004)
KLCI	0.020	-0.018	0.025	-0.297		0.087	0.207***	-0.004	0.253	0.018	0.059
	(0.225)	(0.782)	(0.785)	(0.421)		(0.277)	(0.009)	(0.995)	(0.072)	(0.741)	(0.574)
KOSPI	-0.154*	0.078	-0.236*	0.013	0.487***		0.344***	-0.041	0.238**	0.149	-0.085
	(0.019)	(0.470)	(0.025)	(0.867)	(0.005)		(0.001)	(0.614)	(0.001)	(0.237)	(0.439)
PSE	0.020	0.131	0.274***	-0.061	0.203***	0.360***		0.183**	0.225***	0.277**	0.086*
	(0.082)	(0.431)	(0.003)	(0.356)	(0.001)	(0.002)		(0.003)	(0.001)	(0.001)	(0.009)
SSE	-0.092	-0.064	0.164	-0.001*	0.074	0.062	0.185***		0.039	0.036	-0.170
	(0.324)	(0.299)	(0.050)	(0.973)	(0.155)	(0.152)	(0.002)		(0.414)	(0.483)	(0.071)
STI	-0.258**	0.035	-0.015	0.121*	0.130	0.228***	0.223***	0.018		-0.024	0.247*
	(0.002)	(0.676)	(0.789)	(0.049)	(0.230)	(0.007)	(0.001)	(0.789)		(0.651)	(0.001)
TAIEX	-0.067	0.030	-0.034	-0.152	0.043	0.176**	0.176**	-0.170	0.152		-0.016
	(0.269)	(0.811)	(0.665)	(0.149)	(0.622)	(0.005)	(0.005)	(0.071)	(0.215)		(0.568)
SET	0.001	-0.164*	-0.010	0.303*	0.024	0.092**	0.034	0.036	0.129	-0.063	
	(0.986)	(0.070)	(0.864)	(0.034)	(0.789)	(0.005)	(0.355)	(0.483)	(0.123)	(0.252)	

Notes: This table presents the "news surprises" with estimated parameters from bivariate GARCH-BEKK method. P-values are denoted within parentheses. *, **, *** indicate 10%, 5%, and 1% significance level, respectively.

Table 6.17: GARCH-BEKK results for β_{ij}: Covid Crisis Period

β_{ij}	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET
SP500		0.206 (0.059)	0.095 (0.415)	-0.244*** (0.001)	0.001 (0.641)	-0.003 (0.986)	0.051** (0.007)	0.138 (0.565)	-0.465** (0.001)	0.125 (0.501)	0.268** (0.004)
NIKKEI	-0.007 (0.911)		0.142 (0.363)	0.084 (0.322)	0.010 (0.477)	0.072 (0.466)	-0.047 (0.704)	0.171 (0.166)	0.001 (0.982)	0.358** (0.005)	0.255 (0.077)
HSI	0.324*** (0.001)	0.143 (0.289)		-0.321 (0.064)	-0.093 (0.499)	0.067 (0.554)	0.229*** (0.001)	0.255 (0.053)	0.008 (0.451)	-0.207 (0.196)	0.110 (0.482)
JCI	0.068** (0.002)	-0.422** (0.001)	0.047 (0.453)		-0.282 (0.196)	0.061 (0.380)	-0.179*** (0.002)	-0.004** (0.005)	0.027** (0.003)	0.284 (0.052)	0.015 (0.710)
KLCI	0.010 (0.176)	0.016 (0.403)	-0.092 (0.652)	0.027 (0.885)		-0.086 (0.063)	-0.133*** (0.001)	-0.041 (0.294)	0.039* (0.015)	-0.048 (0.615)	-0.017 (0.861)
KOSPI	0.239*** (0.001)	-0.002 (0.994)	0.153 (0.121)	0.040 (0.097)	-0.036*** (0.005)		0.186** (0.006)	0.011 (0.883)	-0.157 (0.183)	0.171 (0.161)	-0.219* (0.020)
PSE	0.010 (0.468)	-0.157 (0.716)	-0.024 (0.662)	-0186** (0.009)	-0.138*** (0.001)	-0.062 (0.419)		0.024 (0.313)	0.015 (0.463)	0.086 (0.282)	0.015 (0463)
SSE	-0.013 (0.608)	-0.116 (0.191)	-0.220 (0.089)	-0.088 (0.178)	-0.033 (0.488)	-0.044 (0.186)	0.024 (0.305)		-0.031 (0.430)	-0.084 (0.322)	-0.133 (0.871)
STI	0.040 (0.056)	-0.187 (0.509)	0.293 (0.220)	0.102* (0.023)	0.073 (0.975)	0.138** (0.008)	0.015 (0.341)	0.270*** (0.003)		0.121 (0.282)	0.089** (0.001)
TAIEX	0.112 (0.052)	0.094*** (0.001)	-0.194 (0.215)	0.345 (0.264)	-0.469*** (0.001)	0.062* (0.017)	0.034 (0.355)	-0.084 (0.322)	0.044* (0.960)		-0.001 (0.950)
SET	-0.082 (0.372)	0.037 (0.104)	0.021** (0.001)	-0.021 (0.237)	0.095** (0.004)	0.082 (0.628)	0.092*** (0.003)	0.118 (0.356)	-0.041 (0.125)	-0.057 (0.484)	

Notes: This table presents the "volatility spillover" from bivariate GARCH-BEKK method. P-values are denoted within parentheses.
*, **, *** indicate 10%, 5%, and 1% significance level, respectively.

In order to provide a better understanding of the direction and intensity of volatility spillovers across selected markets Diebold and Yilmaz (2012) methodology based on generalized VAR specification is employed. The detail analysis of volatility transmission mechanisms between markets is depicted in tables 6.18, 6.19, and 6.20 for each selected subperiod. The reported total volatility spillover index is lowest during the Asian financial crisis with 19.033%, while it is the highest during the GFC period with 39.671%. The index is equal 28.582% during the GFC crisis period, suggesting some co-movements between markets, yet larger percentage of external shocks between markets is explained by idiosyncratic shocks. When it comes to the magnitude of *Contribution to Others,* Hong Kong is the source of the largest volatility transmission in the region especially during the GFC period, confirming the earlier results by GARCH-BEKK model. USA has the highest values for Asian and Covid Crisis periods, while the contribution of Thailand is lowest among all, supporting the earlier findings of Wang and Liu (2016). Consequently, the strength of regional spillovers is higher than the intensity of international volatility spillovers.

Based on the obtained results it can be said that the greater number of markets react to their own shocks, such as, Japan during the GFC period with 8.930%, and Thailand during the Asian and Covid crisis periods with 8.643% and 8.797% respectively, making them the least dependent markets in the sample. On the other hand, Singapore is the least independent among all with less than 3.0% forecast error variance in GFC and Covid Crisis periods, indicating the lowest reaction to domestic shocks. The column *Contribution from Others* reports notable results in terms of sensitivity to foreign news shocks. According to the tables, Singapore is one of the highest spillover recipients in each crisis period, followed by Hong Kong during the Asian crisis period, the Philippines during the GFC period, and Korea for the Covid Crisis period. Japan and USA are the two immune countries regarding external financial distress with the lowest sensitivity level. In terms of pairwise spillover channels, Hong Kong and USA are net contributors of volatility shock propagations, while China, Thailand, Taiwan, and the Philippines are the net recipients of cross-country shocks. As a result, these findings display important implications in terms of portfolio diversification opportunities especially in the developed equity markets of Asia since the impact of external shocks are limited compared to the emerging economies. However, the lower dependency to foreign shocks reduces the chances of estimating volatility of these markets based on external news transmission. Therefore, developed markets might be considered in terms of risk management perspective, but risk averse investors should be more careful when investing in emerging markets of Asia as external shocks might create larger declines due to the phenomenon of meteor shower effect proposed by Engle et al. (1990).

Table 6.18: Comparison of DY framework across markets: Asian Crisis Period

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET	C. from others
SP500	7.881	0.978	0.024	0.007	0.061	0.000	0.037	0.036	0.040	0.021	0.006	1.210
NIKKEI	0.688	7.809	0.240	0.057	0.189	0.002	0.021	0.009	0.035	0.037	0.004	1.282
HSI	2.909	0.532	4.681	0.089	0.183	0.083	0.116	0.119	0.129	0.244	0.007	4.410
JCI	0.385	0.106	0.131	7.973	0.139	0.056	0.173	0.025	0.059	0.026	0.018	1.118
KLCI	1.538	0.066	0.066	0.196	6.930	0.002	0.034	0.039	0.129	0.081	0.010	2.161
KOSPI	0.157	0.039	0.100	0.045	0.009	8.624	0.063	0.037	0.006	0.006	0.006	0.467
PSE	0.324	0.034	0.208	0.698	0.048	0.018	7.521	0.019	0.182	0.037	0.001	1.570
SSE	0.284	0.226	0.097	0.047	0.026	0.001	0.001	8.285	0.014	0.045	0.064	0.806
STI	1.040	0.067	1.539	1.058	0.222	0.134	0.564	0.054	5.294	0.105	0.012	3.796
TAIEX	0.796	0.073	0.315	0.018	0.227	0.037	0.046	0.040	0.193	7.326	0.021	1.765
SET	0.078	0.008	0.016	0.037	0.005	0.080	0.102	0.083	0.032	0.007	8.643	0.448
C. to others (spillover)	8.198	2.129	2.736	2.254	1.111	0.413	1.156	0.462	0.818	0.608	0.148	19.033%
C. to others incl. own	16.078	9.939	6.417	10.227	8.040	9.037	8.677	8.747	6.113	7.934	8.791	

Notes: C.from others – Directional spillovers from all market *j* to market *i* ; C. to others (spillover) – Directional spillovers from market *i* to all markets *j* C. to others including own – Directional spillovers from market *i* to all markets *j* including its own contribution. Remaining columns indicate net pairwise (*i*,*j*)-th spillovers between markets. Total Volatility spillover index is given in the lower right corner.

Table 6.19: Comparison of DY framework across markets: GFC Period

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET	C. from others
SP500	8.562	0.004	0.048	0.062	0.018	0.075	0.185	0.005	0.017	0.111	0.003	0.529
NIKKEI	0.027	8.930	0.005	0.003	0.007	0.008	0.017	0.086	0.004	0.003	0.001	0.161
HSI	0.645	0.041	6.386	0.334	0.066	0.276	0.475	0.005	0.383	0.474	0.007	2.705
JCI	0.653	0.033	1.132	6.574	0.012	0.333	0.153	0.017	0.085	0.088	0.012	2.517
KLCI	0.171	0.025	1.168	0.610	6.487	0.147	0.252	0.099	0.068	0.061	0.004	2.604
KOSPI	1.113	0.022	1.305	0.513	0.276	4.680	0.992	0.004	0.069	0.114	0.004	4.411
PSE	0.655	0.046	1.829	0.112	0.316	0.802	4.525	0.023	0.461	0.311	0.009	4.565
SSE	0.080	0.045	0.580	0.018	0.059	0.071	0.013	8.152	0.066	0.005	0.002	0.938
STI	0.484	0.061	1.988	0.394	0.587	1.303	1.308	0.008	2.804	0.146	0.008	6.287
TAIEX	0.317	0.033	1.881	0.401	0.164	0.418	0.142	0.041	0.072	5.617	0.006	3.474
SET	0.026	0.019	0.008	0.007	0.072	0.002	0.052	0.078	0.012	0.114	8.700	0.391
C. to others (spillover)	4.171	0.328	9.944	2.455	1.577	3.432	3.589	0.367	1.238	1.426	0.055	28.582%
C. to others including own	12.733	9.259	16.330	9.029	8.065	8.112	8.114	8.519	4.042	7.043	8.756	

Notes: C.from others – Directional spillovers from all market *j* to market *i* ; C. to others (spillover) – Directional spillovers from market *i* to all markets *j* C. to others including own – Directional spillovers from market *i* to all markets *j* including its own contribution. Remaining columns indicate net pairwise (*i*,*j*)-th spillovers between markets. Total Volatility spillover index is given in the lower right corner.

Table 6.20: Comparison of DY framework across markets: Covid Crisis Period

	SP500	NIKKEI	HSI	JCI	KLCI	KOSPI	PSE	SSE	STI	TAIEX	SET	C. from others
SP500	5.865	0.009	0.387	0.035	0.611	0.201	0.457	0.009	1.419	0.084	0.012	3.226
NIKKEI	0.145	8.700	0.056	0.014	0.016	0.017	0.035	0.015	0.073	0.011	0.008	0.391
HSI	0.528	0.069	6.945	0.108	0.381	0.280	0.563	0.014	0.148	0.040	0.016	2.146
JCI	2.395	0.012	0.581	3.172	0.444	1.173	0.359	0.011	0.861	0.061	0.023	5.919
KLCI	1.018	0.014	0.291	0.095	3.902	0.686	2.577	0.043	0.387	0.051	0.026	5.189
KOSPI	1.547	0.020	0.990	0.239	1.070	3.320	0.864	0.014	0.895	0.105	0.028	5.771
PSE	1.852	0.032	0.267	0.066	0.524	1.319	4.569	0.045	0.358	0.025	0.034	4.522
SSE	0.035	0.049	1.228	0.065	0.188	0.099	0.121	7.140	0.018	0.024	0.124	1.951
STI	1.360	0.006	1.040	0.315	1.411	1.128	1.207	0.017	2.375	0.215	0.016	6.716
TAIEX	0.957	0.034	0.236	0.085	0.362	0.705	0.815	0.018	0.320	5.546	0.014	3.545
SET	0.003	0.006	0.011	0.007	0.077	0.011	0.002	0.126	0.045	0.006	8.797	0.294
C. to others (spillover)	9.840	0.252	5.089	1.029	5.084	5.620	7.000	0.312	4.523	0.622	0.301	39.671%
C. to others including own	15.705	8.952	12.033	4.200	8.986	8.940	11.569	7.452	6.898	6.168	9.098	

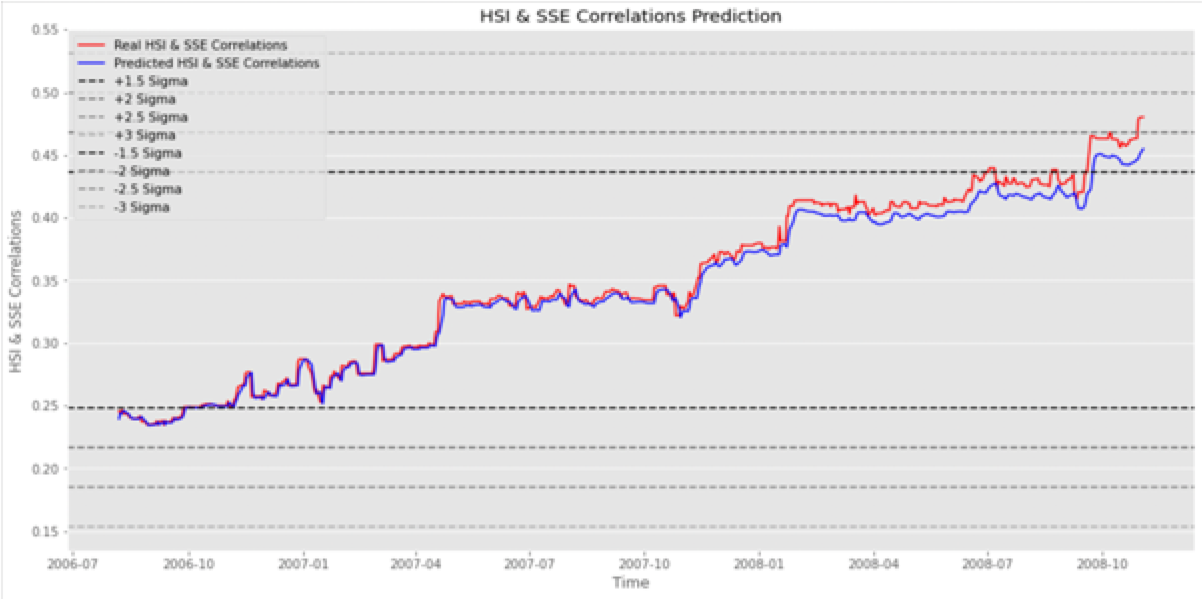
Notes: C.from others – Directional spillovers from all market *j* to market *i* ; C. to others (spillover) – Directional spillovers from market *i* to all markets *j* C. to others including own – Directional spillovers from market *i* to all markets *j* including its own contribution. Remaining columns indicate net pairwise (*i*,*j*)-th spillovers between markets. Total Volatility spillover index is given in the lower right corner.

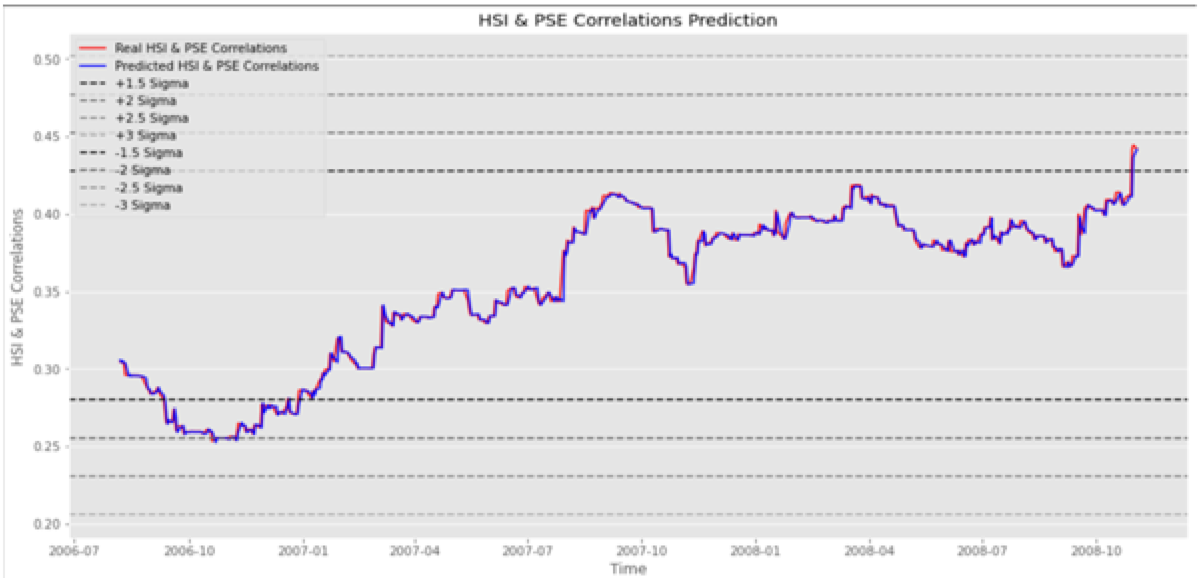
6.4.3 LSTM based Early Warning System: Experimental Evaluation

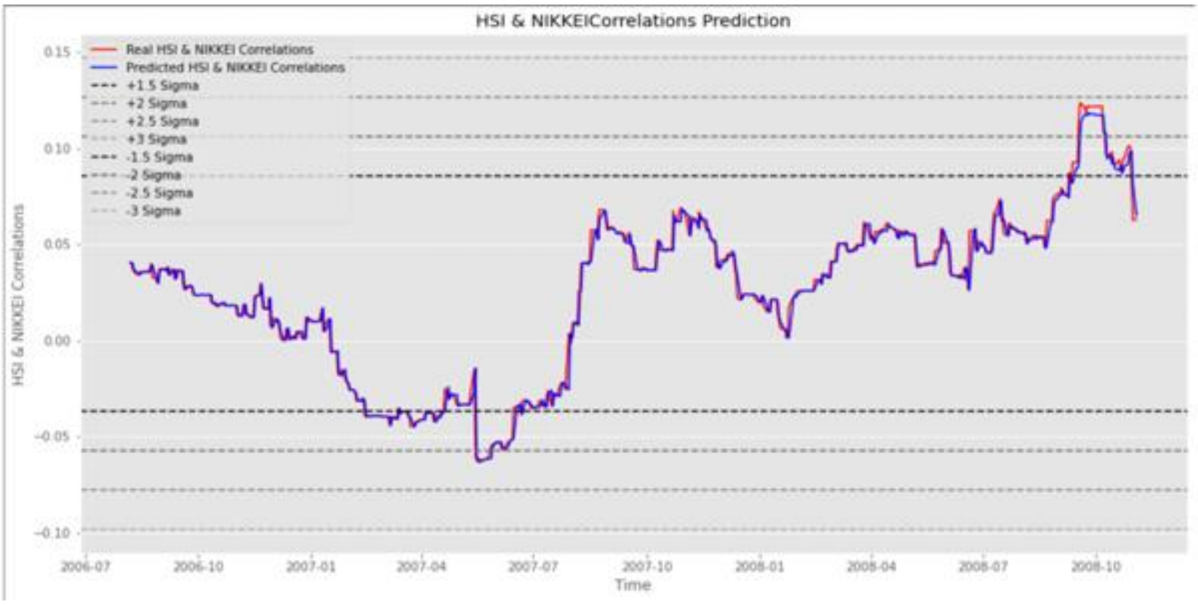
In the final section, a comprehensive experimental evaluation is conducted by applying the LSTM based early warning system during the GFC and Covid Crisis periods separately. In order to understand the precision and robustness of the proposed model with empirical evidence, we evaluate the LSTM model based on two stages. In the first stage, the early warning signals are identified based on the varying sigma levels in accordance with Sevim (2012) and Sevim et al. (2014), and in the second stage the accuracy of the signals are tested with RMSE and MSE error criteria. Two different LSTM model is created to improve the prediction capability for two distinct phases and to avoid the model learning from dissimilar paths. Therefore, the training process of the model covers two different periods for each crisis. The data from 03 July 1997 to 29 August 2006 is used for training to estimate the GFC period, while the period of 31 July 2009 and 10 March 2017 is used in the training process to predict Covid Crisis period. However, as we want to reveal potential spillovers effect before the actual crisis begins, our testing period starts before each crisis to identify potential transmission channels. Lastly, since the main focus of the study is the Asian markets, the early warning detection analysis is conducted based on Hong Kong stock market as it is identified as the centre of shock transmissions during the crisis periods based on the empirical results in the previous section.

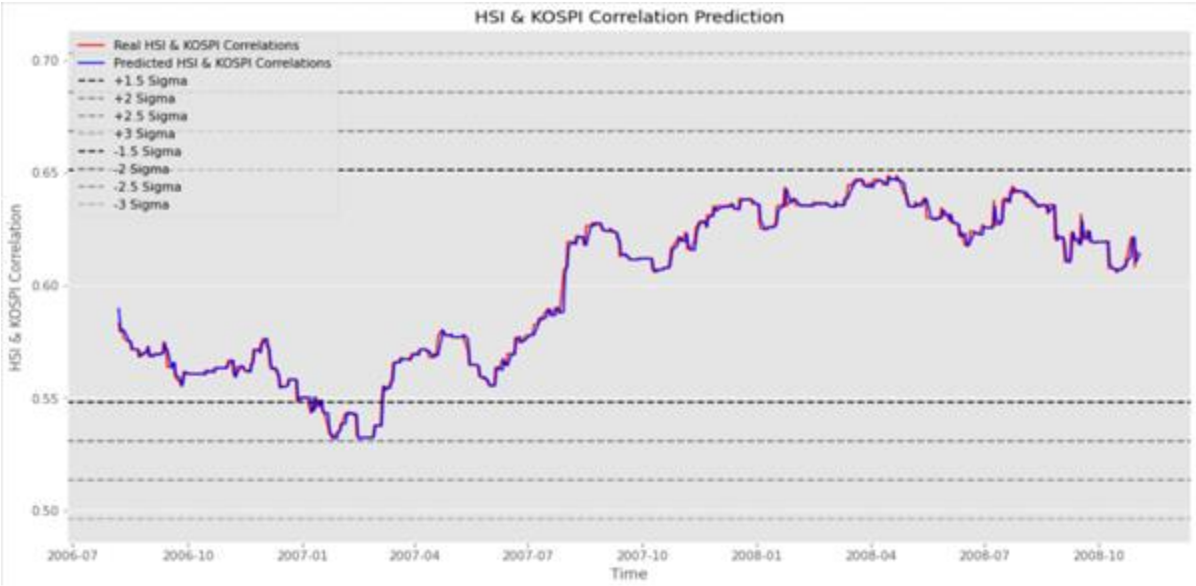
Figure 6.7 below depicts the graphical representation of EWS analysis for each pair of market with the Hong Kong's Hang Seng index during the GFC period. The red line shows the real correlation paths based on Dynamic Conditional Correlation method, while the blue line indicates the correlations based on LSTM predictions. The absolute value of sigma parameter ranges between 1.5 and 3 according to the empirical finance literature (Tarantino and Cernauskas, 2009) where it represents a heuristic value to improve the signal performance. The threshold values are based on the various sigma levels where absolute values of higher sigma levels indicate expected persistence of potential volatility spillovers. Based on obtained results, the proposed model is able to generate signals well before the actual contagion began, except for the Hong Kong and Japan case where the first signal was detected only a few months ago. The prediction capability of the LSTM for information transmission channels is also strong and close to the actual path in most cases, except for the later stages in Singapore and China. In some cases, such as USA and Japan, the model signals several times within the 12-month period before the crisis occurs which is highlighting the potential risk of financial contagion between markets.

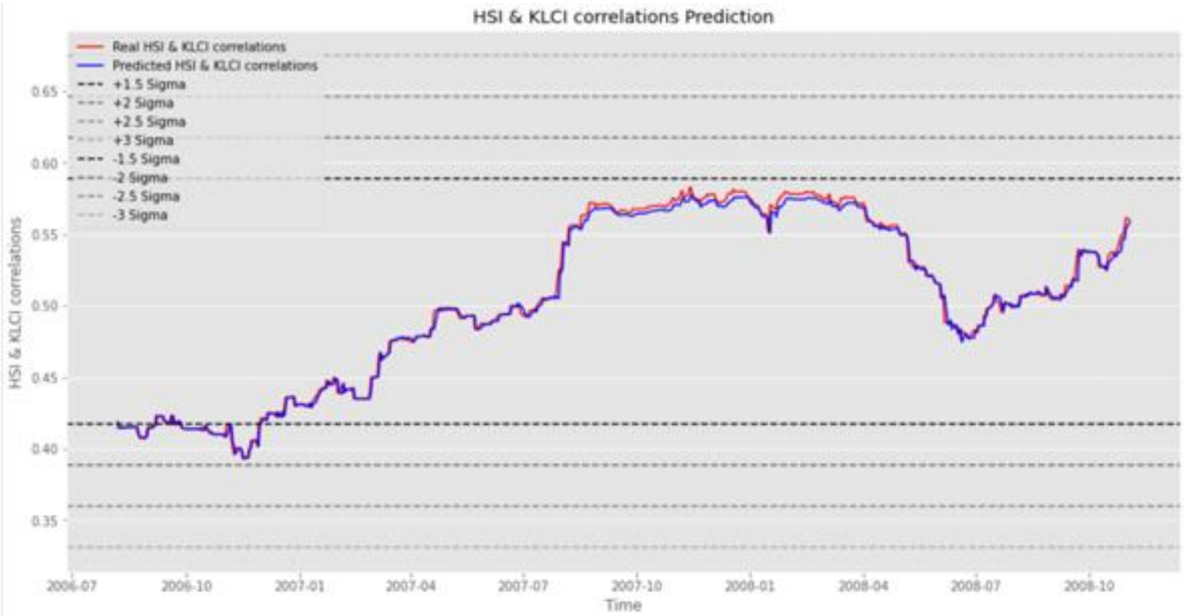
Figure 6.7: Prediction of correlations based on LSTM network for the GFC period

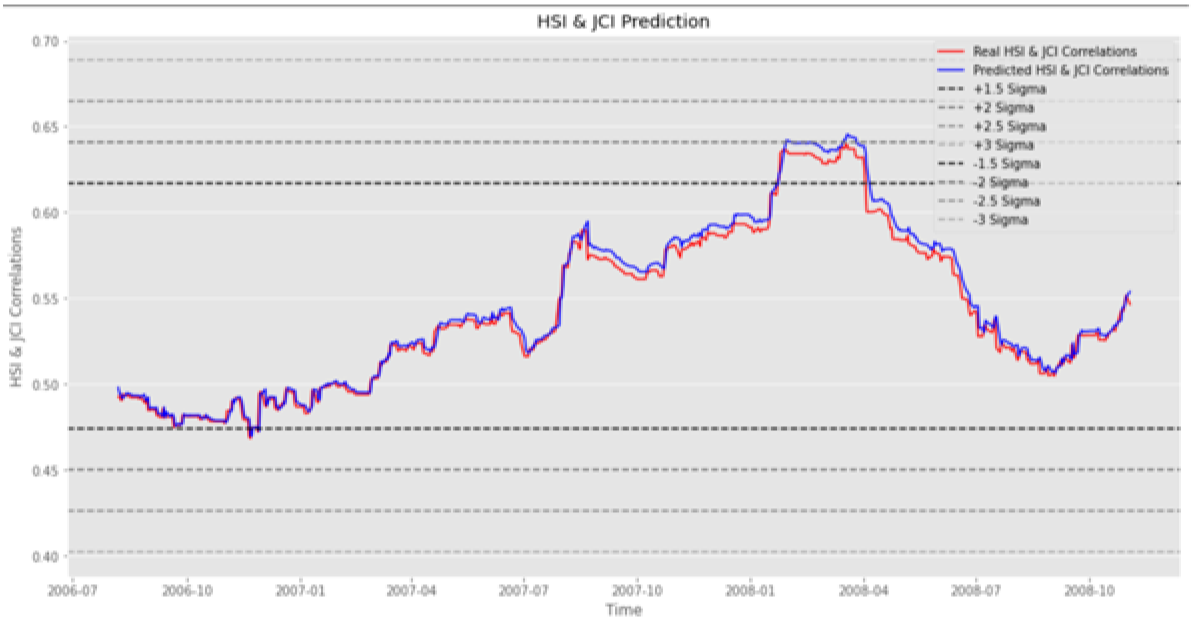

HSI & SSE Correlations Prediction
Real HSI & SSE Correlations
Predicted HSI & SSE Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & SSE Correlations
Time


HSI & PSE Correlations Prediction
Real HSI & PSE Correlations
Predicted HSI & PSE Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & PSE Correlations
Time


HSI & NIKKEICorrelations Prediction
Real HSI & NIKKEI Correlations
Predicted HSI & NIKKEI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & NIKKEI Correlations
Time


HSI & KOSPI Correlation Prediction
Real HSI & KOSPI Correlations
Predicted HSI & KOSPI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & KOSPI Correlation
0.70
0.65
0.60
0.55
0.50
2006-07
2006-10
2007-01
2007-04
2007-07
2007-10
2008-01
2008-04
2008-07
2008-10
Time

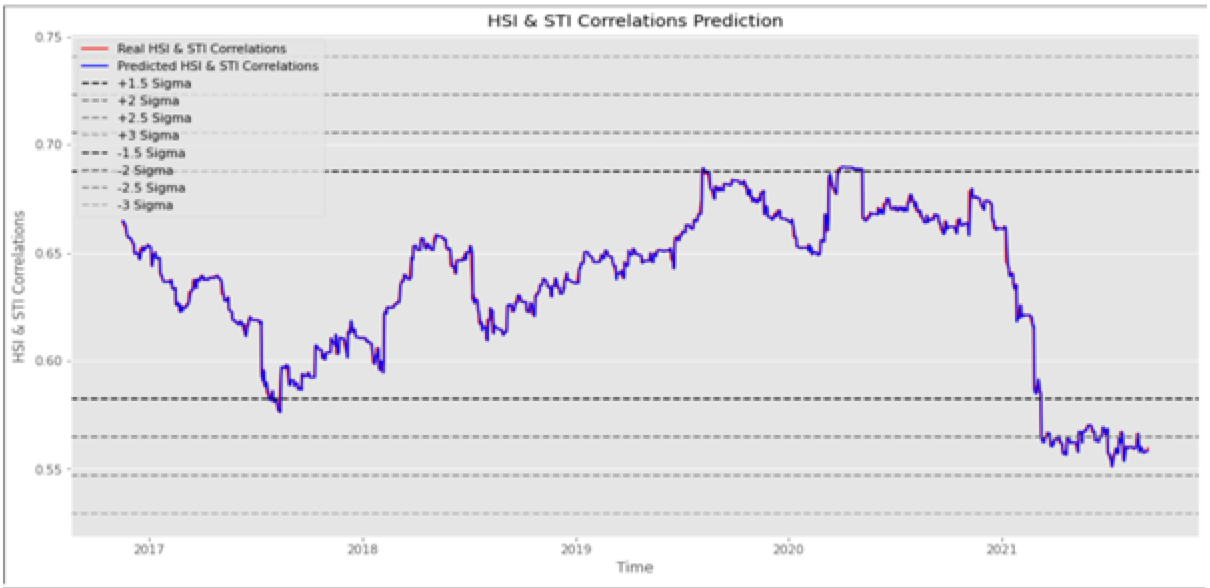

HSI & KLCI correlations Prediction
Real HSI & KLCI correlations
Predicted HSI & KLCI correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & KLCI correlations
0.65
0.60
0.55
0.50
0.45
0.40
0.35
2006-07
2006-10
2007-01
2007-04
2007-07
2007-10
2008-01
2008-04
2008-07
2008-10
Time

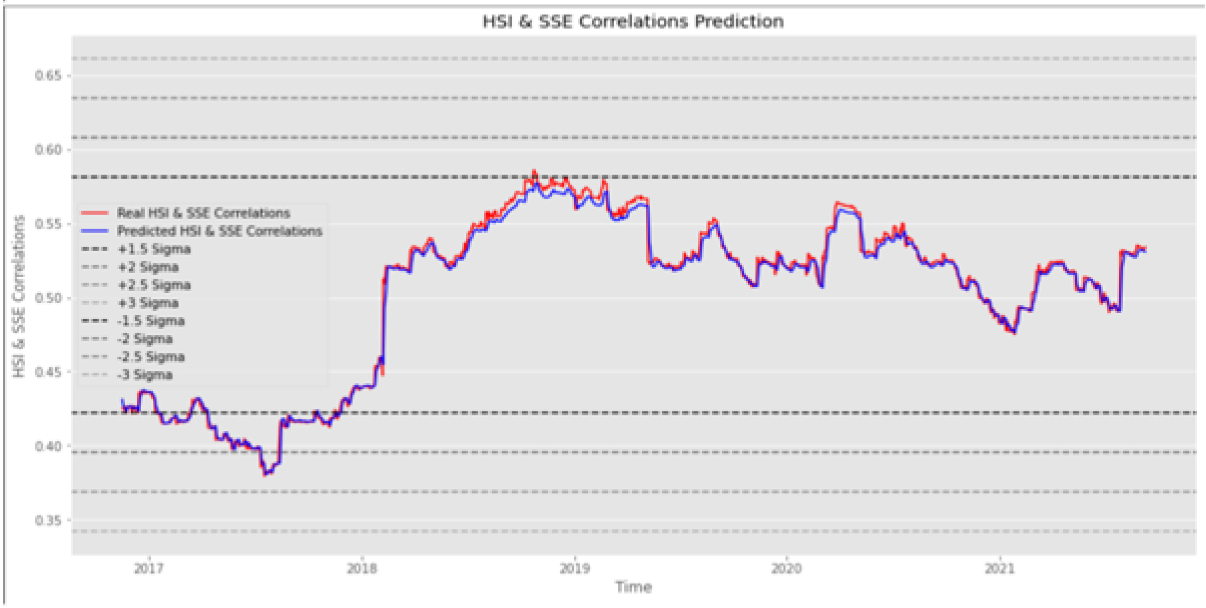

HSI & JCI Prediction
Real HSI & JCI Correlations
Predicted HSI & JCI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & JCI Correlations
0.70
0.65
0.60
0.55
0.50
0.45
0.40
2006-07
2006-10
2007-01
2007-04
2007-07
2007-10
2008-01
2008-04
2008-07
2008-10
Time

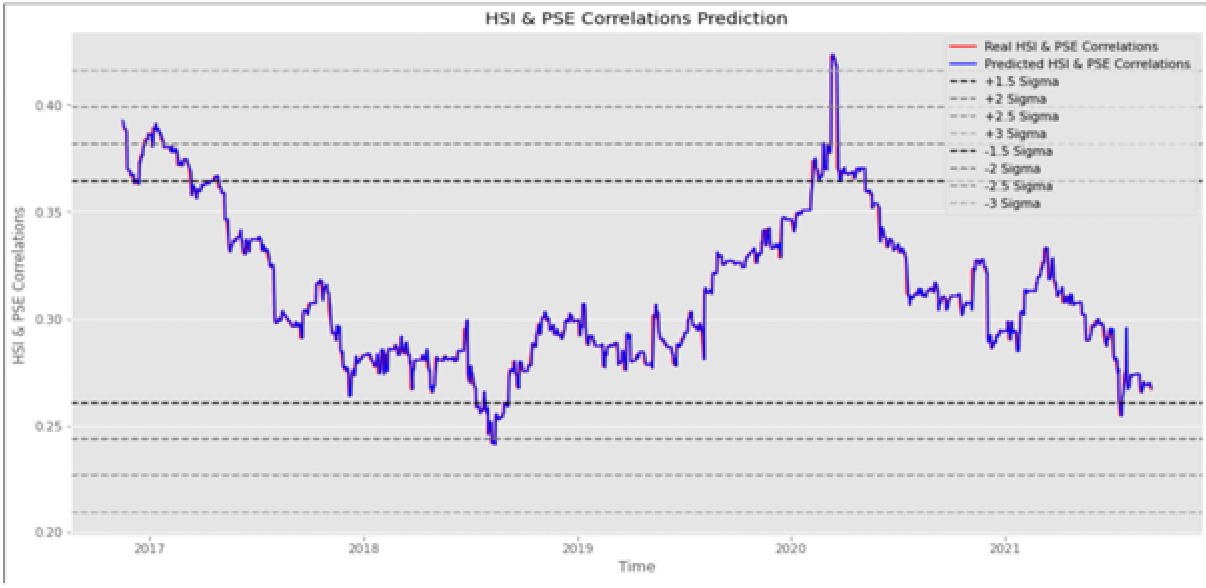
The picture is slightly different during the Covid Crisis period as presented in the Figure 6.8. The test results of the model are stronger compared to the GFC period, thus making the risk contagion predictions highly accurate. As we can see in the blue lines, the LSTM model predicted most of the significant correlations and triggered alert well before the crisis occurs. Although, we focus on the Covid Crisis, one thing that should also be mentioned here is the trade war between China and the US in 2018 which caused a rapid decline in major stock market indices all around the world in early 2018. Specifically, in February 2018, the S&P 500 wiped out $2.8 trillion, while global indices had lost more than $5 trillion. The huge jumps in risk contagion during that time can be seen in the figure below, especially in the correlations with China, Taiwan, Malaysia, and Indonesia. The proposed model was able to predict the unexpected shock transmission in advance and signalled potential contagion effect. In some cases, multiple signals were detected such as Hong Kong and Japan, and Hong Kong and Taiwan cases. When it comes to the Covid Crisis period, the proposed model identified financial distress among market pairs and signalled for the potential crisis event. However, the EWS system did not signal within the last 12-month period before the crisis occured, which might be due to the unidirectional volatility spillovers from China to Hong Kong as revealed by Ahmed et al. (2021). Apart from that, we obtain strong evidence supporting the high degree of efficacy and generalization capacity of the proposed deep learning system.

Figure 6.8: Prediction of correlations based on LSTM network for the Covid crisis period


HSI & TAIEX Correlations Prediction
Real HSI & TAIEX Correlations
Predicted HSI & TAIEX Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & TAIEX Correlations
Time

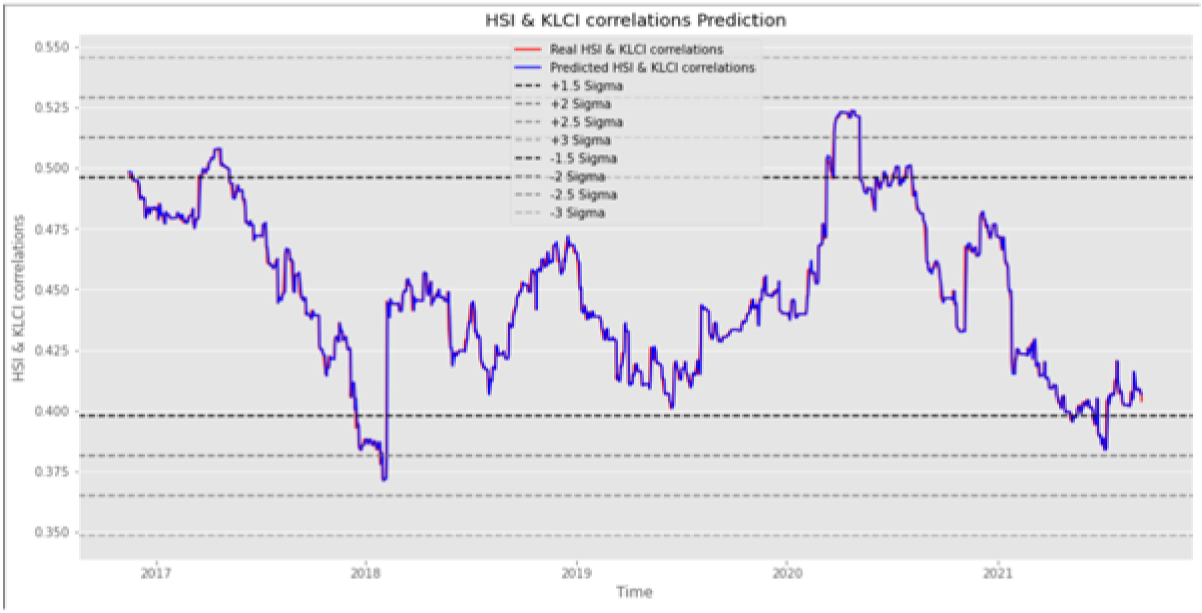

HSI & STI Correlations Prediction
Real HSI & STI Correlations
Predicted HSI & STI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & STI Correlations
Time


HSI & SSE Correlations Prediction
Real HSI & SSE Correlations
Predicted HSI & SSE Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & SSE Correlations
Time


HSI & PSE Correlations Prediction
Real HSI & PSE Correlations
Predicted HSI & PSE Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & PSE Correlations
Time


HSI & NIKKEICorrelations Prediction
Real HSI & NIKKEI Correlations
Predicted HSI & NIKKEI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & NIKKEI Correlations
Time


HSI & KOSPI Correlation Prediction
Real HSI & KOSPI Correlations
Predicted HSI & KOSPI Correlations
+1.5 Sigma
+2 Sigma
+2.5 Sigma
+3 Sigma
-1.5 Sigma
-2 Sigma
-2.5 Sigma
-3 Sigma
HSI & KOSPI Correlation
Time



Finally, the predictions are tested by using the RMSE and MSE criteria for each crisis period as shown in Table 6.21. Based on the given empirical results, it can be clearly said that the proposed model provides extreme accuracy regarding volatility contagion effects between selected pairs. Specifically, the estimated correlations with Korea and the Philippines stock markets have smallest values for MSE criterion during the GFC period, followed by Malaysia with 0.7%. On the other hand, the prediction results are more superior for China and Korea during the Covid Crisis period based on the MSE loss function. Moreover, the highest error rate among all selected markets is found in the correlation series with Taiwan Stock Market based on MSE in both periods. Although the general failure rate is slightly higher in RMSE series, similar results are found. When two crisis periods are compared in terms of model accuracy, the results draw a more complicated framework as it is hard to evaluate the clear superiority. It should be noted that the accuracy of the predictions is highly dependent on the architecture of the deep learning model and training process. According to the train scores, there are no distinct differences for the predicted series except for Indonesia during the GFC period and Taiwan during the Covid Crisis period. In these two series, the model provides the largest error rates which may lead a bias for the testing period. Yet, the test scores are less affected, confirming the predictive accuracy of the proposed model.

Table 6.21: Comparison of accuracy for prediction results

	Train Score		Test Score			Train Score		Test Score	
GFC Period	**RMSE**	**MSE**	**RMSE**	**MSE**	**Covid Crisis Period**	**RMSE**	**MSE**	**RMSE**	**MSE**
HSI&SP500	0.036	0.013	0.022	0.016	**HSI&SP500**	0.017	0.009	0.011	0.009
HSI&TAIEX	0.07	0.051	0.084	0.057	**HSI&TAIEX**	0.082	0.040	0.064	0.038
HSI&STI	0.021	0.011	0.016	0.010	**HSI&STI**	0.062	0.038	0.048	0.026
HSI&SSE	0.057	0.036	0.045	0.037	**HSI&SSE**	0.011	0.007	0.009	0.005
HSI&PSE	0.015	0.007	0.012	0.006	**HSI&PSE**	0.026	0.014	0.016	0.014
HSI&NIKKEI	0.025	0.014	0.016	0.014	**HSI&NIKKEI**	0.078	0.045	0.055	0.010
HSI&KOSPI	0.012	0.006	0.009	0.004	**HSI&KOSPI**	0.013	0.006	0.010	0.008
HSI&KLCI	0.013	0.007	0.009	0.007	**HSI&KLCI**	0.069	0.038	0.049	0.028
HSI&JCI	0.089	0.046	0.069	0.038	**HSI&JCI**	0.057	0.023	0.041	0.033
HSI&SET	0.021	0.017	0.018	0.011	**HSI&SET**	0.067	0.056	0.049	0.015

6.5 Conclusion and Future Work

Increased incidence of financial crises in the last few decades has reignited interest in the role of financial linkages and crisis prediction models. Moreover, the pace of globalisation in the international financial markets has raised the question of whether interconnectedness between markets, a source for volatility transmission and possible contagion risk, can provide an early warning signal for crises. This chapter examine volatility transmission channels across ten Asian markets and the US market for three different crisis periods and two calm periods by applying DCC, GARCH-BEKK, and Diebold-Yilmaz spillover index. In addition, we developed an early warning system to predict financial crises using the LSTM algorithm based on deep learning approach. The empirical results indicate that the climb in external shock transmissions has long lasting impacts in domestic markets due to contagion effect during the crisis periods, leading a more permanent surge in volatility spillovers across markets. Compared to the calm periods, all selected equity markets exposed intensified volatility spillovers during the crisis periods, confirming the findings of Suleman et al. (2017). However, it is revealed that the degree of volatility spillovers among advanced and emerging equity markets is less compared to the pure spillovers between advanced markets or emerging markets, offering window of opportunity for international market participants in terms of portfolio diversification and risk management. Thus, the outcome of the present study is not only relevant to academics, but also to a wide range of investors. On the other hand, the proposed EWS system is able to identify intensifying volatility transfers and generate signals within the last 12-month period before the crisis occurs, suggesting important implications for policy makers since they need to take economic decisions during the crises times to prevent irreversible impacts on the broad economy due to the financial contagion. Of equal importance are the implications for risk and asset management practitioners, due to the fact that diversification advantages may continue to exist in turbulent periods.

The contribution of this paper to the field of empirical finance and existing literature is three-fold. First and foremost, this study explores all key relevant crises periods in the last three decades, including the recent Covid Crisis where there are still huge gaps due to the ongoing impacts. Therefore, the present study contributes to the literature by providing comparison of interdependencies and changing intensity of contagion channels between markets for different periods. Second, the magnitudes and directions of volatility spillovers are verified for each selected calm and turbulent episodes, which offer key information for investors and financial regulators in terms of diversification benefits and macroeconomic stability. Third, instead of following earlier studies, we developed a novel EWS system and successfully predicted correlations and transmission channels with high accuracy, providing supplementary information that contributes the decision-making process of practitioners, as well as offering indicative evidence that facilitate the assessment of market vulnerability to policy-makers. The effectiveness and reliability of the LSTM model is also confirmed with two different loss function to avoid false signals. Finally, the findings of the present study reveal that the results of the estimations regarding volatility spillovers are sensitive to the selection of the empirical model used, which is in line with the existing studies about ambiguity on the direction of volatility spillovers across markets. Thus, this study recommends that different range of transmission models should be included to minimize possible biases in the results.

In a nutshell, the framework introduced here improves our ability to empirically evaluate as well as quantify volatility spillover and contagion channels in terms of financial market perspective. Furthermore, the proposed deep learning method in the present chapter, allows us to identify and predict financial contagion risk across selected countries. Consequently, the model provides significant implications, not only for government related institutions, but also for market participants in terms of possible contagion risks between selected markets. Thus, through the provided analysis in this chapter, policy makers can concentrate volatility transmission channels and make use of the model to maintain the financial stability, while market participants can benefit for managing their portfolio allocations and limit their risk exposure. Although the present study adopts wide range of Asian markets with a large dataset, the methodology here can be applied to EMEA region or different financial instruments, such as energy, bonds, currencies or cryptos after appropriate modifications. Moreover, a further direction can be drawn by extending the parameters and propose an adaptive or coactive network-based hybrid models. The value of such novel developments remains to be examined in future research endeavours.

CHAPTER 7

Concluding Remarks

Volatility and movements are important components of market risk analysis and play a key role in many financial activities, such as risk management, asset pricing, hedging and diversification strategies. Financial markets in emerging and developed countries have exposure to different types of domestic, regional, and external shocks. Recent financial crises such as the Asian financial crisis, Global financial crisis and Covid-19 financial crisis has triggered the implementation of a comprehensive stock market volatility analysis in order to accurately and effectively model volatility risk factor in the financial markets. The present thesis draws motivation from the ongoing volatility forecasting debate and inconclusive results on the empirical literature concerning the impact of local and international shocks on volatility of Asian stock markets (see, for instance, Park and Lee, 2011; Joshi, 2012; Chow, 2017). It takes a deeper look at the sources of the increasing volatility and correlation dynamics across the Asian markets.

The first essay (Chapter 3) has demonstrated an in-depth analysis on the characteristics of volatility phenomenon in Asian stock markets. To the best of my knowledge, there has been no detail investigation on stylized facts of volatility, such as leverage effects, volatility persistence and volatility clustering in emerging and developed markets of Asia focusing on three different frequencies with 24 years of data. This is the gap in the empirical finance literature that we have sought to address in the first essay. The results indicate that the applied models were able to remove heteroscedasticity successfully in the return series. To identify the best-fitted model among the selected GARCH applications, Akaike information criteria (AIC), Schwarz information criteria (SIC) and Hannah Quinn information criteria (HQIC) are used as well as comparison of log likelihood values. Although asymmetric GARCH models outperform in daily and weekly return series according to the criteria mentioned above, symmetric GARCH models would seem to outperform in monthly return series. The findings of the study also showed that there is strong persistence of volatility, which means that the impact of shocks continue for a long period on return series. Lastly, the chapter reveal that examining volatility with different frequencies provides different results which may have implications for making decisions, and it concludes that different frequencies have their own structure and characteristics with one common point that higher frequency data is more volatile than lower frequency data, suggesting market participants should be aware of the structure of volatility in these indices at different time horizons.

The second essay (Chapter 4) has concentrated on the question of: If volatility is forecastable, which econometric model will provide the best forecasts? To address this question, the forecast ability of a number of representative econometric models belonging to two main model groups are compared based on recursive and rolling window methods by using three different frequencies. First, we find that GARCH type models can appropriately adopt to the volatility behaviour of Asian stock indices and provide satisfactory degree of forecast accuracy in all selected frequencies. Superiority of asymmetric models are more evident for higher frequency of data, while symmetric models tend to outperform in lower frequencies. Second, given the level of risk associated in investment in stock markets, day traders, investors, financial analysts, and empirical finance professionals should consider alternative error distributions while specifying predictive volatility model, as less contributing error distributions implies incorrect specification, which could lead to loss of efficiency in the model. Also, investors should not ignore the impact of news while forming expectations on investments. Finally, the obtained results report that frequency of the data and choice of forecast method have strong effect on performance of the models, therefore depending on the investment perspective and risk sensitivity, correct method and frequency should be applied.

The third essay (Chapter 5) is motivated by the continuing search on identifying key methods for improving the accuracy of volatility forecasts. The periods of economic turmoil, such as the 2008 global recession, and the growing transformation of financial markets with the new technologies show the necessity of more advanced solutions and improved volatility models that can adapt to changing market environments and exploit nonlinearities in the data. In order to address this gap, the chapter evaluated wide range of Machine Learning methods to predict the volatility of ten Asian benchmark stock market indices. The empirical results of the ANN models are promising. Out-of-sample forecast evaluation results show that ANN models are superior in each index compared to the GARCH and EGARCH models. Notably, the results show that neural network prediction models exhibit improved forecasting accuracy across both statistical and economic based metrics and offer new insights for market participants, academics, and policymakers. The contribution of the chapter to the field of empirical finance and existing literature is three-fold. First and foremost, this study explores all key relevant machine learning models to address the problem of financial volatility forecasting. Previous studies tend to evaluate small sets of Neural Network methods. Using a wider range of ANN architectures has different advantages. For example, in stock market prediction exercises, the recurrent ANNs are recommended due to their memory component features that increase prediction accuracy. Second, comprehensive performance measures for model evaluation are utilized, namely, both a range of statistical measures (RMSE, MAE, MAPE, MSE and QLIKE) and economic based ones (VaR and ES). Third, a wide range of Asian markets are studied in order to have an in-depth examination for an extended set of volatility models across markets that are less studied.

The fourth essay (Chapter 6) is motivated by the question of whether interconnectedness between markets, a source for volatility transmission and possible contagion risk, can provide an early warning signal for crises. In this regard, the Long Short-Term Memory (LSTM) algorithm is combined with DCC model to obtain an accurate system for estimating periods of contagion among Asian and the US markets during crisis events in the financial markets. To the best of our knowledge, the LSTM model has not been covered in the literature to develop EWS based correlations and transmission channels among developed and emerging stock markets. Moreover, the Dynamic Conditional Correlation (DCC) method is integrated for the first time with an advanced deep learning algorithm to examine the impact of foreign information in a domestic market during the major crises. In addition, we examine volatility transmission channels across ten Asian markets and the US market for three different crisis periods and two calm periods by applying DCC, GARCH-BEKK, and Diebold-Yilmaz spillover index.

The empirical results report that the climb in external shock transmissions has long lasting impacts in domestic markets due to contagion effect during the crisis periods, leading a more permanent surge in volatility spillovers across markets. Compared to the calm periods, all selected equity markets exposed intensified volatility spillovers during the crisis periods. However, it is revealed that the degree of volatility spillovers among advanced and emerging equity markets is less compared to the pure spillovers between advanced markets or emerging markets, offering window of opportunity for international market participants in terms of portfolio diversification and risk management. On the other hand, the experimental analysis of Long short-term memory (LSTM) network finds evidence of contagion risk across selected markets. The proposed model successfully verified bursts in volatility spillovers and generate signals with high accuracy before the 12-month period of crisis, providing supplementary information that contributes the decision-making process of practitioners, as well as offering indicative evidence that facilitate the assessment of market vulnerability to policymakers.

The present thesis uncovers a wide range of interesting points regarding to the volatility phenomenon in Asian financial markets; in addition, the findings of this empirical work offer key information for investors and financial regulators in terms of diversification benefits and macroeconomic stability. Although the present research employed well-known and reliable methodologies, there are further areas that need to be considered. These research areas can, potentially, be addressed by future researchers. The data availability is one of the main problems for emerging markets of Asia, especially for the higher frequencies. Future research could extend on this thesis by including high frequency observations with the integration of more diverse set of ANN architectures. For example, according to Partaourides and Chatzis (2017), further regularizations methods may increase the capacity of the machine learning systems. In addition, hidden layers can be extended over two, more data frequencies can be added, and alternative input variables and activation functions can be studied. Furthermore, the methodology in the current thesis can be applied to EMEA region or different financial instruments, such as energy, bonds, currencies or cryptos after appropriate modifications. Finally, a further direction can be drawn by extending the parameters and propose an adaptive or coactive network-based hybrid models for an EWS system. The value of such novel developments remains to be examined in future research endeavours.

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APPENDICES

APPENDIX A

Table A.1: Estimation result of GARCH family models for HANG SENG Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.055965*	0.072595*	0.074216*
	Crisis			-0.016285
Variance equation	*ω (Constant)*	0.010975*[2.760911]	0.013071*[2.881559]	0.011582*[3.878812]
	α (ARCH effect)	0.050684*[7.023718]	0.064617*[7.550792]	0.057690*[10.33047]
	β (GARCH effect)	0.945017*[126.7177]	0.930564*[103.6672]	0.938032*[161.7515]
	α+β	0.995701	0.995181	0.995722
	Log likelihood	-4870.989	-4707.121	-9595.263
	Durbin Watson	2.035064	2.035652	1.990544
	T-distribution	6.534521(0.0000)	7.826514(0.0000)	7.082900(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.793342	1.246141	0.247309
	Prob.	0.1273	0.2644	0.619

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.036216***	0.050753*	0.063532*
	Crisis			-0.03466
Variance equation	*ω (Constant)*	-0.08226*[-6.763900]	-0.100397*[-8.346282]	-0.089950*[-10.71725]
	α (ARCH effect)	0.116217*[7.222597]	0.138079*[8.463073]	0.124954*[11.08098]
	β (GARCH effect)	0.989289*[375.8781]	0.987252*[324.8990]	0.988867*[510.0803]
	γ (Leverage effect)	-0.062873*[-6.305015]	-0.06348*[-6.231221]	-0.061484*[-8.996196]
	α+β	0.989289	0.987252	0.988867
	Log likelihood	-4847.286	-4691.605	-9555.287
	Durbin Watson	2.044391	2.03715	1.991666
	T-distribution	7.211917(0.0000)	8.212001(0.0000)	7.606188(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.460061	1.272342	0.864298
	Prob.	0.7651	0.2594	0.3525

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.039071***	0.052280*	0.065875*
	Crisis			-0.034552
Variance equation	*ω (Constant)*	0.018945*[3.984034]	0.018964*[3.923465]	0.017609*[5.413462]
	α (ARCH effect)	0.015343***[1.740790]	0.026803*[2.844931]	0.021426*[3.409322]
	β (GARCH effect)	0.937757*[104.6690]	0.923792*[98.55279]	0.932587*[147.8284]
	γ (Leverage effect)	0.076409*[5.878911]	0.077171*[5.451434]	0.073611*[8.031860]
	α+β	0.9913045	0.9891805	0.990606
	Log likelihood	-4852.805	-4692.003	-9562.629
	Durbin Watson	2.047618	2.037071	1.991573
	T-distribution	7.151477(0.0000)	8.429835(0.0000)	7.652193(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.34401	2.298525	2.464241
	Prob.	0.8483	0.1296	0.1165

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.0501	0.065974	0.065347
	Crisis			-0.015911
	λ (risk premium)	0.005226	0.006293	0.007987
Variance equation	*ω (Constant)*	0.011016*[2.762916]	0.013130*[2.882639]	0.011644*[3.883115]
	α (ARCH effect)	0.050791*[6.996961]	0.064736*[7.536157]	0.057826*[10.30235]
	β (GARCH effect)	0.944893*[126.0442]	0.930413*[103.2123]	0.937866*[160.8979]
	α+β	0.995684	0.995149	0.995692
	Log likelihood	-4870.984	-4707.115	-9595.24
	Durbin Watson	2.035117	2.035389	1.990398
	T-distribution	6.539245(0.0000)	7.831325(0.0000)	7.089201(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.778988	1.27201	0.267621
	Prob.	0.1302	0.2595	0.6049

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.035847***	0.049561**	0.063971*
	Crisis			-0.037301
Variance equation	*ω (Constant)*	0.015444*[4.113065]	0.019768*[4.461726]	0.016614*[5.963271]
	α (ARCH effect)	0.059089*[5.857455]	0.072231*[7.264372]	0.064743*[9.477288]
	β (GARCH effect)	0.942441*[115.9341]	0.926674*[104.6422]	0.936472*[160.5369]
	γ (Leverage effect)	0.556930*[4.693368]	0.469603*[5.125847]	0.506202*[7.044442]
	δ (Power Parameter)	1.164146*[5.506020]	1.230886*[5.131698]	1.169995*[7.530305]
	α+β	1.00153	0.998905	1.001215
	Log likelihood	-4846.661	-4688.287	-9551.978
	Durbin Watson	2.045407	2.037209	1.991704
	T-distribution	7.287842(0.0000)	8.460406(0.0000)	7.745800(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.367239	1.703872	1.141596
	Prob.	0.8321	0.1919	0.2853

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.2: Estimation result of GARCH family models for SSE Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.012595	0.060688*	0.011566
	Crisis			0.046079
Variance equation	*ω (Constant)*	0.115520*[4.742173]	0.005537**[2.011221]	0.021960*4.486385]
	α (ARCH effect)	0.132883*[7.023294]	0.058227*[7.101900]	0.084449*[10.32202]
	β (GARCH effect)	0.840028*[46.90393]	0.944511*[138.9417]	0.915927*[136.6417]
	α+β	0.972911	1.002738	1.000376
	Log likelihood	-5045.378	-4867.402	-9945.953
	Durbin Watson	1.923079	1.992277	1.956415
	T-distribution	4.006128(0.0000)	4.792550(0.0000)	4.275795(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.003326	0.922231	0.066722
	Prob.	0.954	0.4776	0.7962

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.012007	0.058175*	0.007582
	Crisis			0.046954
Variance equation	*ω (Constant)*	-0.148583*[-8.968930]	-0.094174*[-8.361525]	-0.123862*[-13.19463]
	α (ARCH effect)	0.261671*[10.00061]	0.134717*[8.303295]	0.188165*[13.30699]
	β (GARCH effect)	0.957875*[109.0531]	0.995127*[475.2061]	0.986137*[359.1308]
	γ (Leverage effect)	-0.035124**[-2.248112]	-0.005586[-0.625612]	-0.023318*[-2.857053]
	α+β	0.957875	0.995127	0.986137
	Log likelihood	-5032.688	-4863.995	-9922.566
	Durbin Watson	1.927993	1.977675	1.952914
	T-distribution	4.115033(0.0000)	4.859826(0.0000)	4.385534(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.020745	1.384543	0.689746
	Prob.	0.8855	0.2169	0.4063

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.006677	0.060804*	0.006995
	Crisis			0.047323
Variance equation	*ω (Constant)*	0.107265*[4.629842]	0.005510**[2.005270]	0.022675*[4.547392]
	α (ARCH effect)	0.108153*[5.431833]	0.058537*[5.321701]	0.071273*[7.503200]
	β (GARCH effect)	0.842122*[48.58464]	0.944612*[138.5053]	0.913639*[135.7159]
	γ (Leverage effect)	0.053970**[1.979040]	-0.000749[-0.062837]	0.030100**[2.532581]
	α+β	0.97726	1.0027745	0.999962
	Log likelihood	-5043.2	-4867.4	-9942.67
	Durbin Watson	1.927151	1.99202	1.960501
	T-distribution	4.027441(0.0000)	4.793337(0.0000)	4.288279(0.0000)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.010568	0.927618	0.073614
	Prob.	0.9181	0.4737	0.7862

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.161682***	-0.003932	-0.100379**
	Crisis			0.061582**
	λ (risk premium)	0.124437**	0.061639	0.083489*
Variance equation	*ω (Constant)*	0.119317*[4.775274]	0.006040**[2.088585]	0.023374*[4.570449]
	α (ARCH effect)	0.132322*[7.018201]	0.058902*[7.055413]	0.084829*[10.27424]
	β (GARCH effect)	0.839018*[46.55543]	0.943709*[136.6018]	0.915029*[134.6877]
	α+β	0.97134	1.002611	0.999858
	Log likelihood	-5042.761	-4866.109	-9942.23
	Durbin Watson	1.915581	1.9838	1.94797
	T-distribution	3.983963(0.0000)	4.739399(0.0000)	4.242881(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.000335	0.976426	0.040374
	Prob.	0.9854	0.4394	0.8408

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.011224	0.059427*	0.008048
	Crisis			0.047115
Variance equation	*ω (Constant)*	0.061870*[3.914741]	0.005847**[2.158346]	0.016232*[4.257035]
	α (ARCH effect)	0.139949*[8.642689]	0.070562*[8.006505]	0.096956*[12.31160]
	β (GARCH effect)	0.865505*[56.17628]	0.945105*[140.8883]	0.920956*[144.7120]
	γ (Leverage effect)	0.121454**[1.996417]	0.029601[0.442499]	0.121152*[2.671521]
	δ (Power Parameter)	1.149303*[5.966051]	1.160336*[4.219168]	1.012809*[7.481873]
	α+β	1.005454	1.015667	1.017912
	Log likelihood	-5036.568	-4874.052	-9926.584
	Durbin Watson	1.93037	1.980734	1.95276
	T-distribution	4.081169(0.0000)	4.857125(0.0000)	4.352325(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.517755	0.209428	2.134121
	Prob.	0.4719	0.6473	0.1184

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.3: Estimation result of GARCH family models for JCI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.065128*	0.090709*	0.087304*
	Crisis			0.007645
Variance equation	*ω (Constant)*	0.064320*[4.503415]	0.023557*[3.957587]	0.031922*[5.711359]
	α (ARCH effect)	0.146420*[7.843741]	0.112323*[8.049121]	0.124770*[11.37358]
	β (GARCH effect)	0.839532*[49.88738]	0.880203*[67.67546]	0.869142*[89.65151]
	α+β	0.985952	0.992526	0.993912
	Log likelihood	-4859.069	-4215.712	-9057.079
	Durbin Watson	1.96249	1.836217	1.900872
	T-distribution	5.007519(0.0000)	5.384919(0.0000)	5.110864(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.743252	0.934246	6.589232
	Prob.	0.1868	0.3338	0.3605

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.045535**	0.068641*	0.075645*
	Crisis			-0.003232
Variance equation	*ω (Constant)*	-0.186561*[-10.14953]	-0.154703*[-9.358309]	-0.171274*[-14.22376]
	α (ARCH effect)	0.286799*[10.27693]	0.211297*[9.229364]	0.245211*[14.07861]
	β (GARCH effect)	0.963979*[131.5123]	0.977231*[202.0990]	0.974965*[254.3363]
	γ (Leverage effect)	-0.060956*[-3.945009]	-0.079876*[-5.421294]	-0.060150*[-6.126354]
	α+β	0.963979	0.977231	0.974965
	Log likelihood	-4855.634	-4197.926	-9039.469
	Durbin Watson	1.963201	1.855408	1.903117
	T-distribution	5.027530(0.0000)	5.664209(0.0000)	5.202852(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.421642	0.133272	6.076828
	Prob.	0.2415	0.7151	0.4146

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.050418*	0.075948*	0.079935*
	Crisis			-0.002499
Variance equation	*ω (Constant)*	0.074989*[4.825393]	0.026017*[4.467168]	0.036537*[6.195329]
	α (ARCH effect)	0.102844*[5.327423]	0.055333*[3.493017]	0.085419*[7.073614]
	β (GARCH effect)	0.829546*[46.21514]	0.882250*[68.77519]	0.864587*[86.27279]
	γ (Leverage effect)	0.098280*[3.518698]	0.096204*[4.341853]	0.078200*[4.904294]
	α+β	0.98153	0.985685	0.989106
	Log likelihood	-4851.348	-4204.885	-9043.545
	Durbin Watson	1.968469	1.854555	1.911533
	T-distribution	5.083957(0.0000)	5.597022(0.0000)	5.226001(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.347167	0.184044	4.388398

	Prob.	0.2459	0.668	0.6243

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.078407	-0.016216	0.049649
	Crisis			0.014864
	λ (risk premium)	-0.011214	0.119328**	0.032987
Variance equation	*ω (Constant)*	0.064265*[4.499734]	0.026194*[4.099031]	0.032199*[5.725776]
	α (ARCH effect)	0.146054*[7.835335]	0.119690*[8.065022]	0.125980*[11.38089]
	β (GARCH effect)	0.839860*[49.97069]	0.872045*[63.63982]	0.868003*[88.93287]
	α+β	0.985914	0.991735	0.993983
	Log likelihood	-4859.045	-4212.712	-9056.613
	Durbin Watson	1.96242	1.815191	1.898202
	T-distribution	5.003040(0.0000)	5.339238(0.0000)	5.111267(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	1.782012	0.860877	6.468652
	Prob.	0.182	0.3536	0.3728

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.049992**	0.068663*	0.078575*
	Crisis			-0.004216
Variance equation	*ω (Constant)*	0.071519*[4.371323]	0.026075*[4.511316]	0.033564*[6.093897]
	α (ARCH effect)	0.151004*[7.130980]	0.118155*[8.854685]	0.132132*[11.69224]
	β (GARCH effect)	0.832902*[44.95359]	0.889021*[72.12884]	0.872474*[89.96239]
	γ (Leverage effect)	0.173254*[3.613072]	0.389278[4.375390]	0.208218*[5.126986]
	δ (Power Parameter)	1.867080*[5.871402]	1.074357*[6.066218]	1.468024*[8.722499]
	α+β	0.983906	1.007176	1.004606
	Log likelihood	-4851.242	-4199.187	-9039.926
	Durbin Watson	1.967608	1.856561	1.908021
	T-distribution	5.087764(0.0000)	5.660038(0.0000)	5.239055(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	1.538062	0.166129	5.386065
	Prob.	0.215	0.6836	0.4953

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.4: Estimation result of GARCH family models for KLCI Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	0.013893	0.031964*	0.028820**
Mean equation	*Crisis*			-0.002653
	ω (Constant)	0.012166*[3.642892]	0.008780*[4.139428]	0.007901*[5.331283]
	α (ARCH effect)	0.131632*[8.658922]	0.121700*[8.309031]	0.123133*[12.20263]
	β (GARCH effect)	0.872196*[74.54265]	0.866181*[60.22146]	0.876560*[104.6628]
Variance equation	*α+β*	1.003828	0.987881	0.999693
	Log likelihood	-4064.239	-2601.564	-6668.121
	Durbin Watson	2.172917	1.957022	2.149217
	T-distribution	5.166595(0.0000)	6.418204(0.0000)	5.683711(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.985706	0.515461	4.947137
	Prob.	0.4249	0.6716	0.4224

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	0.002251	0.024963*	0.022183***
Mean equation	*Crisis*			-0.006629
	ω (Constant)	-0.164526*[-10.60991]	-0.174917*[-9.355076]	-0.161879*[-14.59355]
	α (ARCH effect)	0.221248*[10.31248]	0.205957*[9.271227]	0.207504*[14.20661]
	β (GARCH effect)	0.987368*[323.5488]	0.980849*[209.0225]	0.987996*[472.7331]
	γ (Leverage effect)	-0.061505*[-4.899205]	-0.059444*[-4.644014]	-0.058247*[-6.766684]
Variance equation	*α+β*	0.987368	0.980849	0.987996
	Log likelihood	-4041.891	-2593.474	-6638.964
	Durbin Watson	2.16989	1.960441	2.147724
	T-distribution	5.296138(0.0000)	6.612265(0.0000)	5.858310(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.880422	1.774037	14.53948
	Prob.	0.0944	0.1499	0.0125

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	0.002161	0.025839*	0.024996**
Mean equation	*Crisis*			-0.009558
	ω (Constant)	0.011707*[3.838816]	0.009103*[4.284597]	0.007995*[5.577316]
	α (ARCH effect)	0.073648*[5.273966]	0.086940*[4.818792]	0.078769*[7.315338]
	β (GARCH effect)	0.880096*[80.58228]	0.865204*[59.19461]	0.879247*[107.2008]
	γ (Leverage effect)	0.101036*[4.578134]	0.067941*[3.065591]	0.081625*[5.479654]
Variance equation	*α+β*	1.004262	0.9861145	0.9988285
	Log likelihood	-4051.535	-2596.576	-6651.659
	Durbin Watson	2.17724	1.965137	2.154066
	T-distribution	5.292361(0.0000)	6.617355(0.0000)	5.838525(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.920461	0.288208	4.623786
	Prob.	0.4665	0.834	0.4635

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.00571	-0.040519	-0.002884
	Crisis			0.005604
	λ (risk premium)	0.010997	0.142304*	0.045165
Variance equation	*ω (Constant)*	0.012206*[3.647785]	0.008382*[4.084794]	0.007838*[5.313065]
	α (ARCH effect)	0.131970*[8.665145]	0.121029*[8.354234]	0.123618*[12.23245]
	β (GARCH effect)	0.871856*[74.40556]	0.867865*[61.51524]	0.876245*[104.6095]
	α+β	1.003826	0.988894	0.999863
	Log likelihood	-4064.196	-2597.545	-6666.96
	Durbin Watson	2.173269	1.934823	2.14723
	T-distribution	5.176685(0.0000)	6.399906(0.0000)	5.708648(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.975598	0.517423	4.676816
	Prob.	0.4312	0.6703	0.4566

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.002129	0.024885*	0.023385***
	Crisis			-0.008125
Variance equation	*ω (Constant)*	0.012152*[3.783204]	0.010831*[3.731657]	0.009232*[5.165851]
	α (ARCH effect)	0.120637*[9.740258]	0.115129*[8.555876]	0.113611*[13.26141]
	β (GARCH effect)	0.899027*[91.39158]	0.891987*[71.93481]	0.902606*[128.6038]
	γ (Leverage effect)	0.284801*[4.751405]	0.258371*[3.638164]	0.280275*[6.123607]
	δ (Power Parameter)	1.104873*[5.734932]	1.244636*[6.041739]	1.142452*[8.333480]
	α+β	1.019664	1.007116	1.016217
	Log likelihood	-4042.7	-2593.451	-6638.511
	Durbin Watson	2.167238	1.961511	2.146621
	T-distribution	5.353455(0.0000)	6.654084(0.0000)	5.918390(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.695788	1.406188	13.77086
	Prob.	0.1179	0.239	0.0171

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.5: Estimation result of GARCH family models for KOSPI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.034388	0.059176*	-0.043751
	Crisis			0.115014*
Variance equation	*ω (Constant)*	0.015010**[2.569526]	0.010512*[3.168783]	0.007022*[3.369670]
	α (ARCH effect)	0.059842*[7.038917]	0.073891*[7.475028]	0.067983*[10.83858]
	β (GARCH effect)	0.937454*[113.2701]	0.920159*[92.81237]	0.931828*[159.2102]
	α+β	0.997296	0.99405	0.999811
	Log likelihood	-5731.944	-4174.869	-9913.451
	Durbin Watson	2.011271	1.965013	1.992785
	T-distribution	8.496605(0.0000)	6.352042(0.0000)	7.261458(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.582729	1.844393	1.499841
	Prob.	0.2085	0.1745	0.2207

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.020526	0.039204*	-0.035789
	Crisis			0.085723*
Variance equation	*ω (Constant)*	-0.101088*[-7.906059]	-0.109400*[-8.826646]	-0.109199*[-12.56829]
	α (ARCH effect)	0.140746*[8.127688]	0.142241*[8.672869]	0.147493*[12.52653]
	β (GARCH effect)	0.993552*[403.5329]	0.985756*[321.6221]	0.994068*[665.4424]
	γ (Leverage effect)	-0.036704*[-3.983259]	-0.090998*[-7.990163]	-0.054973*[-8.008332]
	α+β	0.993552	0.985756	0.994068
	Log likelihood	-5724.025	-4143.7	-9881.55
	Durbin Watson	2.0163	1.966556	2.008802
	T-distribution	8.604347(0.0000)	6.660431(0.0000)	7.489757(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.484141	1.243855	1.707115
	Prob.	0.2232	0.2648	0.1914

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.019121	0.038392*	-0.027146
	Crisis			0.075501**
Variance equation	*ω (Constant)*	0.016077*[2.941401]	0.018937*[5.041999]	0.008717*[4.112854]
	α (ARCH effect)	0.032062*[3.410417]	0.010588[1.061718]	0.035006*[4.970547]
	β (GARCH effect)	0.939220*[116.0129]	0.906704*[88.94056]	0.928570*[155.7200]
	γ (Leverage effect)	0.050134*[4.072802]	0.129160*[6.969275]	0.069006*[7.051944]
	α+β	0.996349	0.981872	0.998079
	Log likelihood	-5723.323	-4146.837	-9888.609
	Durbin Watson	2.004112	1.966598	1.998405
	T-distribution	8.572456(0.0000)	6.784605(0.0000)	7.542259(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	2.261861	2.260943	3.374548

	Prob.	0.1327	0.1328	0.0663

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.029636	-0.050826	-0.199597*
	Crisis			0.170799*
	λ (risk premium)	0.046615	0.131364**	0.112314*
Variance equation	*ω (Constant)*	0.014946*[2.568831]	0.011305*[3.245388]	0.007239*[3.402214]
	α (ARCH effect)	0.059540*[7.021950]	0.075944*[7.415079]	0.068734*[10.81827]
	β (GARCH effect)	0.937765*[113.5835]	0.917576*[89.31600]	0.931106*[157.4422]
	α+β	0.997305	0.99352	0.99984
	Log likelihood	-5731.493	-4171.729	-9907.663
	Durbin Watson	2.010477	1.949652	1.985375
	T-distribution	8.443579(0.0000)	6.251347(0.0000)	7.087403(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	1.655687	1.680466	1.582857
	Prob.	0.1983	0.195	0.2084

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.019748	0.036674**	-0.031615
	Crisis			0.079735*
Variance equation	*ω (Constant)*	0.013524**[2.563102]	0.018134*[5.088324]	0.008380*[4.217194]
	α (ARCH effect)	0.066594*[6.381888]	0.076116*[6.947332]	0.078208*[11.30823]
	β (GARCH effect)	0.937900*[113.5318]	0.920456*[101.6769]	0.933162*[167.5591]
	γ (Leverage effect)	0.250408*[3.596630]	0.673425*[6.000780]	0.363001*[6.803768]
	δ (Power Parameter)	1.513723*[5.410471]	1.179664*[6.650711]	1.205649*[8.008862]
	α+β	1.004494	0.996572	1.01137
	Log likelihood	-5721.941	-4140.297	-9879.76
	Durbin Watson	2.009374	1.966681	2.006502
	T-distribution	8.627902(0.0000)	6.752806(0.0000)	7.550733(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	1.861435	1.327684	1.833768
	Prob.	0.1726	0.2493	0.1757

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.6: Estimation result of GARCH family models for NIKKEI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.032687	0.082430*	0.043809**
	Crisis			0.029654
Variance equation	*ω (Constant)*	0.025029*[3.015759]	0.039992*[3.866456]	0.030288*[4.820191]
	α (ARCH effect)	0.062911*[6.656392]	0.111959*[8.413420]	0.084040*[10.93812]
	β (GARCH effect)	0.927172*[84.18600]	0.874411*[60.70944]	0.904749*[105.0007]
	α+β	0.990083	0.98637	0.988789
	Log likelihood	-4915.683	-4832.349	-9756.037
	Durbin Watson	2.016434	2.019014	2.022536
	T-distribution	8.732321(0.0000)	6.873481(0.0000)	7.751297(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.164748	5.788872	7.741545
	Prob.	0.9563	0.0162	0.1015

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.005455	0.049959**	0.015028
	Crisis			0.018701
Variance equation	*ω (Constant)*	-0.086368*[-5.777049]	-0.127183*[-8.004525]	-0.106777*[-10.01839]
	α (ARCH effect)	0.130889*[6.603253]	0.185999*[8.746187]	0.158589*[11.18761]
	β (GARCH effect)	0.975454*[180.4864]	0.966071*[176.6309]	0.971515*[258.4335]
	γ (Leverage effect)	-0.073341*[-6.564178]	-0.122506*[-9.467434]	-0.098558*[-11.66354]
	α+β	0.975454	0.966071	0.971515
	Log likelihood	-4893.072	-4792.369	-9693.16
	Durbin Watson	2.02712	2.038	2.031063
	T-distribution	9.593912(0.0000)	7.500296(0.0000)	8.511725(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.524318	0.197722	3.563484
	Prob.	0.7179	0.6566	0.4683

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.012415	0.058153*	0.027227
	Crisis			0.014415
Variance equation	*ω (Constant)*	0.033675*[3.870625]	0.055520*[5.397156]	0.043181*[6.471524]
	α (ARCH effect)	0.020940**[2.278754]	0.025014***[1.938424]	0.024864*[3.217135]
	β (GARCH effect)	0.921098*[78.83768]	0.865227*[59.16886]	0.894844*[97.80766]
	γ (Leverage effect)	0.085622*[5.594151]	0.163007*[7.425627]	0.119263*[9.341806]
	α+β	0.98485	0.9717445	0.9793395
	Log likelihood	-4897.831	-4804.135	-9711.966
	Durbin Watson	2.026977	2.041785	2.038468
	T-distribution	9.318072(0.0000)	7.565176(0.0000)	8.478194(0.0000)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.51804	0.037288	2.065585
	Prob.	0.7225	0.8469	0.7237

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.063737	-0.023061	-0.001648
	Crisis			0.031009
	λ (risk premium)	-0.02498	0.092503	0.037641
Variance equation	*ω (Constant)*	0.024766*[3.007991]	0.040955*[3.882238]	0.030767*[4.834787]
	α (ARCH effect)	0.062649*[6.662615]	0.112548*[8.368676]	0.084521*[10.91511]
	β (GARCH effect)	0.927559*[84.77217]	0.873352*[59.91346]	0.904047*[103.9246]
	α+β	0.990208	0.9859	0.988568
	Log likelihood	-4915.621	-4830.997	-9755.671
	Durbin Watson	2.016472	2.008008	2.020468
	T-distribution	8.725196(0.0000)	6.828723(0.0000)	7.747365(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.154227	5.617911	7.34598
	Prob.	0.9611	0.0178	0.1187

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.006004	0.047966**	0.013544
	Crisis			0.018688
Variance equation	*ω (Constant)*	0.031822[4.346959]	0.047425*[6.524496]	0.038407*[7.617416]
	α (ARCH effect)	0.067317*[5.589845]	0.104153*[8.566780]	0.084889*[10.33626]
	β (GARCH effect)	0.924114*[82.75689]	0.885968*[72.96217]	0.906585*[113.1385]
	γ (Leverage effect)	0.557909*[5.129701]	0.741436*[7.661556]	0.668181*[9.001091]
	δ (Power Parameter)	1.165320*[4.827006]	0.938329*[7.241715]	1.022707*[8.909389]
	α+β	0.991431	0.990121	0.991474
	Log likelihood	-4892.714	-4787.714	-9690.025
	Durbin Watson	2.026974	2.039783	2.031456
	T-distribution	9.576230(0.0000)	7.568931(0.0000)	8.546371(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.586017	0.734614	4.119109
	Prob.	0.6728	0.3915	0.3901

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.7: Estimation result of GARCH family models for PSE Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.010525	0.076872*	-0.016881
	Crisis			0.093057*
Variance equation	*ω (Constant)*	0.124246*[5.307956]	0.055036*[4.640075]	0.086337*[7.079269]
	α (ARCH effect)	0.182601*[7.712877]	0.134362*[8.300062]	0.160264*[11.47203]
	β (GARCH effect)	0.767956*[31.16253]	0.832143*[45.86755]	0.796884*[52.40875]
	α+β	0.950557	0.966505	0.957148
	Log likelihood	-4647.188	-4325.149	-8980.577
	Durbin Watson	1.989499	1.932251	1.967964
	T-distribution	5.142988(0.0000)	7.511368(0.0000)	6.011887(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.124941	0.224438	0.101975
	Prob.	0.7238	0.6357	0.7495

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.028606	0.055493*	-0.033171
	Crisis			0.091178*
Variance equation	*ω (Constant)*	-0.176961*[-9.400145]	-0.166913*[-9.004226]	-0.178352*[-13.72745]
	α (ARCH effect)	0.280494*[9.833083]	0.225976*[9.063101]	0.258619*[14.04714]
	β (GARCH effect)	0.942436*[85.66671]	0.957085*[116.5551]	0.952287*[144.5518]
	γ (Leverage effect)	-0.056358*[-3.522316]	-0.081773*[-5.678579]	-0.064332*[-6.149195]
	α+β	0.942436	0.957085	0.952287
	Log likelihood	-4648.954	-4313.043	-8971.967
	Durbin Watson	1.97413	1.934941	1.957379
	T-distribution	5.108416(0.0000)	8.247513(0.0000)	6.123630(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.000002	0.343025	0.074741
	Prob.	0.9989	0.5581	0.7846

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.024934	0.056586*	-0.030154
	Crisis			0.087431*
Variance equation	*ω (Constant)*	0.117741*[5.323558]	0.057498*[5.040310]	0.083240*[7.246731]
	α (ARCH effect)	0.122125*[5.464040]	0.066671*[3.779220]	0.097146*[7.107697]
	β (GARCH effect)	0.779407*[32.89643]	0.838415*[47.63311]	0.807278*[55.59810]
	γ (Leverage effect)	0.103846*[3.246448]	0.109545*[4.683299]	0.104535*[5.401541]
	α+β	0.953455	0.9598585	0.9566915
	Log likelihood	-4641.275	-4314.074	-8965.08
	Durbin Watson	1.986461	1.939955	1.968224
	T-distribution	5.216154(0.0000)	8.143501(0.0000)	6.197639(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.071211	0.024332	0.041862
	Prob.	0.7896	0.8761	0.8379

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.054348	-0.036542	-0.11121**
	Crisis			0.102310*
	λ (risk premium)	0.03802	0.116064***	0.083910***
Variance equation	*ω (Constant)*	0.124814*[5.330054]	0.057088*[4.668827]	0.087692*[7.124840]
	α (ARCH effect)	0.183594*[7.731324]	0.135836*[8.252333]	0.161911*[11.48744]
	β (GARCH effect)	0.766843*[31.11921]	0.829155*[44.65015]	0.794586*[51.88266]
	α+β	0.950437	0.964991	0.956497
	Log likelihood	-4646.99	-4323.496	-8978.754
	Durbin Watson	1.989761	1.922562	1.964529
	T-distribution	5.145761(0.0000)	7.477715(0.0000)	6.009163(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.122235	0.198895	0.096929
	Prob.	0.7266	0.6556	0.7556

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.025561	0.054557*	-0.031878
	Crisis			0.089179*
Variance equation	*ω (Constant)*	0.108273*[4.719567]	0.052068*[4.889906]	0.073002*[6.707127]
	α (ARCH effect)	0.170881*[7.348564]	0.121466*[7.748975]	0.147388*[11.04889]
	β (GARCH effect)	0.790077*[32.68558]	0.854317*[50.08722]	0.823474*[57.95523]
	γ (Leverage effect)	0.155194*[3.226443]	0.321489*[4.148464]	0.200023*[5.193325]
	δ (Power Parameter)	1.804940*[6.198542]	1.430850*[6.091271]	1.641220*[8.629516]
	α+β	0.960958	0.975783	0.970862
	Log likelihood	-4641.038	-4311.394	-8963.326
	Durbin Watson	1.983371	1.93998	1.964363
	T-distribution	5.211568(0.0000)	8.285277(0.0000)	6.201531(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.056213	0.252587	0.00481
	Prob.	0.8126	0.6153	0.9447

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.8: Estimation result of GARCH family models for SET Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.011234	0.080838*	-0.012047
	Crisis			0.081036*
Variance equation	*ω (Constant)*	0.037669*[3.498107]	0.010980*[3.331336]	0.009388*[3.717077]
	α (ARCH effect)	0.087564*[7.441314]	0.125138*[9.008803]	0.108899*[12.25217]
	β (GARCH effect)	0.902062*[74.40009]	0.877895*[76.38038]	0.896090*[122.0224]
	α+β	0.989626	1.003033	1.004989
	Log likelihood	-5214.793	-3982.524	-9209.346
	Durbin Watson	1.939112	1.966095	1.978974
	T-distribution	7.412743(0.0000)	5.944600(0.0000)	6.455673(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.559017	0.07397	0.316752
	Prob.	0.2105	0.7857	0.8535

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.029093	0.066195*	-0.011895
	Crisis			0.063211*
Variance equation	*ω (Constant)*	-0.134715*[-8.476309]	-0.150331*[-9.945928]	-0.145120*[-14.08136]
	α (ARCH effect)	0.202694*[8.750987]	0.196957*[9.735965]	0.199566*[14.11198]
	β (GARCH effect)	0.977850*[173.1057]	0.978585*[243.4848]	0.984879*[382.0299]
	γ (Leverage effect)	-0.034381*[-2.885846]	-0.057563*[-4.871906]	-0.041092*[-5.192023]
	α+β	0.97785	0.978585	0.984879
	Log likelihood	-5211.196	-3967.746	-9188.99
	Durbin Watson	1.923942	1.967576	1.973124
	T-distribution	7.359208(0.0000)	6.166187(0.0000)	6.660227(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	4.639138	0.003454	0.193439
	Prob.	0.0097	0.9531	0.9078

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.025582	0.071183*	-0.013017
	Crisis			0.068285**
Variance equation	*ω (Constant)*	0.047550*[3.760997]	0.014756*[4.118357]	0.011492[4.145095]
	α (ARCH effect)	0.073859*[5.930255]	0.074785*[4.642053]	0.081439*[8.269030]
	β (GARCH effect)	0.887336*[63.59751]	0.871019*[74.17486]	0.888567*[114.8771]
	γ (Leverage effect)	0.054697*[2.894851]	0.101865*[4.762270]	0.069991*[5.094680]
	α+β	0.9885435	0.9967365	1.0050015
	Log likelihood	-5209.916	-3970.94	-9195.526
	Durbin Watson	1.934475	1.967131	1.979098
	T-distribution	7.448528(0.0000)	6.174726(0.0000)	6.628368(0.0000)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.402431	0.02846	0.174221
	Prob.	0.2462	0.866	0.9166

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	0.077816	0.04216	-0.019167
Mean equation	*Crisis*			0.083979*
	λ (risk premium)	-0.066732	0.050549	0.005301
	ω (Constant)	0.035536*[3.430791]	0.010705*[3.280921]	0.009374*[3.712123]
	α (ARCH effect)	0.083844*[7.408711]	0.125871*[9.031020]	0.109021*[12.25121]
	β (GARCH effect)	0.906270*[77.66389]	0.877625*[76.57496]	0.896000*[121.9346]
Variance equation	*α+β*	0.990114	1.003496	1.005021
	Log likelihood	-5214.147	-3981.714	-9209.332
	Durbin Watson	1.936008	1.95704	1.978779
	T-distribution	7.328797(0.0000)	5.960363(0.0000)	6.459410(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.875709	0.064299	0.312295
	Prob.	0.1534	0.7998	0.8554

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	-0.026794	0.066764*	-0.01205
Mean equation	*Crisis*			0.063524**
	ω (Constant)	0.041633*[3.475799]	0.016723*[4.330367]	0.012918*[4.621542]
	α (ARCH effect)	0.104324*[7.050719]	0.118632*[9.278311]	0.113150*[13.01056]
	β (GARCH effect)	0.892180*[65.37644]	0.892120*[85.77518]	0.903183*[129.1398]
	γ (Leverage effect)	0.151038*[3.164721]	0.297130*[4.550321]	0.208300*[5.419313]
	δ (Power Parameter)	1.671580*[5.196105]	1.227961*[7.391735]	1.303004*[9.379091]
Variance equation	*α+β*	0.996504	1.010752	1.016333
	Log likelihood	-5209.315	-3964.207	-9186.506
	Durbin Watson	1.931983	1.967528	1.974075
	T-distribution	7.456829(0.0000)	6.190317(0.0000)	6.670498(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	2.221124	0.481574	1.646919
	Prob.	0.1087	0.4878	0.4389

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.9: Estimation result of GARCH family models for STI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.053821*	0.036618*	0.066666*
	Crisis			-0.034541
Variance equation	*ω (Constant)*	0.019632*[2.995886]	0.006573*[2.893830]	0.008006*[3.899937]
	α (ARCH effect)	0.102472*[7.488039]	0.068174*[6.489355]	0.085134*[10.44438]
	β (GARCH effect)	0.891204*[66.36434]	0.922393*[80.11400]	0.910978*[114.3038]
	α+β	0.993676	0.990567	0.996112
	Log likelihood	-3600.204	-2718.33	-6330.508
	Durbin Watson	1.981511	1.900098	1.944206
	T-distribution	7.952633(0.0000)	10.86090(0.0000)	8.903578(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	1.837199	1.382457	0.072297
	Prob.	0.1754	0.2512	0.788

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.034329***	0.01983	0.062961*
	Crisis			-0.054941**
Variance equation	*ω (Constant)*	-0.133278*[-7.474810]	-0.095804*[-6.881971]	-0.117098*[-10.83682]
	α (ARCH effect)	0.180048*[7.639253]	0.115856*[6.834588]	0.148231*[10.75163]
	β (GARCH effect)	0.976508*[177.4639]	0.991768*[388.1025]	0.988367*[444.3161]
	γ (Leverage effect)	-0.076435*[-5.497470]	-0.066611*[-6.535421]	-0.067960*[-8.328103]
	α+β	0.976508	0.991768	0.988367
	Log likelihood	-3588.621	-2705.506	-6308.843
	Durbin Watson	1.983828	1.915516	1.945294
	T-distribution	8.421891(0.0000)	13.32567(0.0003)	9.701878(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.706519	1.581482	0.209634
	Prob.	0.4007	0.2059	0.6471

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.034193***	0.022254	0.060557*
	Crisis			-0.046112**
Variance equation	*ω (Constant)*	0.025391*[3.666699]	0.005319*[3.125867]	0.008326*[4.581096]
	α (ARCH effect)	0.049360*[3.276357]	0.017403***[1.777060]	0.035462*[4.044538]
	β (GARCH effect)	0.889499*[64.49039]	0.936330*[94.54524]	0.918673*[122.2578]
	γ (Leverage effect)	0.094252*[4.487390]	0.074616*[5.334608]	0.077430*[6.521374]
	α+β	0.985985	0.991041	0.99285
	Log likelihood	-3589.784	-2702.847	-6308.294
	Durbin Watson	1.983841	1.910455	1.945256
	T-distribution	8.389593(0.0000)	13.32474(0.0000)	9.752482(0.0000)

ARCH-LM Test for heteroscedasticity

	ARCH-LM test statistic	1.437593	0.592884	0.104033
	Prob.	0.2307	0.5528	0.747

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.094804	-0.04261	0.054378
	Crisis			-0.031993
	λ (risk premium)	-0.043045	0.120347***	0.013935
Variance equation	*ω (Constant)*	0.019303*[2.979827]	0.006736*[2.902645]	0.008025*[3.902122]
	α (ARCH effect)	0.102243*[7.506563]	0.069103*[6.463281]	0.085234*[10.43721]
	β (GARCH effect)	0.891697*[66.86712]	0.921196*[78.28261]	0.910860*[114.0617]
	α+β	0.99394	0.990299	0.996094
	Log likelihood	-3599.914	-2716.599	-6330.446
	Durbin Watson	1.985381	1.903376	1.943361
	T-distribution	7.931119(0.0000)	11.06474(0.0000)	8.918591(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.824086	1.308013	0.074766
	Prob.	0.177	0.2706	0.7845

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.033817***	0.020035	0.062616*
	Crisis			-0.051976**
Variance equation	*ω (Constant)*	0.025924*[3.858117]	0.006213*[2.751774]	0.009457*[4.602904]
	α (ARCH effect)	0.096196*[6.358588]	0.053329*[4.101936]	0.075048*[8.103465]
	β (GARCH effect)	0.897604*[68.18869]	0.939465*[99.68069]	0.923770*[129.2836]
	γ (Leverage effect)	0.346908*[3.966389]	0.489916*[3.697125]	0.368467*[5.490527]
	δ (Power Parameter)	1.462370*[5.010680]	1.576693*[4.258488]	1.513681*[6.950445]
	α+β	0.9938	0.992794	0.998818
	Log likelihood	-3588.278	-2702.28	-6306.255
	Durbin Watson	1.983878	1.912904	1.945259
	T-distribution	8.409414(0.0000)	13.70063(0.0005)	9.811703(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.979117	0.824738	0.000882
	Prob.	0.3225	0.4385	0.9763

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.10: Estimation result of GARCH family models for TAIEX Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.041078***	0.070652*	0.064669*
	Crisis			-0.008688
Variance equation	*ω (Constant)*	0.020734*[2.784794]	0.008626*[2.996728]	0.007418*[3.444316]
	α (ARCH effect)	0.064852*[7.159357]	0.059263*[7.245975]	0.058657*[10.45187]
	β (GARCH effect)	0.928515*[95.52910]	0.935694*[110.2335]	0.939505*[170.6072]
	α+β	0.993367	0.994957	0.998162
	Log likelihood	-5070.529	-4205.628	-9282.969
	Durbin Watson	1.972071	1.957171	1.962311
	T-distribution	7.119588(0.0000)	5.987068(0.0000)	6.391861(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.340252	2.024896	0.770316
	Prob.	0.5597	0.1548	0.3802

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.01894	0.056289*	0.071401*
	Crisis			-0.046790**
Variance equation	*ω (Constant)*	-0.102162*[-7.150328]	-0.095428*[-8.388557]	-0.094458*[-11.22395]
	α (ARCH effect)	0.153239*[7.824392]	0.123876*[8.259957]	0.127188*[11.41037]
	β (GARCH effect)	0.978553*[188.9649]	0.989670*[370.0929]	0.989788*[501.2680]
	γ (Leverage effect)	-0.066497*[-5.935068]	-0.068174*[-6.977400]	-0.063347*[-9.144042]
	α+β	0.978553	0.98967	0.989788
	Log likelihood	-5047.681	-4187.141	-9242.48
	Durbin Watson	1.973777	1.966844	1.968871
	T-distribution	8.003733(0.0000)	6.520657(0.0000)	7.094252(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.623939	1.63747	0.06541
	Prob.	0.2026	0.2008	0.7982

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.022275	0.056006*	0.070851*
	Crisis			-0.041610***
Variance equation	*ω (Constant)*	0.034733*[3.672365]	0.013098*[4.263653]	0.009739*[4.369408]
	α (ARCH effect)	0.035347*[3.347643]	0.015399[1.553287]	0.025270*[3.791010]
	β (GARCH effect)	0.912815*[79.21095]	0.929806*[106.0588]	0.918673*[165.8666]
	γ (Leverage effect)	0.078717*[4.895874]	0.080416*[5.959836]	0.063130*[7.038608]
	α+β	0.9875205	0.985413	0.975508
	Log likelihood	-5056.622	-4189.319	-9258.327
	Durbin Watson	1.978289	1.979521	1.972392
	T-distribution	7.717379(0.0000)	6.453476(0.0000)	6.864979(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	2.00356	0.192487	0.056152
	Prob.	0.157	0.6609	0.8127

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.001878	0.013949	0.045971
	Crisis			-0.00356
	λ (risk premium)	0.034	0.066866	0.015878
Variance equation	*ω (Constant)*	0.021611*[2.826727]	0.009057*[3.034339]	0.007521*[3.458337]
	α (ARCH effect)	0.066351*[7.168544]	0.060600*[7.217540]	0.059103*[10.44536]
	β (GARCH effect)	0.926707*[93.46169]	0.934038*[106.9282]	0.939026*[169.1465]
	α+β	0.993058	0.994638	0.998129
	Log likelihood	-5070.384	-4204.832	-9282.879
	Durbin Watson	1.972096	1.949883	1.961776
	T-distribution	7.166708(0.0000)	5.973598(0.0000)	6.401139(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.399026	1.731208	0.704722
	Prob.	0.5276	0.1884	0.4012

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.018478	0.054465*	0.072337*
	Crisis			-0.047904**
Variance equation	*ω (Constant)*	0.031176*[4.181052]	0.012336*[4.151918]	0.011909*[5.101451]
	α (ARCH effect)	0.083309*[7.719650]	0.061980*[5.701471]	0.068308*[10.46566]
	β (GARCH effect)	0.915455*[82.97220]	0.936019*[121.3952]	0.937748*[172.5028]
	γ (Leverage effect)	0.470674*[5.561050]	0.551365*[4.884370]	0.498676*[7.612017]
	δ (Power Parameter)	0.965110*[4.959958]	1.273477*[5.730858]	1.054546*[7.821232]
	α+β	0.998764	0.997999	1.006056
	Log likelihood	-5047.24	-4184.665	-9241.964
	Durbin Watson	1.973306	1.971857	1.968522
	T-distribution	7.943564(0.0000)	6.547524(0.0000)	7.064958(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.429744	0.964801	0.069987
	Prob.	0.2319	0.3261	0.7914

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.11: Estimation result of GARCH family models for HANG SENG Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.215295**	0.241015**	0.292230*
	Crisis			-0.139715
Variance equation	*ω (Constant)*	0.070515[1.058244]	0.171832***[1.733076]	0.118607**[2.154578]
	α (ARCH effect)	0.058056*[3.121936]	0.072113*[2.982294]	0.065919*[4.317356]
	β (GARCH effect)	0.935228*[45.62410]	0.909466*[30.65943]	0.922007*[53.26457]
	α+β	0.993284	0.981579	0.987926
	Log likelihood	-1561.074	-1501.35	-3059.577
	Durbin Watson	1.940237	1.986605	1.948001
	T-distribution	12.06875(0.0032)	9.708966(0.0007)	10.61475(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.257572	1.48909	1.848517
	Prob.	0.612	0.2228	0.3968

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.151055	0.167455***	0.239865**
	Crisis			-0.190392
Variance equation	*ω (Constant)*	-0.081333**[-2.395525]	-0.055737[-1.320609]	-0.067979*[-2.593975]
	α (ARCH effect)	0.139927*[3.487157]	0.161001*[3.224246]	0.147493*[4.677557]
	β (GARCH effect)	0.986382*[108.9690]	0.964735*[68.74464]	0.976693*[132.1965]
	γ (Leverage effect)	-0.046174***[-1.753221]	-0.076308*[-2.719341]	-0.066562*[-3.486174]
	α+β	0.986382	0.964735	0.976693
	Log likelihood	-1559.529	-1498.85	-3055.143
	Durbin Watson	1.942195	1.989792	1.958115
	T-distribution	13.63699(0.0118)	11.34251(0.0034)	12.02717(0.0001)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.01395	0.535576	1.08919
	Prob.	0.906	0.4646	0.5801

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.184844	0.176814***	0.265037**
	Crisis			-0.21093
Variance equation	*ω (Constant)*	0.113213[1.453711]	0.235067**[2.384525]	0.179905*[3.026049]
	α (ARCH effect)	0.034255[1.248113]	0.012840[0.460144]	0.016311[0.824869]
	β (GARCH effect)	0.928460*[41.52158]	0.901117*[31.33399]	0.915166*[51.53368]
	γ (Leverage effect)	0.049437[1.452429]	0.110109*[2.824295]	0.092542*[3.507640]
	α+β	0.962715	0.9690115	0.977748
	Log likelihood	-1559.846	-1496.556	-3053.179
	Durbin Watson	1.941327	1.989512	1.97843
	T-distribution	13.90882(0.0128)	11.39874(0.0019)	12.63023(0.0001)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.039859	0.450946	0.826097
	Prob.	0.8418	0.5021	0.6616

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.388276	0.376101	0.462495
	Crisis			-0.146587
	λ (risk premium)	-0.063794	-0.053858	-0.064086
Variance equation	*ω (Constant)*	0.068196[1.045101]	0.168582***[1.725514]	0.115547**[2.137303]
	α (ARCH effect)	0.056987*[3.138606]	0.071390*[2.982265]	0.065012*[4.335052]
	β (GARCH effect)	0.936467*[46.70865]	0.910609*[31.11620]	0.923213*[54.29932]
	α+β	0.993454	0.981999	0.988225
	Log likelihood	-1560.95	-1501.291	-3059.365
	Durbin Watson	1.942864	1.988284	1.950062
	T-distribution	11.94307(0.0031)	9.602304(0.0006)	10.49073(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.251485	1.509116	1.906025
	Prob.	0.6162	0.2197	0.3856

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.166701	0.176435***	0.155086
	Crisis			-0.156299
Variance equation	*ω (Constant)*	0.063053[1.134759]	0.229392[1.317462]	10.84835[0.346142]
	α (ARCH effect)	0.068884*[2.918537]	0.054578[1.293856]	0.150000[1.142884]
	β (GARCH effect)	0.927737*[42.83408]	0.901210*[31.30319]	0.600000***[1.950174]
	γ (Leverage effect)	0.294117[1.244301]	0.512548[1.312689]	0.050000[0.158451]
	δ (Power Parameter)	1.407131**[2.554767]	1.976171*[2.629361]	2.000000[1.368816]
	α+β	0.996621	0.955788	0.75
	Log likelihood	-1559.275	-1496.55	-3405.838
	Durbin Watson	1.941838	1.989524	1.997882
	T-distribution	13.99007(0.0135)	11.37579(0.0024)	20.00000(0.4228)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.012839	0.4582	7.366607
	Prob.	0.9098	0.4987	0.0251

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.12: Estimation result of GARCH family models for SSE Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.026684	0.153583	-0.043186
	Crisis			0.193728
Variance equation	*ω (Constant)*	1.477481**[2.424423]	0.136744[1.508902]	0.342165*[2.741891]
	α (ARCH effect)	0.179140*[3.119719]	0.135438*[4.240691]	0.141400*[5.281433]
	β (GARCH effect)	0.717776*[8.893522]	0.863858*[27.48351]	0.841136*[30.90924]
	α+β	0.896916	0.999296	0.982536
	Log likelihood	-1541.52	-1524.715	-3076.639
	Durbin Watson	2.009444	1.848142	1.935643
	T-distribution	5.384394(0.0000)	9.544364(0.0034)	6.288235(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.002559	0.104105	0.08387
	Prob.	0.9597	0.7471	0.7722

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.009668	0.168037	0.016993
	Crisis			0.127924
Variance equation	*ω (Constant)*	0.009410[0.100793]	-0.160738*[-3.801961]	-0.114779*[-3.601246]
	α (ARCH effect)	0.287930*[3.887428]	0.253573*[4.694538]	0.245197*[6.173800]
	β (GARCH effect)	0.908692*[21.58404]	0.984296*[89.61642]	0.969435*[86.83108]
	γ (Leverage effect)	-0.001432[-0.035348]	0.044214***[1.928707]	0.004549[0.239134]
	α+β	0.908692	0.984296	0.969435
	Log likelihood	-1540.987	-1523.731	-3073.27
	Durbin Watson	2.010826	1.84795	1.93663
	T-distribution	5.318023(0.0000)	9.733107(0.0044)	6.300072(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.026475	0.68582	0.598107
	Prob.	0.8708	0.4079	0.4395

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.021356	0.183348***	-0.041857
	Crisis			0.193457
Variance equation	*ω (Constant)*	1.537069**[2.398597]	0.110231[1.322200]	0.342750*[2.742927]
	α (ARCH effect)	0.188153*[2.719685]	0.162677*[3.995693]	0.142878*[4.545059]
	β (GARCH effect)	0.713364*[8.669034]	0.874368*[28.22051]	0.841191*[30.86014]
	γ (Leverage effect)	-0.020792[-0.248182]	-0.068073***[-1.756946]	-0.003247[-0.091628]
	α+β	0.891121	0.968972	0.9824455
	Log likelihood	-1541.49	-1523.192	-3076.635
	Durbin Watson	2.009668	1.847683	1.935662
	T-distribution	5.372497(0.0000)	10.00322(0.0037)	6.288463(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.004615	0.388376	0.083466
	Prob.	0.9459	0.5334	0.7727

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	-1.082464**	0.279759	-0.308158
Mean equation	*Crisis*			0.227952
	λ (risk premium)	0.32357***	-0.050812	0.084663
	ω (Constant)	1.423546**[2.508663]	0.136210[1.503063]	0.360029*[2.763579]
	α (ARCH effect)	0.186157*[3.327356]	0.135711*[4.254221]	0.143471*[5.273163]
	β (GARCH effect)	0.716622*[9.484424]	0.863719*[27.45928]	0.837749*[30.06842]
Variance equation	*α+β*	0.902779	0.99943	0.98122
	Log likelihood	-1539.338	-1524.567	-3076.099
	Durbin Watson	2.013289	1.853112	1.934794
	T-distribution	5.319991(0.0000)	9.533928(0.0033)	6.263650(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.008805	0.155638	0.091785
	Prob.	0.9253	0.6933	0.762

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
	μ (Constant)	-0.012994	0.183517***	0.003987
Mean equation	*Crisis*			0.144699
	ω (Constant)	0.584017[1.124488]	0.086052[1.058188]	0.104331***[1.876264]
	α (ARCH effect)	0.168512*[3.330753]	0.131269*[3.617861]	0.132375*[5.661678]
	β (GARCH effect)	0.768464*[10.91919]	0.877749*[28.88106]	0.873577*[38.15256]
	γ (Leverage effect)	-0.024163[-0.179239]	-0.142295[-1.617519]	-0.023390[-0.301871]
	δ (Power Parameter)	1.405687**[2.369489]	1.724613*[2.824817]	1.155710*[3.315223]
Variance equation	*α+β*	0.936976	1.009018	1.005952
	Log likelihood	-1540.935	-1523.102	-3073.317
	Durbin Watson	2.010004	1.84768	1.936436
	T-distribution	5.374569(0.0000)	9.960580(0.0044)	6.315288(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.027547	0.424048	1.024051
	Prob.	0.8682	0.5152	0.3118

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.13: Estimation result of GARCH family models for JCI Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.315728*	0.401450*	0.368923*
	Crisis			-0.075044
Variance equation	*ω (Constant)*	0.326487**[2.021327]	0.577443**[2.412847]	0.238816*[2.665979]
	α (ARCH effect)	0.086075*[3.648179]	0.263437*[3.428276]	0.152439*[5.022412]
	β (GARCH effect)	0.895167*[34.17393]	0.709455*[10.65437]	0.846452*[35.11195]
	α+β	0.981242	0.972892	0.998891
	Log likelihood	-1613.162	-1397.322	-2996.198
	Durbin Watson	2.057367	2.157128	2.058321
	T-distribution	7.056937(0.0043)	3.967649(0.0000)	4.381390(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	5.174149	0.038011	1.725136
	Prob.	0.0233	0.8455	0.8857

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.255558**	0.354457*	0.345922*
	Crisis			-0.132416
Variance equation	*ω (Constant)*	-0.058526[-1.430108]	-0.136467**[-2.307872]	-0.114196*[-3.676772]
	α (ARCH effect)	0.198473*[4.053915]	0.414155*[4.815198]	0.279185*[6.085138]
	β (GARCH effect)	0.964772*[73.90897]	0.911709*[29.61174]	0.958037*[84.12826]
	γ (Leverage effect)	-0.073868*[-2.891278]	-0.083106***[-1.723427]	-0.101827*[-3.756685]
	α+β	0.964772	0.911709	0.958037
	Log likelihood	-1612.22	-1394.642	-2988.975
	Durbin Watson	2.05928	2.160122	2.072873
	T-distribution	7.286734(0.0027)	4.212744(0.0000)	4.655540(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.341239	0.249597	1.38917
	Prob.	0.2473	0.6175	0.9255

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.277230**	0.381671*	0.365047*
	Crisis			-0.134822
Variance equation	*ω (Constant)*	0.425034**[2.559810]	0.618132*[2.678271]	0.270897*[3.033567]
	α (ARCH effect)	0.036329[1.354008]	0.170105**[1.987440]	0.083428**[2.502237]
	β (GARCH effect)	0.886820*[31.22682]	0.697768*[10.55618]	0.842579*[34.19840]
	γ (Leverage effect)	0.096496*[2.778870]	0.178874***[1.643277]	0.126610*[2.917334]
	α+β	0.971397	0.95731	0.989312
	Log likelihood	-1609.304	-1395.715	-2991.5
	Durbin Watson	2.058692	2.158518	2.072095
	T-distribution	7.990268(0.0071)	4.090273(0.0000)	4.550801(0.0001)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.778672	0.169201	1.535889
	Prob.	0.3779	0.681	0.9089

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.582984	0.071746	0.314473
	Crisis			-0.059589
	λ (risk premium)	-0.082054	0.151134	0.017588
Variance equation	*ω (Constant)*	0.324917**[2.016096]	0.597487**[2.442259]	0.238159*[2.660232]
	α (ARCH effect)	0.086682*[3.634141]	0.276316*[3.464070]	0.152383*[5.026766]
	β (GARCH effect)	0.894787*[33.87407]	0.697928*[10.26014]	0.846529*[35.15758]
	α+β	0.981469	0.974244	0.998912
	Log likelihood	-1613.006	-1396.25	-2996.171
	Durbin Watson	2.056954	2.104969	2.057464
	T-distribution	6.991703(0.0041)	3.968881(0.0000)	4.386544(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	5.330242	0.079187	1.691197
	Prob.	0.0213	0.7785	0.89

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.281268**	0.344174*	0.352434*
	Crisis			-0.14789
Variance equation	*ω (Constant)*	1.990413[0.549692]	0.243380**[2.213535]	0.124627*[2.914571]
	α (ARCH effect)	0.041603*[1.151694]	0.264342*[4.300357]	0.155755*[5.842472]
	β (GARCH effect)	0.876447*[22.37937]	0.712337*[11.71284]	0.846122*[34.90316]
	γ (Leverage effect)	0.252329***[1.798230]	0.265654***[1.929180]	0.430270*[3.491746]
	δ (Power Parameter)	3.279166**[2.330601]	0.911293*[2.587665]	0.984765*[3.538698]
	α+β	0.91805	0.976679	1.001877
	Log likelihood	-1608.666	-1394.242	-2988.145
	Durbin Watson	2.05857	2.160635	2.073886
	T-distribution	8.450660(0.0135)	4.287073(0.0000)	4.707660(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.57375	0.129553	1.430292
	Prob.	0.4491	0.719	0.921

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.14: Estimation result of GARCH family models for KLCI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.069694	0.157999*	0.168487**
	Crisis			-0.055897
Variance equation	*ω (Constant)*	0.035686[1.166866]	0.048508***[1.731537]	0.023659***[1.874061]
	α (ARCH effect)	0.061185*[3.591853]	0.116914*[3.584159]	0.073144*[5.031039]
	β (GARCH effect)	0.933862*[54.88129]	0.874074*[27.94435]	0.923577*[67.77317]
	α+β	0.995047	0.990988	0.996721
	Log likelihood	-1407.973	-1105.274	-2528.896
	Durbin Watson	2.041258	1.890703	2.043309
	T-distribution	5.412276(0.0000)	5.460396(0.0000)	5.497063(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.8331	0.009685	0.74195
	Prob.	0.56	0.9216	0.8633

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.000122	0.146325*	0.150338**
	Crisis			-0.072313
Variance equation	*ω (Constant)*	-0.087664*[-2.961560]	-0.159885*[-4.283480]	-0.117128*[-5.488663]
	α (ARCH effect)	0.133445*[3.281495]	0.240246*[4.444791]	0.166681*[5.753452]
	β (GARCH effect)	0.991639*[190.2864]	0.972965*[68.93870]	0.990882*[242.6586]
	γ (Leverage effect)	-0.088456*[-3.297748]	-0.039378[-1.443199]	-0.063601*[-3.639709]
	α+β	0.991639	0.972965	0.990882
	Log likelihood	-1402.705	-1103.983	-2522.39
	Durbin Watson	2.035295	1.891276	2.042563
	T-distribution	6.150905(0.0001)	5.811593(0.0000)	5.785797(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.87023	0.013927	1.169779
	Prob.	0.5297	0.9061	0.7603

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.018001	0.150799*	0.1822847***
	Crisis			-0.107895
Variance equation	*ω (Constant)*	0.041740[1.583354]	0.050812***[1.768948]	0.025476**[2.202786]
	α (ARCH effect)	0.009220[0.499064]	0.094183*[2.594214]	0.022936[1.460013]
	β (GARCH effect)	0.938390*[56.22538]	0.872888*[27.52249]	0.930485*[71.43965]
	γ (Leverage effect)	0.094395*[3.351558]	0.041538[0.938940]	0.078306*[3.562445]
	α+β	0.9948075	0.98784	0.992574
	Log likelihood	-1401.448	-1104.742	-2522.112
	Durbin Watson	2.056763	1.891077	2.061927

	T-distribution	6.287054(0.0001)	5.488436(0.0000)	5.696164(0.0001)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.723849	0.007352	0.781612
	Prob.	0.6518	0.9317	0.8539

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.080695	-0.103907	0.13857
	Crisis			-0.046377
	λ (risk premium)	-0.005619	0.209039***	0.016088
Variance equation	*ω (Constant)*	0.035692[1.166766]	0.051798***[1.759285]	0.023713***[1.872752]
	α (ARCH effect)	0.061168*[3.591561]	0.128145*[3.532547]	0.073697*[5.027467]
	β (GARCH effect)	0.933887*[54.90352]	0.863389*[25.24295]	0.923088*[67.29043]
	α+β	0.995055	0.991534	0.996785
	Log likelihood	-1407.971	-1103.281	-2528.87
	Durbin Watson	2.041343	1.858575	2.041553
	T-distribution	5.404954(0.0000)	5.396755(0.0000)	5.506750(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.833395	0.002077	0.738973
	Prob.	0.5598	0.9637	0.864

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.010377	0.148414*	0.172121**
	Crisis			-0.100359
Variance equation	*ω (Constant)*	0.034768[1.506488]	0.042472***[1.797146]	0.023461**[2.285613]
	α (ARCH effect)	0.051635***[1.859268]	0.130930*[4.120171]	0.076790*[3.989892]
	β (GARCH effect)	0.938781*[53.80323]	0.875239*[27.62688]	0.924994*[66.62405]
	γ (Leverage effect)	0.665485[1.480112]	0.177190[1.441829]	0.409353*[2.848973]
	δ (Power Parameter)	1.608801*[3.615695]	1.128068***[1.954214]	1.410241*[4.423480]
	α+β	0.990416	1.006069	0.999784
	Log likelihood	-1401.105	-1103.331	-2520.474
	Durbin Watson	2.051729	1.891186	2.050286
	T-distribution	6.289716(0.0001)	5.791257(0.0000)	5.789106(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.752552	0.015564	1.041015
	Prob.	0.6275	0.9008	0.7913

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.15: Estimation result of GARCH family models for KOSPI Index

Estimation results of GARCH (1,1) model

Coefficients		Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.048977	0.266854*	0.232249**
	Crisis			-0.038912
Variance equation	*ω (Constant)*	0.199939***[1.768973]	0.380420**[2.355207]	0.083990**[1.970516]
	α (ARCH effect)	0.061571*[3.665811]	0.147542*[3.562954]	0.092596*[5.516538]
	β (GARCH effect)	0.929258*[51.28469]	0.796526*[15.68147]	0.904830*[57.12193]
	α+β	0.990829	0.944068	0.997426
	Log likelihood	-1712.818	-1364.914	-3075.039
	Durbin Watson	2.14244	2.109187	2.025847
	T-distribution	19.47483(0.1399)	4.983630(0.0000)	7.164474(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.7131	2.033515	1.835458
	Prob.	0.3988	0.1318	0.1031

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

Coefficients		Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.0164	0.206796*	0.232063***
	Crisis			-0.078925
Variance equation	*ω (Constant)*	-0.053099**[-2.078615]	-0.084970***[-1.697933]	-0.107526*[-5.133316]
	α (ARCH effect)	0.103777*[3.245338]	0.265041*[4.741008]	0.170369*[6.133244]
	β (GARCH effect)	0.990290*[192.8363]	0.928388*[34.98975]	0.988920*[206.4463]
	γ (Leverage effect)	-0.041597*[-2.736413]	-0.115524*[-2.977125]	-0.043337**[-2.394661]
	α+β	0.99029	0.928388	0.98892
	Log likelihood	-1711.338	-1362.522	-3072.748
	Durbin Watson	2.14233	2.113364	2.046612
	T-distribution	35.89483(0.4621)	5.250535(0.0000)	7.280490(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.180055	1.466637	1.66486
	Prob.	0.6715	0.2263	0.1402

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

Coefficients		Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.029592	0.222412*	0.245362**
	Crisis			0.075501**
Variance equation	*ω (Constant)*	0.139225***[1.888068]	0.476983*[2.914473]	0.096736**[2.240739]
	α (ARCH effect)	0.020743[0.950587]	0.035488[0.963791]	0.064457*[2.579658]
	β (GARCH effect)	0.947704*[60.32023]	0.778215*[15.82866]	0.903177*[55.21916]
	γ (Leverage effect)	0.048970**[2.111110]	0.191727*[2.869413]	0.049627***[1.645792]
	α+β	0.992932	0.9095665	0.9924475
	Log likelihood	-1710.853	-1360.941	-3073.8
	Durbin Watson	2.142199	2.112471	2.039542
	T-distribution	29.13206(0.3523)	5.226684(0.0000)	7.192483(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.242967	1.224106	1.141653
	Prob.	0.6223	0.269	0.3363

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.424416	-0.44708	0.011
	Crisis			0.03874
	λ (risk premium)	0.133798	0.348137**	0.069046
Variance equation	*ω (Constant)*	0.190572***[1.776326]	0.471113**[2.444266]	0.087384**[1.994250]
	α (ARCH effect)	0.059078*[3.613217]	0.168039*[3.497491]	0.093991*[5.459873]
	β (GARCH effect)	0.932152*[52.86565]	0.761348*[12.76748]	0.903231*[55.41945]
	α+β	0.99123	0.929387	0.997123
	Log likelihood	-1712.297	-1362.107	-3074.67
	Durbin Watson	2.138842	2.015362	2.023936
	T-distribution	19.78215(0.1438)	4.992496(0.0000)	7.180199(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.581684	1.814472	1.795171
	Prob.	0.446	0.1785	0.1109

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.027235	0.217108**	0.247429**
	Crisis			-0.103509
Variance equation	*ω (Constant)*	0.108129[0.792245]	0.361132***[1.789403]	0.043776***[1.925513]
	α (ARCH effect)	0.044344***[1.750993]	0.127594*[2.827043]	0.090337*[5.513571]
	β (GARCH effect)	0.948297*[60.89485]	0.782747*[15.30527]	0.917114*[65.41437]
	γ (Leverage effect)	0.315514*[1.347852]	0.492206**[2.242301]	0.259602**[2.120135]
	δ (Power Parameter)	1.814067***[1.908443]	1.627777*[2.968935]	1.254649*[3.666539]
	α+β	0.992641	0.910341	1.007451
	Log likelihood	-1710.827	-1360.808	-3072.337
	Durbin Watson	2.142225	2.11279	2.047659
	T-distribution	30.15404(0.3748)	5.261046(0.0000)	7.251230(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.224599	1.251749	1.572453
	Prob.	0.6357	0.2637	0.1649

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.16: Estimation result of GARCH family models for NIKKEI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.042633	0.235618**	0.087
	Crisis			0.101211
Variance equation	*ω (Constant)*	0.374459***[1.676956]	0.350072***[1.702583]	0.406315*[2.357979]
	α (ARCH effect)	0.049997**[2.038003]	0.072208*[2.601009]	0.068166*[3.415659]
	β (GARCH effect)	0.906368*[21.55874]	0.890531*[20.52594]	0.886145*[26.15910]
	α+β	0.956365	0.962739	0.954311
	Log likelihood	-1492.957	-1512.353	-3019.381
	Durbin Watson	2.012862	2.039666	2.034536
	T-distribution	12.51128(0.0046)	5.701864(0.0000)	7.752578(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.192888	1.671037	4.33664
	Prob.	0.6607	0.172	0.1144

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.013339	0.140313	0.021733
	Crisis			0.093566
Variance equation	*ω (Constant)*	0.129486***[1.673646]	0.171974***[1.661994]	0.143332**[2.171334]
	α (ARCH effect)	0.065688[1.239480]	0.239532*[3.145278]	0.162885*[3.617227]
	β (GARCH effect)	0.912178*[23.43197]	0.822742*[15.76715]	0.8677*[26.09774]
	γ (Leverage effect)	-0.090611*[-2.903396]	-0.214887*[-4.067071]	-0.153042*[-5.024687]
	α+β	0.912178	0.822742	0.8677
	Log likelihood	-1486.78	-1503.778	-3004.813
	Durbin Watson	2.013136	2.134819	2.078933
	T-distribution	14.59099(0.0208)	8.070021(0.0019)	9.528078(0.0001)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.47289	0.496036	1.458171
	Prob.	0.4919	0.6852	0.4823

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.021474	0.16544	0.044543
	Crisis			0.079541
Variance equation	*ω (Constant)*	0.570463***[1.903269]	1.620535*[3.740967]	1.110782*[3.817856]
	α (ARCH effect)	-0.010720[-0.435590]	-0.027956[-0.645927]	-0.020039[-0.792341]
	β (GARCH effect)	0.885796*[16.76876]	0.659310*[9.055839]	0.775805*[15.64575]
	γ (Leverage effect)	0.107765**[2.430283]	0.343169*[3.709332]	0.214144*[4.378396]
	α+β	0.9289485	0.8029385	0.862838
	Log likelihood	-1488.311	-1505.758	-3008.044
	Durbin Watson	2.018948	2.148559	2.091619
	T-distribution	13.25566(0.0094)	7.949996(0.0034)	9.498522(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.523896	0.56169	1.687593
	Prob.	0.4695	0.6405	0.4301

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.063737	-0.322715	-0.411831
	Crisis			0.09238
	λ (risk premium)	0.016887	0.204416	0.182855
Variance equation	*ω (Constant)*	0.373979***[1.672829]	0.402851***[1.742526]	0.4311**[2.336273]
	α (ARCH effect)	0.050184**[2.040052]	0.076695**[2.563416]	0.069554*[3.377631]
	β (GARCH effect)	0.906246*[21.47223]	0.880185*[18.35600]	0.881727*[24.63164]
	α+β	0.95643	0.95688	0.951281
	Log likelihood	-1492.941	-1511.826	-3018.767
	Durbin Watson	2.012569	2.019409	2.026094
	T-distribution	12.52431(0.0046)	5.685080(0.0000)	7.823542(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.196123	1.513094	4.031936
	Prob.	0.658	0.21	0.1332

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.041928	0.128739	0.022128
	Crisis			0.093694
Variance equation	*ω (Constant)*	0.078769*[3.454549]	0.426875**[2.024378]	0.367044*[2.839801]
	α (ARCH effect)	-0.033044*[-5.833545]	0.128974*[3.200969]	0.085043*[5.369511]
	β (GARCH effect)	0.989897*[217.1009]	0.745096*[11.72738]	0.80709*[20.09329]
	γ (Leverage effect)	-1.000000*[-4.8E+103]	0.978693*[3.128462]	0.999966*[4.8E+103]
	δ (Power Parameter)	0.805078*[4.338409]	0.946770*[2.793327]	1.03761*[4.165561]
	α+β	0.956853	0.87407	0.892133
	Log likelihood	-1489.778	-1502.893	-3003.943
	Durbin Watson	2.024326	2.133085	2.075454
	T-distribution	20.24546(0.0716)	8.156465(0.0016)	9.590278(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.168467	0.496939	1.290265
	Prob.	0.6816	0.6845	0.5246

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.17: Estimation result of GARCH family models for PSE Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.001897	0.351388*	0.095165
	Crisis			0.201786
Variance equation	*ω (Constant)*	0.517299***[1.789008]	0.213874***[1.932465]	0.189106**[2.328655]
	α (ARCH effect)	0.063286**[2.305562]	0.106066*[3.360838]	0.075067*[4.195081]
	β (GARCH effect)	0.891817*[20.28584]	0.865980*[24.42689]	0.905150*[43.54371]
	α+β	0.955103	0.972046	0.980217
	Log likelihood	-1570.63	-1424.125	-3000.407
	Durbin Watson	2.015315	2.130255	2.02536
	T-distribution	5.997741(0.0000)	6.667925(0.0000)	5.972743(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.260254	0.051518	0.606035
	Prob.	0.7709	0.8205	0.5457

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.044273	0.318717*	0.117097
	Crisis			0.104037
Variance equation	*ω (Constant)*	0.002539[0.071258]	-0.089683***[-1.678442]	-0.059414**[-2.176415]
	α (ARCH effect)	0.093340**[2.125161]	0.237095*[3.731507]	0.146477*[4.301004]
	β (GARCH effect)	0.969098*[59.50989]	0.946549*[43.40936]	0.973798*[107.6318]
	γ (Leverage effect)	-0.071346*[-2.640577]	-0.073269**[-2.409571]	-0.064438*[-3.426574]
	α+β	0.969098	0.946549	0.973798
	Log likelihood	-1568.343	-1419.528	-2992.594
	Durbin Watson	1.993794	2.132583	2.022073
	T-distribution	6.101689(0.0000)	6.980603(0.0000)	6.210985(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.806433	0.006806	1.142862
	Prob.	0.4469	0.9343	0.3192

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.06522	0.333229*	0.120466
	Crisis			0.094202
Variance equation	*ω (Constant)*	0.370149**[2.051762]	0.313177**[2.553893]	0.219205*[2.977610]
	α (ARCH effect)	-0.007402[-0.440703]	0.048278[1.197526]	0.016213[0.894801]
	β (GARCH effect)	0.928256*[31.25012]	0.846455*[20.69637]	0.908727*[47.96150]
	γ (Leverage effect)	0.092322**[2.377187]	0.109981**[2.514753]	0.094737*[3.596546]
	α+β	0.967015	0.9497235	0.9723085
	Log likelihood	-1565.734	-1421.255	-2993.457
	Durbin Watson	2.004413	2.131623	2.033207
	T-distribution	6.530107(0.0000)	6.621858(0.0000)	6.141684(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.832225	0.020111	1.044737
	Prob.	0.4356	0.8873	0.3521

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.38711	0.123993	-0.069153
	Crisis			0.235999
	λ (risk premium)	0.120433	0.102291	0.054893
Variance equation	*ω (Constant)*	0.580693***[1.830029]	0.216225***[1.927292]	0.193087**[2.330988]
	α (ARCH effect)	0.067836**[2.280012]	0.106548*[3.355289]	0.075991*[4.175440]
	β (GARCH effect)	0.882112*[18.54809]	0.864974*[24.23690]	0.903837*[42.72634]
	α+β	0.949948	0.971522	0.979828
	Log likelihood	-1570.484	-1423.855	-3000.285
	Durbin Watson	2.018557	2.115468	2.024448
	T-distribution	5.983961(0.0000)	6.711084(0.0000)	5.983987(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.249988	0.031296	0.595592
	Prob.	0.7789	0.8596	0.5514

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.062008	0.320642*	0.12458
	Crisis			0.087102
Variance equation	*ω (Constant)*	0.415279[1.048394]	0.126952***[1.681959]	0.113282**[1.964653]
	α (ARCH effect)	0.022406[0.002364]	0.128351*[3.588573]	0.069671*[3.108809]
	β (GARCH effect)	0.918215*[26.87759]	0.850081*[22.12400]	0.912792*[47.86805]
	γ (Leverage effect)	0.998843[0.002386]	0.339669**[2.044248]	0.491843**[2.447230]
	δ (Power Parameter)	2.019620*[3.328342]	0.998227**[2.426031]	1.357636*[3.958776]
	α+β	0.940621	0.978432	0.982463
	Log likelihood	-1565.793	-1419.244	-2991.761
	Durbin Watson	2.007328	2.132463	2.027854
	T-distribution	6.483326(0.0000)	7.026200(0.0000)	6.179386(0.0000)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.676175	0.005131	1.154228
	Prob.	0.5089	0.9429	0.3156

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.18: Estimation result of GARCH family models for SET Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.005453	0.302759*	0.058607
	Crisis			0.168242
Variance equation	*ω (Constant)*	0.146132[1.289670]	0.095458***[1.683970]	0.039880[1.393401]
	α (ARCH effect)	0.058716*[2.962268]	0.094008*[3.403851]	0.071768*[4.773886]
	β (GARCH effect)	0.932248*[42.55932]	0.895865*[33.46960]	0.926993*[66.51640]
	α+β	0.990964	0.989873	0.998761
	Log likelihood	-1652.688	-1375.555	-3032.267
	Durbin Watson	1.964236	2.025614	1.984632
	T-distribution	9.559155(0.0000)	5.149114(0.0000)	6.613837(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.09845	0.001231	0.061594
	Prob.	0.9063	0.972	0.9697

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.028858	0.293146*	0.074405
	Crisis			0.136963
Variance equation	*ω (Constant)*	-0.075609**[-2.330840]	-0.110736*[-2.898398]	-0.103569*[-4.900006]
	α (ARCH effect)	0.134946*[3.191367]	0.216142*[3.751912]	0.156062*[5.158654]
	β (GARCH effect)	0.988254*[114.3569]	0.968373*[61.47563]	0.991456*[203.2544]
	γ (Leverage effect)	-0.027458[-1.253874]	-0.034796[-1.245875]	-0.027100***[-1.674870]
	α+β	0.988254	0.968373	0.991456
	Log likelihood	-1652.322	-1373.849	-3029.373
	Durbin Watson	1.961315	2.026354	1.993538
	T-distribution	9.924190(0.0001)	5.298834(0.0000)	6.904090(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.092534	0.0051	0.026423
	Prob.	0.9116	0.9431	0.9869

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.02204	0.299006*	0.066413
	Crisis			0.14973
Variance equation	*ω (Constant)*	0.153870[1.356480]	0.099441***[1.742545]	0.041580[1.443601]
	α (ARCH effect)	0.042688***[1.725418]	0.084146***[1.875973]	0.063981*[2.865344]
	β (GARCH effect)	0.932625*[41.37274]	0.895513*[32.12565]	0.926837*[65.09005]
	γ (Leverage effect)	0.029290[0.905988]	0.015845[0.358686]	0.013803[0.563641]
	α+β	0.989958	0.9875815	0.9977195
	Log likelihood	-1652.172	-1375.483	-3032.098
	Durbin Watson	1.964501	2.025909	1.986362
	T-distribution	9.669074(0.0000)	5.178256(0.0000)	6.654565(0.0001)

		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.082178	0.0001	0.071354
	Prob.	0.9211	0.992	0.965

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.476135	0.128858	0.143997
	Crisis			0.132328
	λ (risk premium)	-0.140386	0.086438	-0.023841
Variance equation	*ω (Constant)*	0.143063[1.296083]	0.091796***[1.661373]	0.039714[1.393554]
	α (ARCH effect)	0.056897*[2.998331]	0.092321*[3.420369]	0.071502*[4.777292]
	β (GARCH effect)	0.934122*[44.59772]	0.897931*[34.19225]	0.927245*[66.91840]
	α+β	0.991019	0.990252	0.998747
	Log likelihood	-1652.253	-1375.239	-3032.225
	Durbin Watson	1.962558	2.007236	1.985701
	T-distribution	9.268673(0.0000)	5.140229(0.0000)	6.597563(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.126641	0.002078	0.068069
	Prob.	0.8811	0.9637	0.9665

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.032351	0.295329*	0.062925
	Crisis			0.14638
Variance equation	*ω (Constant)*	0.072920[0.908381]	0.065671[1.425189]	0.025192[1.531205]
	α (ARCH effect)	0.067178*[2.813530]	0.105513*[3.336521]	0.082710*[4.907574]
	β (GARCH effect)	0.932423*[41.11942]	0.896701*[30.93357]	0.928114*[63.51922]
	γ (Leverage effect)	0.194007[1.082739]	0.132245[0.858626]	0.175122[1.468704]
	δ (Power Parameter)	1.354935***[1.888693]	1.310313*[2.680518]	1.111710*[3.076981]
	α+β	0.999601	1.002214	1.010824
	Log likelihood	-1651.679	-1374.669	-3029.15
	Durbin Watson	1.966199	2.02619	1.989114
	T-distribution	9.951370(0.0001)	5.282835(0.0000)	6.911532(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.093667	0.000761	0.027171
	Prob.	0.9106	0.978	0.9865

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.19: Estimation result of GARCH family models for STI Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.206199**	0.172218**	0.289687**
	Crisis			-0.14855
Variance equation	*ω (Constant)*	0.032810[0.734674]	0.125539***[1.911629]	0.084775**[2.226452]
	α (ARCH effect)	0.090516*[3.207528]	0.118654*[3.157693]	0.110813*[4.764111]
	β (GARCH effect)	0.920152*[39.11429]	0.847298*[21.00411]	0.881633*[41.49977]
	α+β	1.010668	0.965952	0.992446
	Log likelihood	-1113.028	-982.2615	-2116.668
	Durbin Watson	1.912568	1.957755	1.918625
	T-distribution	4.748016(0.0000)	6.344701(0.0009)	5.323673(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.667243	0.218088	7.193052
	Prob.	0.141	0.6407	0.2067

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.078092	0.116474***	0.296602*
	Crisis			-0.225448**
Variance equation	*ω (Constant)*	-0.058585[-1.393791]	-0.112812*[-3.066690]	-0.090224*[-3.486894]
	α (ARCH effect)	0.173446*[3.199721]	0.173052*[3.442385]	0.156068*[4.495127]
	β (GARCH effect)	0.960487*[53.64876]	0.977967*[97.97377]	0.977365*[142.5682]
	γ (Leverage effect)	-0.148439*[-3.821434]	-0.123756*[-3.617978]	-0.114928*[-5.412973]
	α+β	0.960487	0.977967	0.977365
	Log likelihood	-1106.866	-976.5634	-2105.512
	Durbin Watson	1.982233	1.957614	1.920978
	T-distribution	5.853478(0.0002)	7.615819(0.0008)	6.232533(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.192998	0.035156	7.404948
	Prob.	0.3115	0.8513	0.1922

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.087494	0.116914***	0.273566*
	Crisis			-0.200787***
Variance equation	*ω (Constant)*	0.176671**[2.020168]	0.080889**[1.999767]	0.079449*[2.904506]
	α (ARCH effect)	0.001884[0.054131]	0.021069[0.662834]	0.008829[0.436100]
	β (GARCH effect)	0.880340*[24.35000]	0.874322*[26.92288]	0.903549*[48.21850]
	γ (Leverage effect)	0.198033*[3.010351]	0.164876*[2.895362]	0.138742*[4.334846]
	α+β	0.9812405	0.976727	0.981749
	Log likelihood	-1107.231	-976.0205	-2104.741
	Durbin Watson	1.969814	1.957625	1.921841
	T-distribution	5.743559(0.0003)	7.437521(0.0006)	6.095378(0.0000)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.768677	0.142821	3.812366
	Prob.	0.5727	0.7057	0.5767

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.477772***	-0.082476	0.300875
	Crisis			-0.150332
	λ (risk premium)	-0.123535	0.164344	-0.005573
Variance equation	*ω (Constant)*	0.023341[0.584272]	0.122720***[1.883167]	0.084662**[2.224648]
	α (ARCH effect)	0.083219*[3.259481]	0.120053*[3.125870]	0.110709*[4.763675]
	β (GARCH effect)	0.927548*[43.83447]	0.846885*[20.53933]	0.881750*[41.57113]
	α+β	1.010767	0.966938	0.992459
	Log likelihood	-1112.443	-981.5699	-2116.666
	Durbin Watson	1.912234	1.973422	1.918855
	T-distribution	4.676546(0.0000)	6.409500(0.0010)	5.320820(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.767472	0.149342	7.181724
	Prob.	0.1181	0.6993	0.2075

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.073759	0.110549	0.291101*
	Crisis			-0.226612*
Variance equation	*ω (Constant)*	0.134961**[1.973036]	0.047033**[2.009879]	0.063082*[2.666847]
	α (ARCH effect)	0.081576[0.688709]	0.090234*[2.686234]	0.068050**[2.097905]
	β (GARCH effect)	0.881698*[25.12188]	0.901101*[33.63921]	0.908905*[50.50206]
	γ (Leverage effect)	0.986038[0.549631]	0.735957**[2.437365]	0.737841**[2.085979]
	δ (Power Parameter)	1.388491*[3.100945]	1.169265**[2.332919]	1.509956*[3.768742]
	α+β	0.963274	0.991336	0.976955
	Log likelihood	-1106.503	-975.4634	-2104.252
	Durbin Watson	1.976501	1.95744	1.921374
	T-distribution	6.046721(0.0004)	7.755623(0.0011)	6.240330(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.939258	0.00679	5.730048
	Prob.	0.4552	0.9344	0.3334

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.20: Estimation result of GARCH family models for TAIEX Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.201331	0.266616*	0.358248***
	Crisis			-0.132415
Variance equation	*ω (Constant)*	0.280919[1.490413]	0.071851[1.549487]	0.075563**[1.952096]
	α (ARCH effect)	0.079747*[2.872997]	0.083608*[3.234666]	0.084120*[4.774754]
	β (GARCH effect)	0.901714*[26.94348]	0.908262*[34.72105]	0.911643*[54.24289]
	α+β	0.981461	0.99187	0.995763
	Log likelihood	-1581.171	-1350.668	-2944.185
	Durbin Watson	2.023791	1.943315	2.050364
	T-distribution	7.166173(0.0000)	6.735988(0.0000)	6.910408(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.039572	0.82039	0.600319
	Prob.	0.8424	0.4407	0.4386

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.152108	0.226105*	0.396250**
	Crisis			-0.224508
Variance equation	*ω (Constant)*	-0.035701[-0.766346]	-0.090832*[-2.600325]	-0.091220*[-3.627489]
	α (ARCH effect)	0.150786*[2.932034]	0.160343*[3.506494]	0.163687*[5.047311]
	β (GARCH effect)	0.966150*[57.35109]	0.978402*[104.8666]	0.981337*[156.6148]
	γ (Leverage effect)	-0.060008***[-1.933237]	-0.065685*[-2.590246]	-0.058562*[-2.981102]
	α+β	0.96615	0.978402	0.981337
	Log likelihood	-1574.808	-1348.752	-2936.22
	Durbin Watson	2.026633	1.954331	2.053214
	T-distribution	7.662809(0.0000)	6.756465(0.0000)	7.188398(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.024363	0.853128	0.331503
	Prob.	0.876	0.4266	0.5649

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.166609	0.226166*	0.463065*
	Crisis			-0.284567
Variance equation	*ω (Constant)*	0.321113***[1.910112]	0.090428**[2.174719]	0.093824*[2.638742]
	α (ARCH effect)	0.004767*[0.201721]	0.020272[0.686506]	0.021973[1.084869]
	β (GARCH effect)	0.914768*[29.62548]	0.917749*[39.44286]	0.922498*[58.61134]
	γ (Leverage effect)	0.101204*[2.780032]	0.080997**[2.363870]	0.080721*[3.304498]
	α+β	0.970137	0.9785195	0.9848315
	Log likelihood	-1576.204	-1348.294	-2938.654
	Durbin Watson	2.025873	1.979432	2.051571
	T-distribution	7.380659(0.0000)	6.701719(0.0000)	6.946860(0.0000)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.068283	0.705901	0.499602
	Prob.	0.7939	0.4941	0.4798

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.490388	0.225659	0.456428
	Crisis			-0.155807
	λ (risk premium)	-0.091169	0.021283	-0.03377
Variance equation	*ω (Constant)*	0.270194[1.488844]	0.072369[1.525408]	0.075127***[1.933420]
	α (ARCH effect)	0.078722*[2.918672]	0.083533*[3.229796]	0.084218*[4.779124]
	β (GARCH effect)	0.903517*[28.04265]	0.908231*[34.54321]	0.911607*[53.94906]
	α+β	0.982239	0.991764	0.995825
	Log likelihood	-1581	-1350.653	-2944.088
	Durbin Watson	2.025786	1.940579	2.053599
	T-distribution	7.134606(0.0000)	6.708349(0.0000)	6.931777(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.014716	0.832444	0.547937
	Prob.	0.9035	0.4355	0.4593

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.109885*	0.222060*	0.399826**
	Crisis			-0.228791
Variance equation	*ω (Constant)*	0.022434[1.354215]	0.066396***[1.782783]	0.052217**[2.345823]
	α (ARCH effect)	0.045015***[1.787013]	0.074841**[2.411594]	0.085008*[4.640029]
	β (GARCH effect)	0.932963*[46.66280]	0.912973*[39.11725]	0.915582*[58.86394]
	γ (Leverage effect)	0.162216[0.549596]	0.426596*[1.752402]	0.370815**[2.450486]
	δ (Power Parameter)	0.007075[0.016561]	1.381953**[2.516601]	1.081369*[3.225210]
	α+β	0.977978	0.987814	1.00059
	Log likelihood	-1573.258	-1347.993	-2935.938
	Durbin Watson	2.028472	1.968672	2.053191
	T-distribution	8.415186(0.0004)	6.782633(0.0000)	7.215454(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.632674	0.755038	0.15706
	Prob.	0.4267	0.4704	0.6919

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.21: Estimation result of GARCH family models for HANG SENG Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.215295**	1.104336*	0.709760**
	Crisis			-0.363734
Variance equation	*ω (Constant)*	95.45100*[3.713440]	3.858638[1.570228]	0.434742[1.442749]
	α (ARCH effect)	-0.053153[-0.718496]	0.254651**[2.174369]	0.169422*[2.966537]
	β (GARCH effect)	-0.432653[-1.219597]	0.658860*[5.161782]	0.816892*[15.66534]
	α+β	-0.485806	0.913511	0.986314
	Log likelihood	-490.6333	-474.8568	-865.1625
	Durbin Watson	1.975876	1.759324	1.84102
	T-distribution	5.823576(0.0407)	6.701387(0.2809)	6.283424(0.0124)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.067392	0.646772	0.214342
	Prob.	0.7956	0.4226	0.6434

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.295507	1.187844*	0.916460*
	Crisis			-0.778391***
Variance equation	*ω (Constant)*	7.209908*[7.639031]	0.153158[0.540345]	-0.101431[-1.486947]
	α (ARCH effect)	0.083232[0.605555]	0.484690*[2.902934]	0.225721*[2.645669]
	β (GARCH effect)	-0.768678*[-3.874190]	0.850559*[9.583419]	0.969311*[63.10784]
	γ (Leverage effect)	0.060839[0.620482]	-0.026339[-0.267790]	-0.147955*[-3.395135]
	α+β	-0.768678	0.850559	0.969311
	Log likelihood	-491.4531	-476.0257	-862.1838
	Durbin Watson	1.979103	1.753954	1.935647
	T-distribution	6.575592(0.1211)	6.647517(0.2830)	7.623001(0.0438)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.051258	0.418559	0.527868
	Prob.	0.8212	0.5187	0.4675

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.486426	1.096242**	0.762962**
	Crisis			-0.576638
Variance equation	*ω (Constant)*	86.50461*[2.929901]	3.884950[1.575281]	0.484688***[1.679369]
	α (ARCH effect)	-0.061609[-0.926671]	0.249253[1.308558]	0.050877[1.117745]
	β (GARCH effect)	-0.352299[-1.078933]	0.657764*[5.148040]	0.829198*[17.63964]
	γ (Leverage effect)	0.197174[1.026769]	0.009179[0.047011]	0.179076**[2.502694]
	α+β	-0.315321	0.9116065	0.969613
	Log likelihood	-490.6592	-474.8557	-862.3879
	Durbin Watson	1.978403	1.759812	1.853168
	T-distribution	5.352180(0.0347)	6.744661(0.2928)	7.268467(0.0363)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.110931	0.620242	0.675846
	Prob.	0.7396	0.4322	0.411

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	3.170325	2.384196	0.383505
	Crisis			-0.235001
	λ (risk premium)	-0.351372	-0.257102	0.07121
Variance equation	*ω (Constant)*	1.577189[0.750062]	3.595137[1.638749]	0.441523[1.457983]
	α (ARCH effect)	0.110697***[1.750664]	0.250643**[2.207718]	0.175836*[2.974697]
	β (GARCH effect)	0.857546*[10.70173]	0.669168*[5.798935]	0.811274*[15.16490]
	α+β	0.968243	0.919811	0.98711
	Log likelihood	-484.7302	-474.4481	-865.0273
	Durbin Watson	1.987705	1.816817	1.832814
	T-distribution	6.148336(0.0734)	6.804868(0.3189)	6.390322(0.0129)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.920842	0.890715	0.205782
	Prob.	0.3389	0.3468	0.6501

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.859802	1.028108**	0.766088**
	Crisis			-0.581137
Variance equation	*ω (Constant)*	43.36972[0.207947]	1692.793[0.140044]	0.308984[0.908589]
	α (ARCH effect)	-0.070091[-0.410302]	0.068890[0.449978]	0.138474**[2.149096]
	β (GARCH effect)	0.359609[1.410531]	0.563113**[2.502995]	0.834646*[17.08956]
	γ (Leverage effect)	-0.071703[-0.135720]	-0.102858[-0.770006]	0.434444**[2.002215]
	δ (Power Parameter)	1.977865[0.784813]	6.048771[1.274407]	1.545239***1.898223]
	α+β	0.289518	0.632003	0.97312
	Log likelihood	-490.6648	-473.0497	-862.3812
	Durbin Watson	1.937533	1.763692	1.861632
	T-distribution	6.529764(0.0609)	8.343406(0.3130)	7.331753(0.0393)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.109897	1.669613	0.740898
	Prob.	0.7408	0.1983	0.3894

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.22: Estimation result of GARCH family models for SSE Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.43642	0.281108	0.52433
	Crisis			-0.621191
Variance equation	*ω (Constant)*	-0.804500[-0.640219]	2.645060[1.019117]	4.337656***[1.742260]
	α (ARCH effect)	-0.041954[-1.351965]	0.276372**[2.227561]	0.152200**[2.467720]
	β (GARCH effect)	1.062974*[14.65343]	0.726383*[7.320755]	0.792039*[11.42540]
	α+β	1.02102	1.002755	0.944239
	Log likelihood	-492.1869	-524.094	-1022.861
	Durbin Watson	2.176242	1.732635	2.169385
	T-distribution	12.20910(0.4248)	6.794637(0.2084)	5.119644(0.0034)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.217196	0.018011	1.620848
	Prob.	0.6419	0.8934	0.1995

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.335569	0.587937	0.405369
	Crisis			-0.310732
Variance equation	*ω (Constant)*	0.134096[1.163410]	6.605354*[10.41765]	0.007113[0.059282]
	α (ARCH effect)	-0.119899[-0.818314]	0.620480*[2.724744]	0.242947*[2.646249]
	β (GARCH effect)	0.987734*[10069.09]	-0.672023*[-5.338567]	0.953083*[31.01921]
	γ (Leverage effect)	-0.083691**[-2.122556]	0.171899[1.630684]	0.039971[0.823345]
	α+β	0.987734	-0.672023	0.953083
	Log likelihood	-490.513	-526.8147	-1021.054
	Durbin Watson	2.18356	1.735764	2.161805
	T-distribution	8.585744(0.1663)	4.220332(0.0192)	5.213430(0.0018)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.431073	0.55994	1.30635
	Prob.	0.5126	0.4555	0.2724

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.395168	0.612021	1.302279**
	Crisis			-1.076536
Variance equation	*ω (Constant)*	-0.856320[-1.561029]	1.184722[0.759191]	90.74467[0.369152]
	α (ARCH effect)	-0.051107*[-4.878458]	0.298315**[2.232132]	-0.034248[-0.500419]
	β (GARCH effect)	1.030629*[51664.80]	0.846710*[10.48790]	0.590943[0.604571]
	γ (Leverage effect)	0.089002***[1.908612]	-0.269432**[-2.134241]	0.043292[0.281343]
	α+β	1.024023	1.010309	0.578341
	Log likelihood	-491.3805	-520.6124	-1039.173
	Durbin Watson	2.19449	1.735819	2.034262
	T-distribution	12.67615(0.1976)	7.575195(0.2102)	2.358797(0.0002)

ARCH-LM Test for heteroscedasticity

	ARCH-LM test statistic	0.085683	0.255128	5.506899
	Prob.	0.7702	0.6142	0.0045

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-5.361366*	-0.073558	0.782443
	Crisis			-0.642596
	λ (risk premium)	0.777757*	0.056555	-0.033965
Variance equation	*ω (Constant)*	39.81270*[8.445652]	2.741643[1.016348]	4.351660***[1.734172]
	α (ARCH effect)	0.738196*[3.062459]	0.274530**[2.175094]	0.150639**[2.442624]
	β (GARCH effect)	-0.181506*[-3.378550]	0.727104*[7.079588]	0.793147*[11.42152]
	α+β	0.55669	1.001634	0.943786
	Log likelihood	-493.4823	-524.0548	-1022.844
	Durbin Watson	2.166532	1.723382	2.171707
	T-distribution	24.09276(0.6285)	6.467633(0.1932)	5.095419(0.0038)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.21762	0.006525	1.598143
	Prob.	0.6416	0.9357	0.2041

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.321209	0.809382	0.407075
	Crisis			-0.380879
Variance equation	*ω (Constant)*	0.025676[0.774769]	0.261234[0.609811]	0.194224[0.712981]
	α (ARCH effect)	0.008106[0.312179]	0.137367***[1.809032]	0.129685**[2.387512]
	β (GARCH effect)	0.971762*[57.45954]	0.866162*[11.66169]	0.856793*[14.37415]
	γ (Leverage effect)	1.000000[4.7E+103]	-0.624998[-1.435972]	-0.257183[-0.996523]
	δ (Power Parameter)	0.067058[0.119985]	1.040742[1.131892]	0.710898[1.361670]
	α+β	0.979868	1.003529	0.986478
	Log likelihood	-494.6757	-519.9966	-1020.028
	Durbin Watson	2.212593	1.73523	2.197198
	T-distribution	6.651968(0.0279)	7.794670(0.2288)	5.438536(0.0018)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.75577	0.307217	1.188592
	Prob.	0.3862	0.5802	0.3061

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.23: Estimation result of GARCH family models for JCI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.041602	1.205176*	1.753758*
	Crisis			-0.988599
Variance equation	*ω (Constant)*	2.899998[0.714578]	2.181580[1.363397]	0.258643[0.633739]
	α (ARCH effect)	0.077065[1.150662]	0.348996***[1.853380]	0.084343**[2.468736]
	β (GARCH effect)	0.885100*[8.718520]	0.671854*[5.592106]	0.911087*[28.31990]
	α+β	0.962165	1.02085	0.99543
	Log likelihood	-494.6442	-456.1789	-962.1316
	Durbin Watson	2.002824	1.695248	1.876946
	T-distribution	6.503499(0.0044)	4.071311(0.0488)	5.098325(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.060088	0.286502	0.081827
	Prob.	0.9417	0.5933	0.7748

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.76529	1.357276*	1.725500*
	Crisis			-1.011227
Variance equation	*ω (Constant)*	0.190921[0.772854]	0.038638[0.166315]	-0.074325[-1.199091]
	α (ARCH effect)	0.140767[0.898622]	0.583929**[2.339153]	0.193904**[2.483766]
	β (GARCH effect)	0.928903*[15.09559]	0.869356*[9.913678]	0.978257*[53.10226]
	γ (Leverage effect)	-0.142507[-1.272434]	0.063287[0.401461]	-0.062284[-1.062406]
	α+β	0.928903	0.869356	0.978257
	Log likelihood	-494.7821	-455.8509	-962.3498
	Durbin Watson	2.034705	1.659309	1.883694
	T-distribution	6.052011(0.0043)	3.952933(0.0294)	5.187989(0.0000)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.107596	0.455156	0.001179
	Prob.	0.8981	0.5009	0.9726

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.230664	1.278467*	1.922412*
	Crisis			-1.322225**
Variance equation	*ω (Constant)*	4.112161***[1.855443]	1.479372[1.168850]	0.278432[0.696269]
	α (ARCH effect)	-0.178607**[-2.454387]	0.439129[1.161404]	0.033856[0.457454]
	β (GARCH effect)	0.960536*[17.65704]	0.723649*[6.374485]	0.922950*[26.58160]
	γ (Leverage effect)	0.309414*[2.690469]	-0.209410[-0.605606]	0.056134[0.685594]
	α+β	0.936636	1.058073	0.984873
	Log likelihood	-491.5086	-455.7456	-961.9876
	Durbin Watson	2.031661	1.677362	1.880522
	T-distribution	8.646506(0.0915)	3.885247(0.0314)	5.245493(0.0000)

ARCH-LM Test for heteroscedasticity

	ARCH-LM test statistic	0.31179	1.421982	0.086222
	Prob.	0.7327	0.235	0.769

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	2.814302	-0.058215	1.606656
	Crisis			-0.930215
	λ (risk premium)	-0.219349	0.279531	0.020288
Variance equation	*ω (Constant)*	2.542424[0.708404]	1.460794[1.170349]	0.258608[0.632752]
	α (ARCH effect)	0.076513[1.218643]	0.266797***[1.781705]	0.084692**[2.462111]
	β (GARCH effect)	0.890097*[9.706503]	0.753929*[7.698641]	0.910843*[28.15743]
	α+β	0.96661	1.020726	0.995535
	Log likelihood	-494.494	-455.1426	-962.1242
	Durbin Watson	2.003363	1.669469	1.876237
	T-distribution	6.379986(0.0038)	3.720963(0.0351)	5.099603(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.051689	0.862892	0.079238
	Prob.	0.9496	0.3544	0.7783

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.153924***	1.816416*	2.091303*
	Crisis			-1.616373**
Variance equation	*ω (Constant)*	5.274707[0.073669]	30.00743[0.113013]	0.317273[0.636990]
	α (ARCH effect)	8.57E-05[1.75E-06]	-0.038315[-0.184541]	0.018637[0.003226]
	β (GARCH effect)	0.837995*[7.157884]	0.553913[0.565198]	0.934191*[29.47857]
	γ (Leverage effect)	0.732236[5.03E-06]	-0.010725[-0.014208]	0.987911[0.003442]
	δ (Power Parameter)	6.801301[1.042523]	2.020310[0.439941]	2.144288*[2.625680]
	α+β	0.923695	0.515598	0.952828
	Log likelihood	-480.6523	-462.2637	-961.922
	Durbin Watson	2.015277	1.597626	1.884426
	T-distribution	7.191766(0.0459)	2.546665(0.0223)	5.316129(0.0000)
		ARCH-LM Test for heteroscedasticity		
	ARCH-LM test statistic	0.16487	3.864862	0.156445
	Prob.	0.975	0.0512	0.6925

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.24: Estimation result of GARCH family models for KLCI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.421417	0.546115**	0.709760**
	Crisis			-0.363734
Variance equation	*ω (Constant)*	2.289490[1.086365]	1.047543[1.238202]	0.434742[1.442749]
	α (ARCH effect)	0.190312***[1.904280]	0.160499[1.473443]	0.169422*[2.966537]
	β (GARCH effect)	0.764028*[7.155028]	0.766525*[6.122337]	0.816892*[15.66534]
	α+β	0.95434	0.927024	0.986314
	Log likelihood	-478.3901	-376.5469	-865.1625
	Durbin Watson	1.881377	1.77281	1.84102
	T-distribution	11.95757(0.2431)	4.341154(0.0438)	6.283424(0.0124)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.785575	0.179064	0.214342
	Prob.	0.377	0.8362	0.6434

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.127564	0.465313**	0.767021**
	Crisis			-0.603531
Variance equation	*ω (Constant)*	0.056222*[0.396744]	0.220767[0.689461]	-0.118525***[-1.712520]
	α (ARCH effect)	0.215864[1.310733]	0.380407[1.506455]	0.251817*[2.942242]
	β (GARCH effect)	0.936186*[28.67322]	0.794467*[5.676223]	0.969479*[60.60366]
	γ (Leverage effect)	-0.224251*[-2.656301]	-0.187857[-1.425627]	-0.134868*[-3.195422]
	α+β	0.936186	0.794467	0.969479
	Log likelihood	-474.9659	-375.5238	-862.3295
	Durbin Watson	1.955588	1.817327	1.87517
	T-distribution	103.3414(0.9095)	3.966958(0.0310)	7.331971(0.0364)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.458941	0.013927	0.705528
	Prob.	0.2292	0.9061	0.4009

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.08413	0.469495**	0.762962**
	Crisis			-0.576638
Variance equation	*ω (Constant)*	2.448825[1.450960]	1.575993***[1.653015]	0.484688***[1.679369]
	α (ARCH effect)	-0.020802[-0.248437]	0.035914[0.444311]	0.050877[1.117745]
	β (GARCH effect)	0.812191*[7.917499]	0.692041*[5.132443]	0.829198*[17.63964]
	γ (Leverage effect)	0.310155**[2.285595]	0.298643[1.427928]	0.179076**[2.502694]
	α+β	0.9464485	0.727955	0.969613
	Log likelihood	-474.7505	-375.2563	-862.3879
	Durbin Watson	1.898782	1.815987	1.853168
	T-distribution	66.02994(0.8479)	4.463891(0.0532)	7.268467(0.0363)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.539997	0.970817	0.675846
	Prob.	0.2167	0.3812	0.411

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.516501	-0.815962	0.383505
	Crisis			-0.235001
	λ (risk premium)	-0.016354	0.492057***	0.07121
Variance equation	*ω (Constant)*	2.272814[1.076592]	1.212163[1.512788]	0.441523[1.457983]
	α (ARCH effect)	0.190289***[1.908377]	0.278168***[1.849883]	0.175836*[2.974697]
	β (GARCH effect)	0.764453*[7.173077]	0.655962*[5.557909]	0.811274*[15.16490]
	α+β	0.954742	0.93413	0.98711
	Log likelihood	-478.3875	-374.706	-865.0273
	Durbin Watson	1.880499	1.620296	1.832814
	T-distribution	11.88478(0.2417)	4.642471(0.0444)	6.390322(0.0129)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.777008	0.090659	0.205782
	Prob.	0.3796	0.9134	0.6501

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.196997	0.463572**	0.766088**
	Crisis			-0.581137
Variance equation	*ω (Constant)*	0.350001[0.891855]	1.038482[0.432337]	0.308984[0.908589]
	α (ARCH effect)	0.138475**[2.038791]	0.169425*[1.197415]	0.138474**[2.149096]
	β (GARCH effect)	0.816937*[8.154926]	0.701805*[3.530087]	0.834646*[17.08956]
	γ (Leverage effect)	0.994738*[3.894518]	0.507630[1.413575]	0.434444**[2.002215]
	δ (Power Parameter)	0.709247[1.113207]	1.633553[1.036234]	1.545239***[1.898223]
	α+β	0.955412	0.87123	0.97312
	Log likelihood	-474.5135	-375.2966	-862.3812
	Durbin Watson	2.006037	1.814956	1.861632
	T-distribution	341.6113(0.0000)	4.422005(0.0551)	7.331753(0.0393)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.894237	0.979552	0.740898
	Prob.	0.171	0.378	0.3894

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.25: Estimation result of GARCH family models for KOSPI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.216369	0.466711	-0.612859
	Crisis			1.212964***
Variance equation	*ω (Constant)*	2.090867[0.784800]	0.310130[0.869412]	0.219448[0.743364]
	α (ARCH effect)	0.090263[1.512008]	0.081264[1.552897]	0.097417**[2.440409]
	β (GARCH effect)	0.889235*[11.44003]	0.896732*[16.31769]	0.900876*[24.50758]
	α+β	0.979498	0.977996	0.998293
	Log likelihood	-502.9278	-437.367	-945.596
	Durbin Watson	1.956478	1.924972	1.96161
	T-distribution	7.813222(0.0364)	7.055252(0.0540)	6.779457(0.0004)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.20277	1.381109	0.55631
	Prob.	0.6532	0.2418	0.4564

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.260743	0.560490***	-0.346322
	Crisis			0.916506
Variance equation	*ω (Constant)*	0.029428[0.295970]	-0.117547[-1.278819]	-0.143765***[-2.143825]
	α (ARCH effect)	0.093134[0.844813]	0.192416***[1.710513]	0.233849*[2.697723]
	β (GARCH effect)	0.975889*[38.00426]	0.987299*[47.66794]	0.988616*[68.57347]
	γ (Leverage effect)	-0.213491*[-2.909493]	0.068738[0.985592]	-0.020814[-0.393788]
	α+β	0.975889	0.987299	0.988616
	Log likelihood	-500.0803	-436.845	-946.204
	Durbin Watson	1.951814	1.924083	1.979755
	T-distribution	29.26702(0.7106)	7.752453(0.0501)	7.371525(0.0055)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.212185	0.927019	0.835101
	Prob.	0.2728	0.3372	0.3616

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.116373	0.527617***	-0.664045
	Crisis			1.300729***
Variance equation	*ω (Constant)*	1.879772[0.753541]	0.242632[0.718857]	0.214102[0.729970]
	α (ARCH effect)	-0.004368[-0.056565]	0.132960[1.267867]	0.107549[1.628180]
	β (GARCH effect)	0.889618*[9.808111]	0.897034*[15.72096]	0.903695*[23.58127]
	γ (Leverage effect)	0.215141***[1.761984]	-0.082957[-0.801634]	-0.026707[-0.385680]
	α+β	0.9928205	0.9885155	0.9978905
	Log likelihood	-501.0217	-436.7945	-945.5077
	Durbin Watson	1.918688	1.924545	1.972064
	T-distribution	12.95607(0.2034)	7.267306(0.0398)	6.543204(0.0006)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.626121	1.036462	0.532663
	Prob.	0.4301	0.3103	0.4661

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.016313	-0.099324	-1.994046
	Crisis			1.840147**
	λ (risk premium)	0.058684	0.157422	0.189712
Variance equation	*ω (Constant)*	2.316172[0.707911]	0.340384[0.891577]	0.234849[0.767659]
	α (ARCH effect)	0.111528***[1.663864]	0.081650[1.539188]	0.098332**[2.479943]
	β (GARCH effect)	0.866105*[9.717704]	0.894735*[15.73424]	0.899278*[24.62462]
	α+β	0.977633	0.976385	0.99761
	Log likelihood	-508.5741	-437.135	-944.7646
	Durbin Watson	1.635656	1.918655	1.962153
	T-distribution	9.525361(0.0571)	6.878460(0.0537)	6.819706(0.0004)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	9.78E-05	1.225367	0.470347
	Prob.	0.9921	0.2701	0.4934

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.024519	0.500172***	-0.802331
	Crisis			1.429567**
Variance equation	*ω (Constant)*	443980.3[0.053227]	12.14991[0.215063]	16.66796[0.418156]
	α (ARCH effect)	0.001021[0.115496]	0.016780[0.378701]	0.011666[0.718512]
	β (GARCH effect)	0.881843*[9.890031]	0.864350*[10.82280]	0.880311*[21.25038]
	γ (Leverage effect)	0.121607[0.531735]	-0.235423[-1.291716]	-0.190192**[-2.121446]
	δ (Power Parameter)	8.375515[0.838368]	5.134292[1.350265]	5.539115*[3.232678]
	α+β	0.882864	0.88113	0.891977
	Log likelihood	-499.68	-436.5454	-944.0716
	Durbin Watson	1.944308	1.924807	1.966094
	T-distribution	11.80568(0.1486)	6.904540(0.0185)	6.260658(0.0001)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.210026	0.819539	0.429296
	Prob.	0.6475	0.3668	0.5129

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.26: Estimation result of GARCH family models for NIKKEI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.26643	0.124581	0.158624
	Crisis			0.299425
Variance equation	*ω (Constant)*	11.04457[1.113547]	22.69366[0.484063]	6.341908[1.025284]
	α (ARCH effect)	0.047313[0.374586]	-0.064459*[-0.394597]	0.102136***[1.762476]
	β (GARCH effect)	0.589989[1.603930]	0.562316[0.765190]	0.693902*[3.012928]
	α+β	0.637302	0.497857	0.796038
	Log likelihood	-447.3383	-465.5004	-921.0858
	Durbin Watson	1.887491	1.875694	1.93758
	T-distribution	6.637096(1.0000)	3.538350(0.0811)	28.40501(0.5322)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.00538	2.152111	0.876259
	Prob.	0.9416	0.1199	0.3492

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.146088	0.357126	0.080247
	Crisis			0.085993
Variance equation	*ω (Constant)*	1.389268**[2.228618]	4.042087*[3.355132]	2.060233**[2.446479]
	α (ARCH effect)	-0.164802[-0.885504]	0.139129[0.714818]	0.006986[0.048521]
	β (GARCH effect)	0.631555*[3.683490]	-0.240368*[-0.748816]	0.394711[1.634974]
	γ (Leverage effect)	-0.218067[-1.600500]	-0.309975**[-2.166461]	-0.239005*[-2.774143]
	α+β	0.631555	-0.240368	0.394711
	Log likelihood	-445.9301	-463.6474	-919.1645
	Durbin Watson	1.885888	1.931255	1.967011
	T-distribution	340.8447(0.9856)	19.82413(0.7305)	340.8457(0.9614)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.069202	0.058065	0.16648
	Prob.	0.7929	0.9436	0.6833

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.020657	0.279192	0.089235
	Crisis			0.089857
Variance equation	*ω (Constant)*	5.982412***[1.697383]	22.81431[0.417301]	20.00453[0.731395]
	α (ARCH effect)	-0.144716**[-2.057914]	0.052438[0.328228]	-0.015881[-0.150563]
	β (GARCH effect)	0.815395*[5.680797]	0.586566[0.820817]	0.567282[1.001862]
	γ (Leverage effect)	0.233954[1.445796]	-0.119352[-0.359522]	-0.037853[-0.210578]
	α+β	0.787656	0.579328	0.5324745
	Log likelihood	-444.9978	-465.7937	-925.4102
	Durbin Watson	1.882502	1.848614	1.797106
	T-distribution	26458.03(0.9998)	3.041171(0.0699)	4.654573(0.0407)

	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.046752	2.147179	6.815799
	Prob.	0.8291	0.1205	0.009

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-1.449905	1.130736	-0.471699
	Crisis			0.30587
	λ (risk premium)	0.212591	-0.08481	0.113763
Variance equation	*ω (Constant)*	10.71997[1.097985]	2.964172[0.949477]	6.320640[0.996988]
	α (ARCH effect)	0.050400[0.384171]	0.122305[1.567248]	0.100583[1.599231]
	β (GARCH effect)	0.597152[1.619884]	0.787258*[5.611480]	0.695825*[2.937995]
	α+β	0.647552	0.909563	0.796408
	Log likelihood	-447.3253	-464.6098	-921.0677
	Durbin Watson	1.883794	1.901262	1.93597
	T-distribution	24964.92(0.9997)	7.615437(0.2582)	29.05305(0.5391)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.001153	0.936913	0.969783
	Prob.	0.973	0.3942	0.3247

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.023193	0.402781	-0.223692
	Crisis			0.322644
Variance equation	*ω (Constant)*	2.021078[0.820128]	20.55542[0.109443]	1.595194*[3.124325]
	α (ARCH effect)	-0.088266[-0.567659]	-0.050908[-0.310065]	-0.028330[-0.151543]
	β (GARCH effect)	0.867614*[7.144991]	0.566083[0.599552]	1.017654*[3519.675]
	γ (Leverage effect)	-0.952949[-0.495520]	-0.016115[-0.022410]	-0.968210[-0.161628]
	δ (Power Parameter)	1.305730[1.488856]	2.044518[0.482478]	2.166077*[317.5875]
	α+β	0.779348	0.515175	0.989324
	Log likelihood	-444.8608	-465.0605	-914.8808
	Durbin Watson	1.882588	1.846076	2.00164
	T-distribution	341.6206(0.0000)	4.082957(0.0845)	98.21550(0.8503)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.669982	2.004432	1.862803
	Prob.	0.4145	0.1385	0.1723

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.27: Estimation result of GARCH family models for PSE Index

Estimation results of GARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.125695	1.041790*	0.888522***
	Crisis			-0.177268
Variance equation	*ω (Constant)*	10.50706[0.803457]	16.55312[0.997425]	1.460583[1.359163]
	α (ARCH effect)	0.025174[0.547007]	-0.045115*[-3.012646]	0.094668**[2.435611]
	β (GARCH effect)	0.818612*[3.854162]	0.578887[1.255698]	0.867912*[18.30126]
	α+β	0.843786	0.533772	0.96258
	Log likelihood	-498.7154	-454.986	-958.387
	Durbin Watson	1.868166	1.834494	1.82888
	T-distribution	5.030838(0.0563)	3.854491(0.0095)	6.251366(0.0077)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.538918	0.062291	1.588985
	Prob.	0.4641	0.8033	0.2085

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.397978	1.263815*	0.924144**
	Crisis			-0.643809
Variance equation	*ω (Constant)*	0.706310**[2.564294]	5.461712*[3.870161]	0.108676[0.886665]
	α (ARCH effect)	-0.152669***[-1.695183]	-0.330052[-1.335830]	0.134692[1.580404]
	β (GARCH effect)	0.854814*[12.47297]	-0.609292[-1.295540]	0.938778*[31.27094]
	γ (Leverage effect)	-0.291852*[-3.321011]	-0.060567[-0.382966]	-0.121894**[-2.447048]
	α+β	0.854814	-0.609292	0.938778
	Log likelihood	-491.9451	-458.5309	-954.5341
	Durbin Watson	1.866668	1.826765	1.879296
	T-distribution	9.751408(0.3766)	6.216989(0.0068)	9.378652(0.0846)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.853262	0.006063	2.49256
	Prob.	0.3572	0.938	0.1155

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	Period		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.526411	0.903438	0.973561**
	Crisis			-0.616908
Variance equation	*ω (Constant)*	6.155809**[4.337797]	21.43388[0.485478]	3.243351**[2.171767]
	α (ARCH effect)	-0.110302*[-4.935754]	-0.010307[-0.239449]	-0.026055[-0.460352]
	β (GARCH effect)	0.885104*[45.90362]	0.575882*[0.632102]	0.827266*[12.12566]
	γ (Leverage effect)	0.236798*[4.102509]	-0.048713[-0.411037]	0.206509*[2.629916]
	α+β	0.893101	0.5412185	0.9544655
	Log likelihood	-489.745	-471.5102	-955.6601
	Durbin Watson	1.864674	1.836032	1.866522
	T-distribution	12.84483(0.3995)	19.03109(0.2981)	9.148047(0.0736)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	1.233609	0.429842	2.288254
	Prob.	0.2686	0.5131	0.1314

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-4.875881	0.61216	1.495855
	Crisis			-0.340267
	λ (risk premium)	0.570806	0.127982	-0.086965
Variance equation	*ω (Constant)*	15.02443[0.771940]	3.316514[1.044020]	1.449071[1.360370]
	α (ARCH effect)	0.027358[0.589886]	0.154724*[1.227469]	0.092924**[2.420136]
	β (GARCH effect)	0.749003**[2.514536]	0.735300*[3.931408]	0.869804*[18.44359]
	α+β	0.776361	0.890024	0.962728
	Log likelihood	-498.608	-457.0826	-958.3014
	Durbin Watson	1.890655	1.805245	1.819672
	T-distribution	5.345439(0.0646)	6.243407(0.0428)	6.227080(0.0077)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.765654	0.848514	1.495275
	Prob.	0.3831	0.3585	0.2224

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.26731	0.92192	0.889228**
	Crisis			-0.583091
Variance equation	*ω (Constant)*	0.354426[0.590436]	17.26714[0.210893]	0.570207[1.001750]
	α (ARCH effect)	0.075247[1.289693]	-0.039118[-0.206646]	0.083459*[3.239809]
	β (GARCH effect)	0.823515*[6.873895]	0.581138*[0.815582]	0.843279*[14.77671]
	γ (Leverage effect)	0.998638*[12.36232]	0.047429[0.036974]	0.999958*[4.7E+103]
	δ (Power Parameter)	0.474031[0.712892]	2.031761[0.626367]	1.036193**[2.158756]
	α+β	0.898762	0.54202	0.926738
	Log likelihood	-495.1153	-464.2084	-954.4575
	Durbin Watson	1.867851	1.835973	1.879507
	T-distribution	7.490857(0.2887)	18.18186(0.1947)	9.324342(0.0889)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	3.098385	0.081558	2.199302
	Prob.	0.0806	0.7756	0.1127

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.28: Estimation result of GARCH family models for SET Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.224132	0.574294	0.447771
	Crisis			0.256912
Variance equation	*ω (Constant)*	2.238142[0.685480]	0.332073[0.356530]	0.217643[0.444358]
	α (ARCH effect)	0.134162***[1.874195]	0.192104*[2.602040]	0.135201*[3.204114]
	β (GARCH effect)	0.841392*[11.30876]	0.808326*[9.385490]	0.864964*[22.45841]
	α+β	0.975554	1.00043	1.000165
	Log likelihood	-520.5178	-443.0487	-981.3162
	Durbin Watson	2.023844	1.895082	1.911819
	T-distribution	11.09624(0.5247)	15.94530(0.5538)	8.627833(0.0548)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.747501	0.498071	0.263269
	Prob.	0.3888	0.6842	0.6079

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.384752	0.743673***	0.471743
	Crisis			0.23
Variance equation	*ω (Constant)*	7.341050*[3.367228]	1.950654**[2.157363]	-0.147456**[-2.093019]
	α (ARCH effect)	-0.056262[-0.352578]	0.710880*[2.682069]	0.215761*[2.948699]
	β (GARCH effect)	-0.571984[-1.292665]	0.212054[0.867431]	0.991843*[77.86438]
	γ (Leverage effect)	0.165915[1.421086]	-0.101222[-0.518322]	-0.039580[-1.060289]
	α+β	-0.571984	0.212054	0.991843
	Log likelihood	-527.6142	-446.3257	-980.2612
	Durbin Watson	2.031927	1.789103	1.911278
	T-distribution	5.879919(0.2298)	8.719385(0.2942)	9.223713(0.0594)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	1.699425	0.197554	0.332304
	Prob.	0.1945	0.8979	0.5643

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.001683	0.613575	0.431102
	Crisis			0.251386
Variance equation	*ω (Constant)*	2.329623[0.780751]	0.287120[0.315914]	0.210182[0.439457]
	α (ARCH effect)	0.055595[0.844330]	0.209356[1.020553]	0.120322[1.633374]
	β (GARCH effect)	0.870034*[12.93043]	0.810007*[8.495533]	0.869323*[21.30659]
	γ (Leverage effect)	0.088579[1.014686]	-0.028064[-0.133092]	0.016950[0.229178]
	α+β	0.9699185	1.005331	0.99812
	Log likelihood	-519.9755	-443.038	-981.2854
	Durbin Watson	2.028465	1.889828	1.912287

	T-distribution	12.39183(0.5552)	14.37023(0.5473)	8.758981(0.0658)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.41552	0.516925	0.253123
	Prob.	0.5202	0.6713	0.6149

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

Coefficients		*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	3.520428	0.010265	0.91652
	Crisis			-0.027217
	λ (risk premium)	-0.387357	0.154398	-0.046038
Variance equation	*ω (Constant)*	1.906603[0.620075]	0.396892[0.395517]	0.215420[0.438217]
	α (ARCH effect)	0.136779***[1.833720]	0.183965**[2.424918]	0.136832*[3.207491]
	β (GARCH effect)	0.845349*[11.39673]	0.812480*[8.746463]	0.863618*[22.29471]
	α+β	0.982128	0.996445	1.00045
	Log likelihood	-519.6771	-442.7872	-981.2756
	Durbin Watson	2.034803	1.867199	1.914284
	T-distribution	8.441989(0.4147)	12.71438(0.4806)	8.825599(0.0580)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.678298	0.505037	0.191585
	Prob.	0.4116	0.6794	0.6616

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

Coefficients		*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.13265	0.674220*	0.385988
	Crisis			0.453915
Variance equation	*ω (Constant)*	-1645.753[-0.097014]	0.013623[0.207033]	0.014389[0.703028]
	α (ARCH effect)	0.005931[0.255802]	0.105991**[2.162444]	0.079667***[1.908616]
	β (GARCH effect)	0.890725*[7.376937]	0.896183*[13.27822]	0.917373*[33.93976]
	γ (Leverage effect)	0.295890[0.397854]	0.315635[0.712565]	0.412816[1.381406]
	δ (Power Parameter)	5.743661[0.996516]	0.200220[0.427978]	0.154940[0.314730]
	α+β	0.896656	1.002174	0.99704
	Log likelihood	-519.2207	-441.5191	-978.3692
	Durbin Watson	2.025975	1.839134	1.912283
	T-distribution	13.38172(0.5451)	21.63137(0.6896)	9.223969(0.0453)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.097106	0.339482	0.999112
	Prob.	0.7558	0.7968	0.3175

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.29: Estimation result of GARCH family models for STI Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.315781*	0.886029*	1.033594*
	Crisis			-0.098093
Variance equation	*ω (Constant)*	0.865735[0.839935]	2.311441[1.243111]	1.601337[1.388997]
	α (ARCH effect)	0.117586[1.286792]	0.250397[1.440777]	0.210919***[1.827336]
	β (GARCH effect)	0.858205*[9.592104]	0.639847*[3.674958]	0.764384*[9.718185]
	α+β	0.975791	0.890244	0.975303
	Log likelihood	-324.078	-317.3263	-649.4311
	Durbin Watson	1.895191	1.558652	1.764731
	T-distribution	4.286986(0.0419)	4.057124(0.0539)	3.423096(0.0015)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.940323	0.053931	0.168984
	Prob.	0.3344	0.9475	0.919

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.511230*	0.669775**	1.047376**
	Crisis			-0.298594
Variance equation	*ω (Constant)*	-0.170016[-0.849391]	0.030331[0.131822]	-0.008539[-0.080907]
	α (ARCH effect)	0.354623***[1.680238]	0.404459**[1.994937]	0.253035**[2.050991]
	β (GARCH effect)	0.979451*[17.87977]	0.874774*[9.263147]	0.938372*[26.41959]
	γ (Leverage effect)	0.122268[0.810689]	-0.183004[-1.518859]	-0.131183***[-1.773397]
	α+β	0.979451	0.874774	0.938372
	Log likelihood	-324.0233	-316.5331	-649.5473
	Durbin Watson	1.869026	1.687372	1.791105
	T-distribution	3.894109(0.0250)	4.586011(0.0867)	3.804224(0.0049)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.840835	0.502806	0.251056
	Prob.	0.3613	0.6062	0.882

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.557108*	0.741486**	1.027107*
	Crisis			0.131503
Variance equation	*ω (Constant)*	0.279773[0.279626]	1.797728[1.158236]	27.82692[0.751969]
	α (ARCH effect)	0.526829[1.109988]	0.107549[0.904169]	-0.012080[-0.098985]
	β (GARCH effect)	0.833235*[9.528437]	0.669712*[4.347222]	0.568593[1.087160]
	γ (Leverage effect)	-0.449967[-0.984878]	0.247992[1.131127]	-0.064496[-0.362865]
	α+β	1.1350805	0.991257	0.524265
	Log likelihood	-323.0129	-316.5912	-662.0521
	Durbin Watson	1.862351	1.645724	1.714283
	T-distribution	3.720511(0.0264)	4.561002(0.0704)	2.343822(0.0000)

ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.750047	0.062918	7.479703
	Prob.	0.3885	0.9391	0.0238

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-484.2513	-0.388681	0.442761
	Crisis			-0.031758
	λ (risk premium)	9.868147	0.346163	0.12864
Variance equation	*ω (Constant)*	2997.535[0.037016]	2.268390[1.179000]	1.640037[1.348622]
	α (ARCH effect)	0.239344[0.840591]	0.244203[1.340124]	0.204478***[1.742778]
	β (GARCH effect)	-0.242124[-0.867449]	0.648653*[3.431882]	0.769810*[9.385613]
	α+β	-0.0011896	0.892856	0.974288
	Log likelihood	-310.6405	-316.6325	-649.1539
	Durbin Watson	1.991044	1.649052	1.76797
	T-distribution	2.006652(0.0000)	4.058207(0.0718)	3.341077(0.0015)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.273679	0.071384	0.184205
	Prob.	0.8443	0.9311	0.912

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	1.463307*	0.650471*	1.024392*
	Crisis			-0.231757
Variance equation	*ω (Constant)*	11.97553[0.265399]	0.157317***[1.878240]	13.85371[0.653590]
	α (ARCH effect)	0.084662[0.484913]	0.153508[1.586806]	0.007879[6.90E-06]
	β (GARCH effect)	0.796781*[7.681011]	0.709584*[5.997535]	0.774798*[8.514982]
	γ (Leverage effect)	-0.449276**[-2.048890]	0.814745*[2.625357]	0.983276[1.28E-05]
	δ (Power Parameter)	4.454873***[1.931269]	0.050149[0.193845]	3.726697*[3.114247]
	α+β	0.881443	0.863092	0.782677
	Log likelihood	-322.0556	-312.5158	-647.1307
	Durbin Watson	1.875787	1.663534	1.803793
	T-distribution	4.755683(0.0921)	5.480768(0.1753)	3.784502(0.0023)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.68054	0.891275	1.94715
	Prob.	0.4113	0.4131	0.3777

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Table A.30: Estimation result of GARCH family models for TAIEX Index

Estimation results of GARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.079113	0.784583*	0.136967
	Crisis			0.548002
Variance equation	*ω (Constant)*	25.59938[1.053017]	0.594283[0.970077]	0.363136[0.994041]
	α (ARCH effect)	0.031573[0.362059]	0.213614**[2.048861]	0.158778*[2.865681]
	β (GARCH effect)	0.565956[1.400072]	0.773837*[9.030007]	0.835718*[18.24831]
	α+β	0.597529	0.987451	0.995958
	Log likelihood	-495.9438	-437.9193	-942.4852
	Durbin Watson	1.885575	1.689938	1.874795
	T-distribution	27.67546(0.7365)	7.860545(0.1794)	11.64843(0.2121)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.030032	0.050524	0.105793
	Prob.	0.8627	0.8225	0.7452

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of EGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.00946	0.835301*	0.267646
	Crisis			0.349059
Variance equation	*ω (Constant)*	0.545228[1.126954]	-0.200875[-1.320668]	-0.155565**[-1.963395]
	α (ARCH effect)	0.081847[0.597182]	-1.320668**[2.357053]	0.302423*[3.414691]
	β (GARCH effect)	0.850642*[7.388277]	0.955037*[24.17899]	0.973387*[53.16304]
	γ (Leverage effect)	-0.135463[-1.514500]	-0.020750[-0.217450]	-0.048439[-0.984568]
	α+β	0.850642	0.955037	0.973387
	Log likelihood	-493.9244	-438.7349	-942.609
	Durbin Watson	1.882353	1.687323	1.874851
	T-distribution	340.7551(0.0000)	8.182608(0.2022)	14.74725(0.3231)
ARCH-LM Test for heteroscedasticity				
	ARCH-LM test statistic	0.021432	0.07211	0.203329
	Prob.	0.8838	0.7887	0.6524

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of TGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-0.086265	0.786584*	0.246195
	Crisis			0.365757
Variance equation	*ω (Constant)*	11.14849***[1.715225]	0.592403[0.966336]	0.399785[1.059804]
	α (ARCH effect)	-0.121924**[-2.002546]	0.215957[1.162499]	0.124367***[1.792445]
	β (GARCH effect)	0.831031*[6.979054]	0.773600*[8.098209]	0.837193*[17.62075]
	γ (Leverage effect)	0.254854*[2.665429]	-0.003144[-0.018918]	0.057718[0.738805]
	α+β	0.837809	0.987985	0.96156
	Log likelihood	-493.1491	-437.9191	-942.2045
	Durbin Watson	1.836743	1.68984	1.875011
	T-distribution	16858.81(0.9997)	7.849976(0.1798)	12.59792(0.2404)

ARCH-LM Test for heteroscedasticity

	ARCH-LM test statistic	0.003347	0.046342	0.231035
	Prob.	0.9539	0.8298	0.6311

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of MGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	-14.25788	1.092652	0.191657
	Crisis			0.516096
	λ (risk premium)	1.777309	-0.094164	-0.006074
Variance equation	*ω (Constant)*	18.14256[0.957754]	0.598333[0.989608]	0.363166[0.987314]
	α (ARCH effect)	0.015131[0.416229]	0.221385**[2.051781]	0.159076*[2.867507]
	β (GARCH effect)	0.700677**[2.444351]	0.767671*[8.962642]	0.835492*[18.20797]
	α+β	0.715808	0.989056	0.994568
	Log likelihood	-499.4903	-437.7991	-942.4844
	Durbin Watson	2.012256	1.703825	1.874486
	T-distribution	32.53358(0.7847)	7.989615(0.1880)	11.64253(0.2132)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.039768	0.087518	0.106694
	Prob.	0.8422	0.7678	0.7442

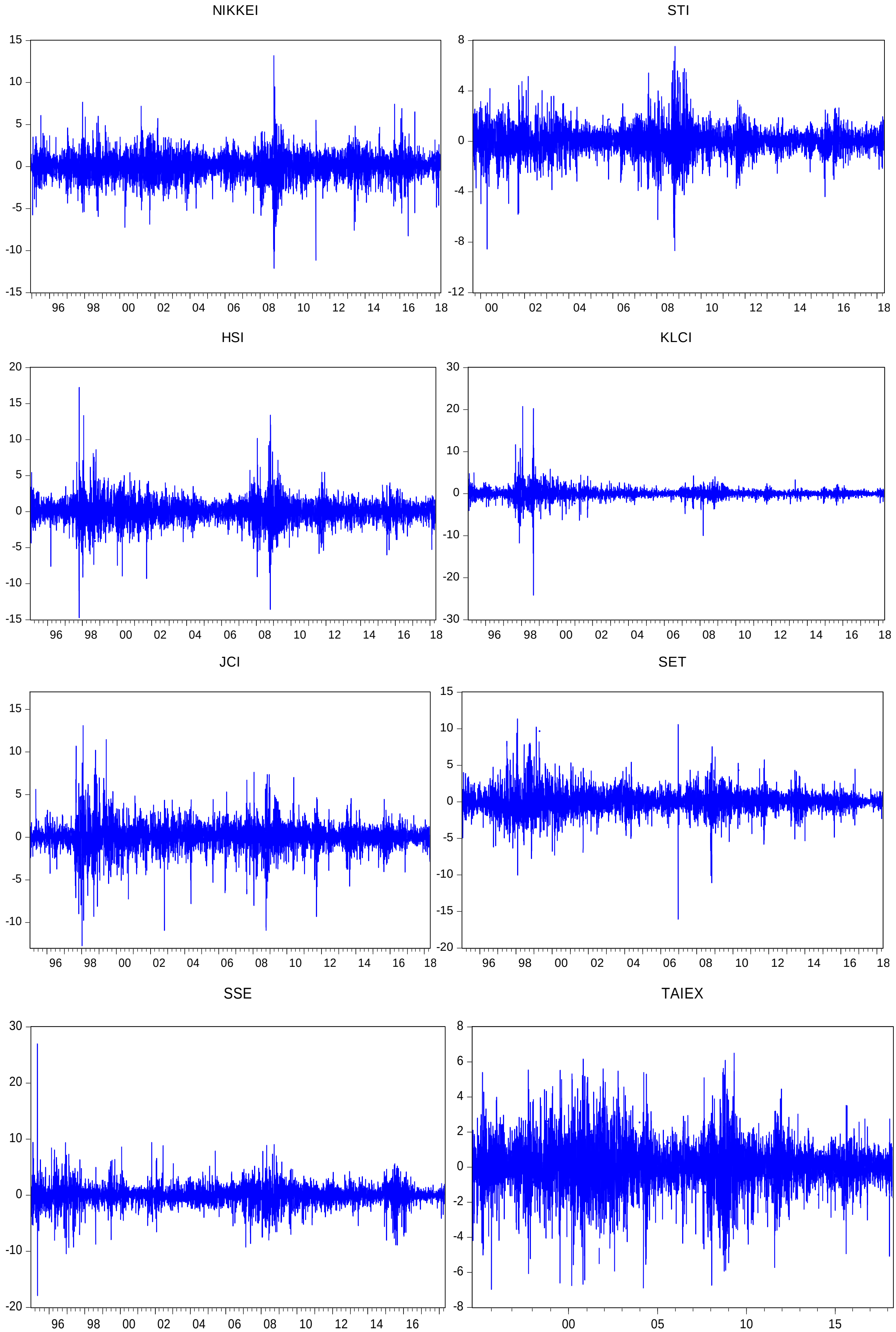
Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Estimation results of PGARCH (1,1) model

	Coefficients	*Period*		
		First Sub-period	*Second Sub-period*	*Full sample period*
Mean equation	*μ (Constant)*	0.058184	0.663685**	0.287045
	Crisis			0.258219
Variance equation	*ω (Constant)*	280.3580[0.105500]	134.8009[0.220550]	17.29145[0.238104]
	α (ARCH effect)	-0.004585[-7.69E-05]	0.029430[0.389068]	0.040415[0.622829]
	β (GARCH effect)	0.562768[1.274127]	0.674336*[4.556745]	0.793791*[9.190638]
	γ (Leverage effect)	-0.970634[-0.000116]	-0.094509[-0.806809]	0.039986[0.444490]
	δ (Power Parameter)	3.064082[0.726221]	7.281787***[1.635068]	5.228952[1.559752]
	α+β	0.558183	0.703766	0.834206
	Log likelihood	-495.1802	-435.5974	-941.8429
	Durbin Watson	1.889414	1.694953	1.875136
	T-distribution	40.76511(0.8364)	11.98406(0.3245)	12.05590(0.2260)
	ARCH-LM Test for heteroscedasticity			
	ARCH-LM test statistic	0.312375	0.000122	0.112789
	Prob.	0.5771	0.9912	0.7372

Notes: * Denotes significance at %1 level, ** at %5 level and *** at %10 level. Student t-Test statistic is stated in [] while p-values in ().

Figure A.1: Daily Log Returns



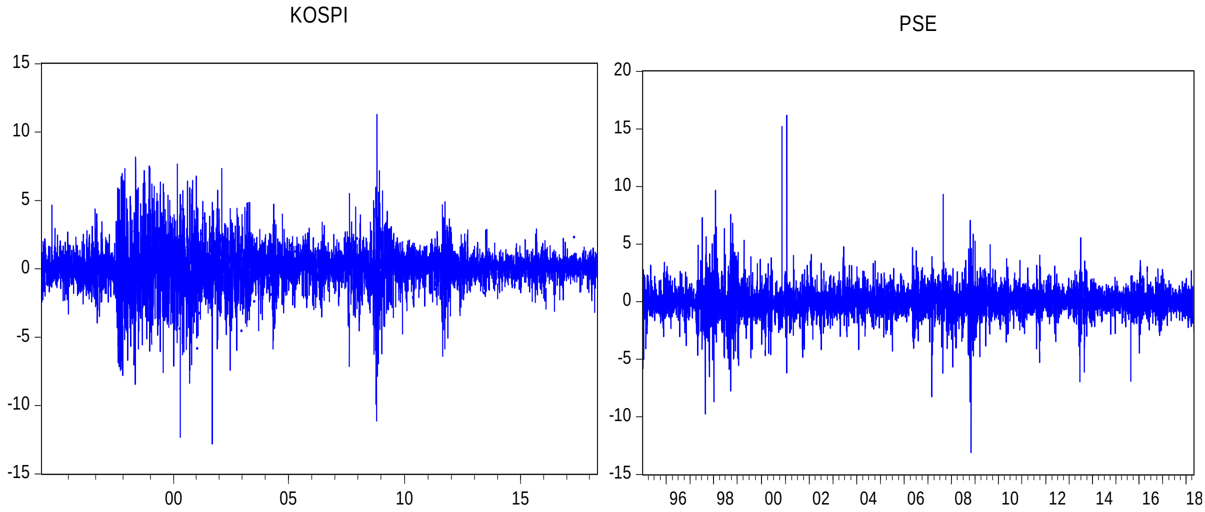
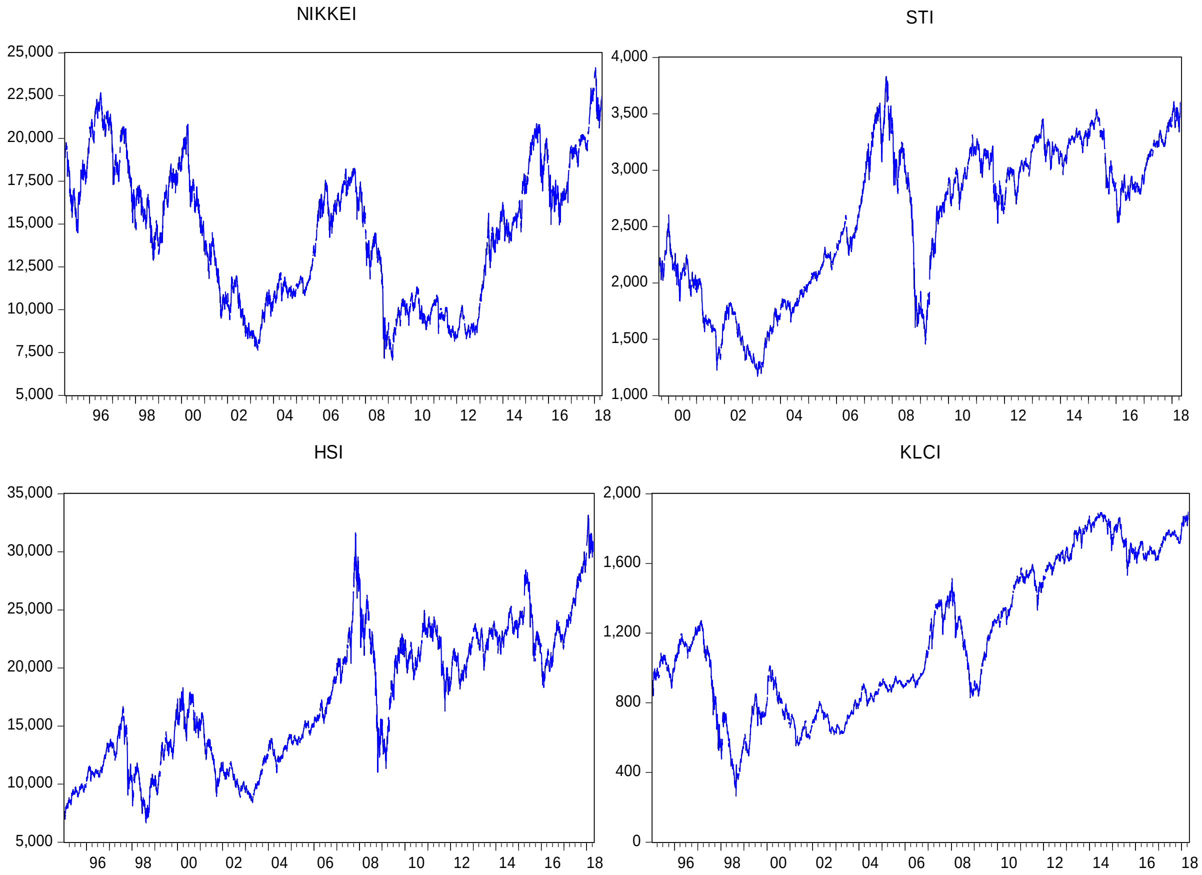


Figure A.2: Daily Closing Prices



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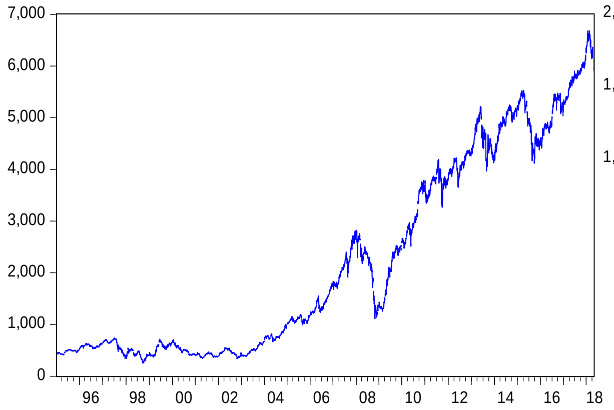

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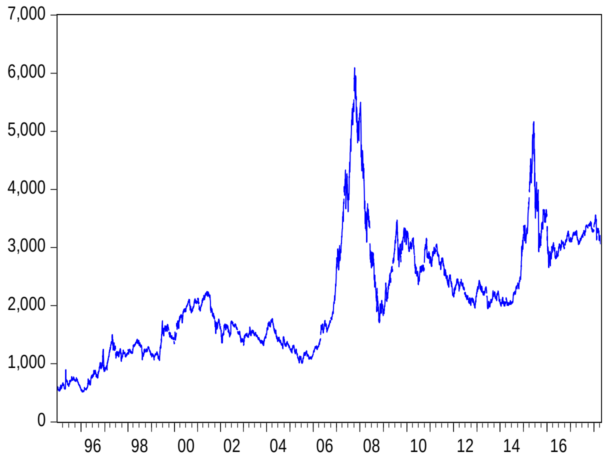
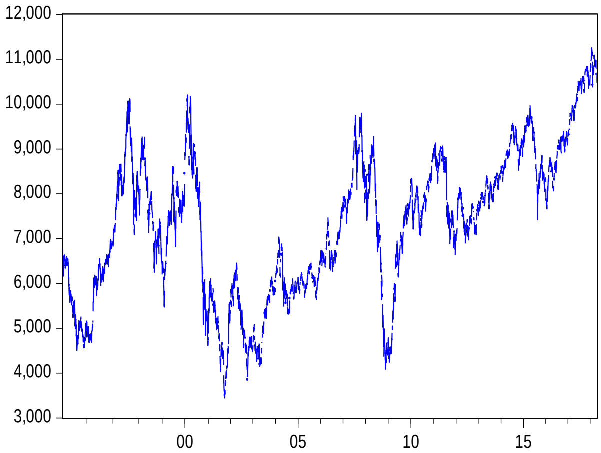


TAIEX



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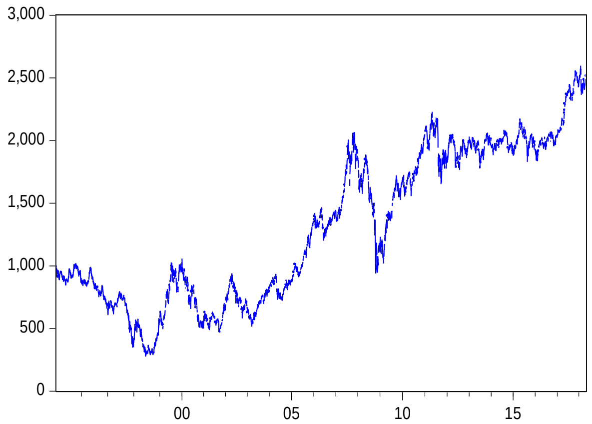

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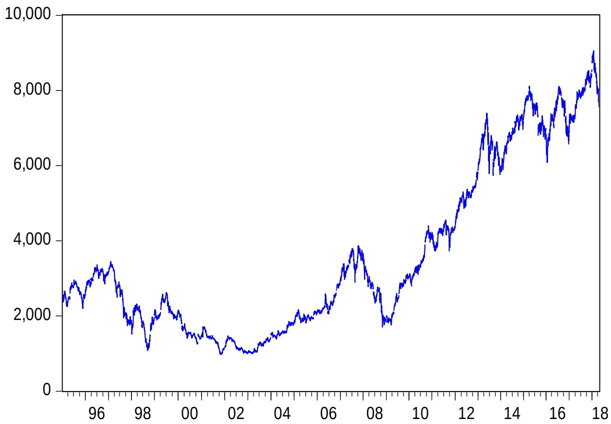
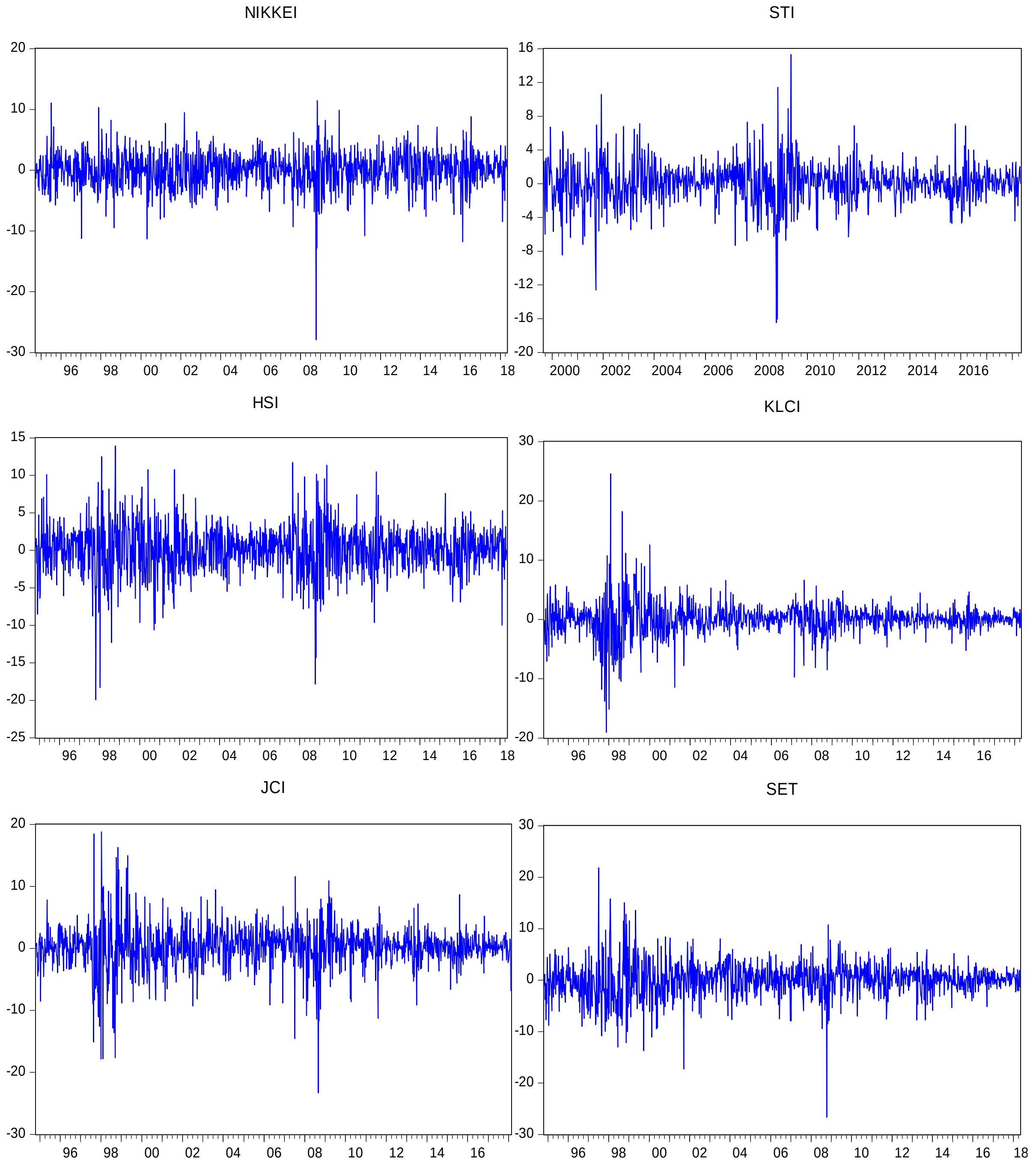


Figure A.3: Weekly Log Returns



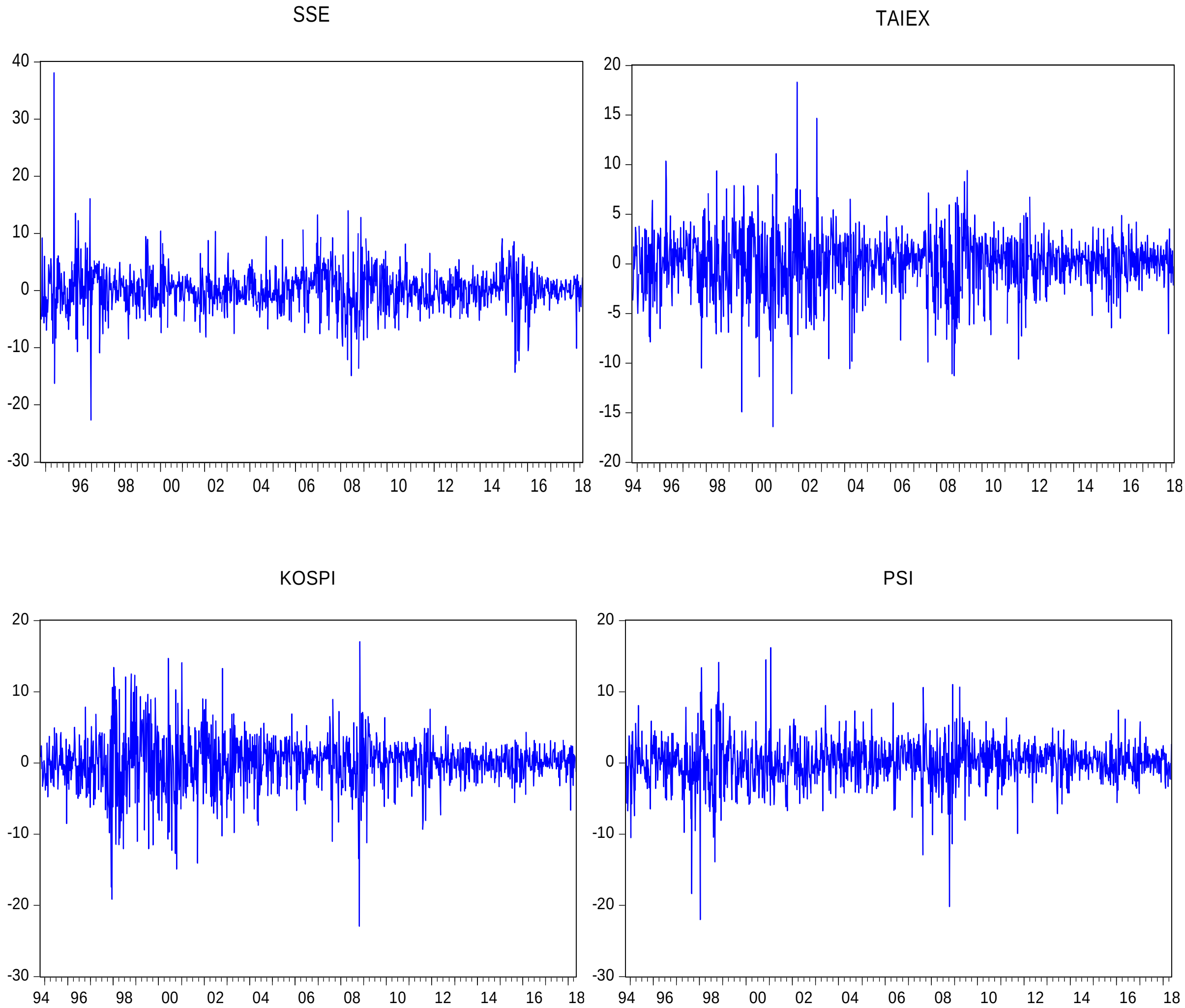
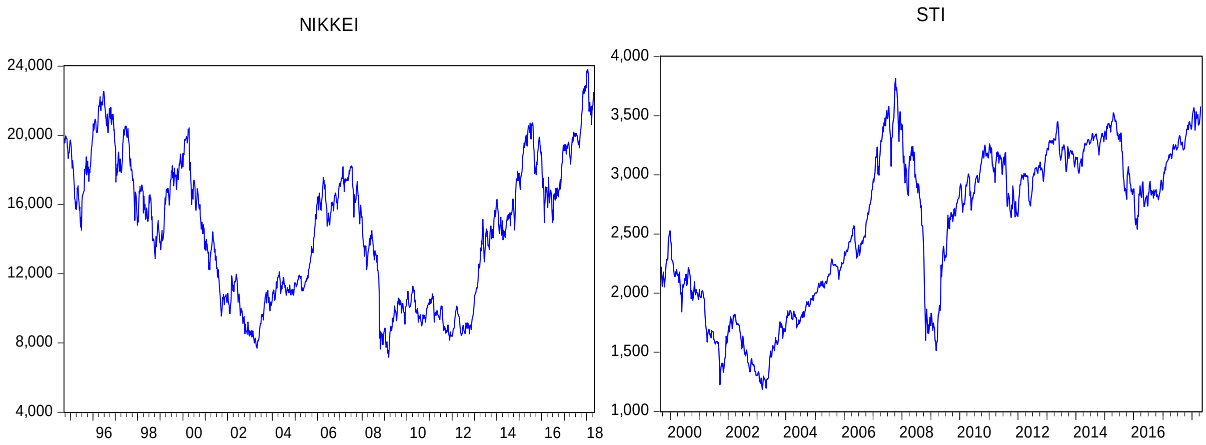


Figure A.4: Weekly Closing Prices



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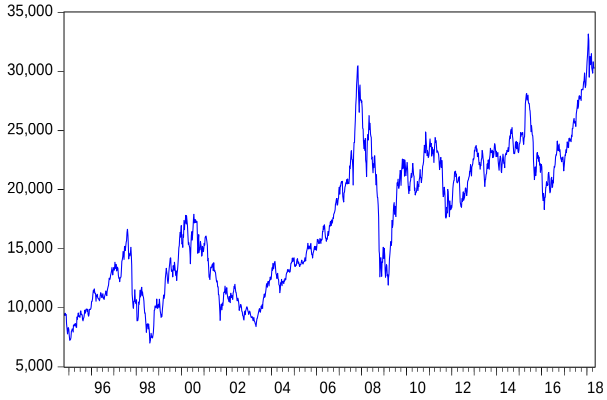

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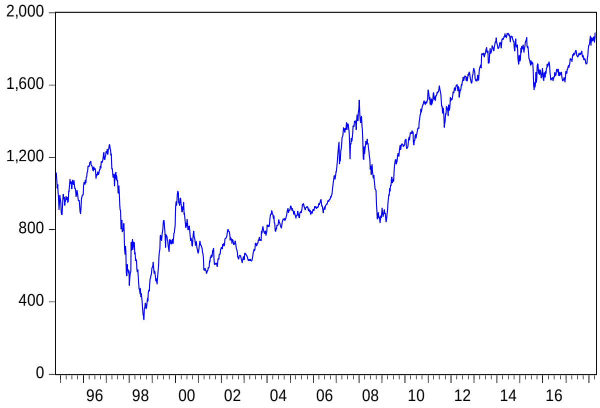

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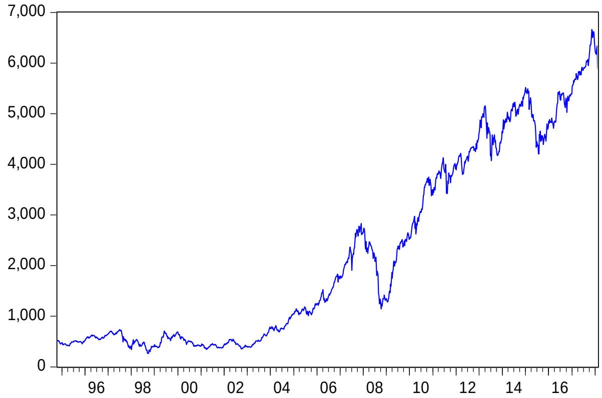

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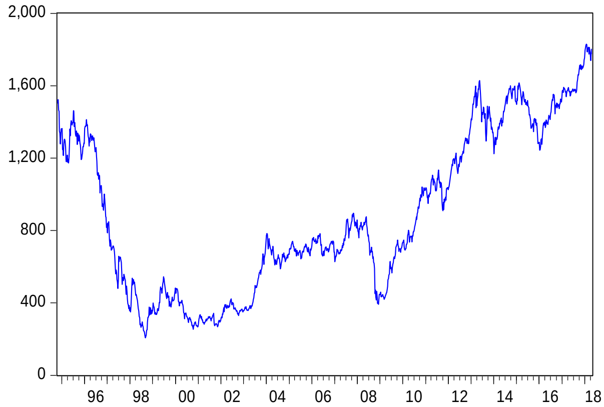

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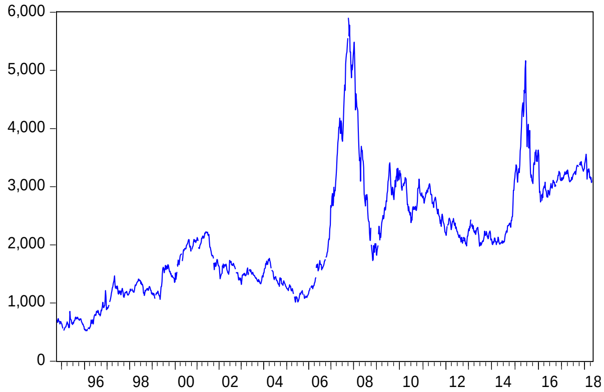

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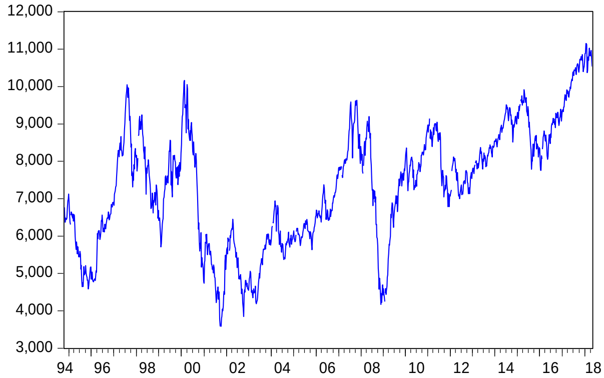

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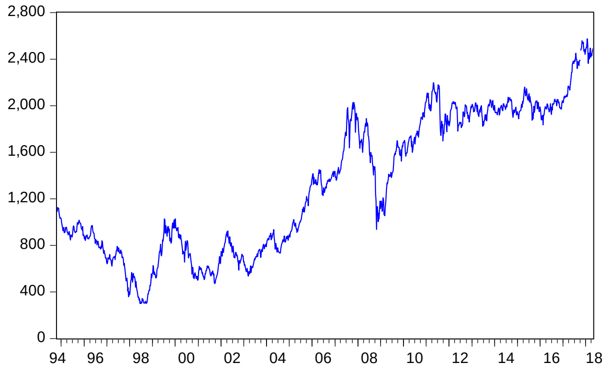


PSI

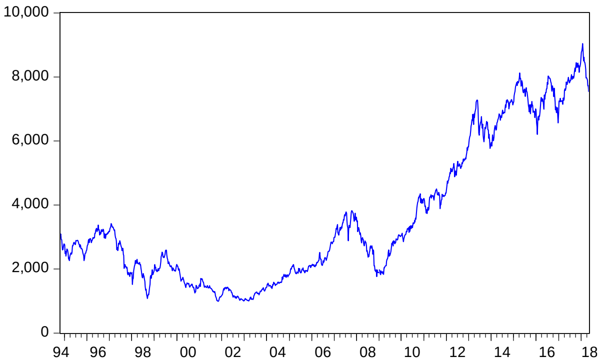
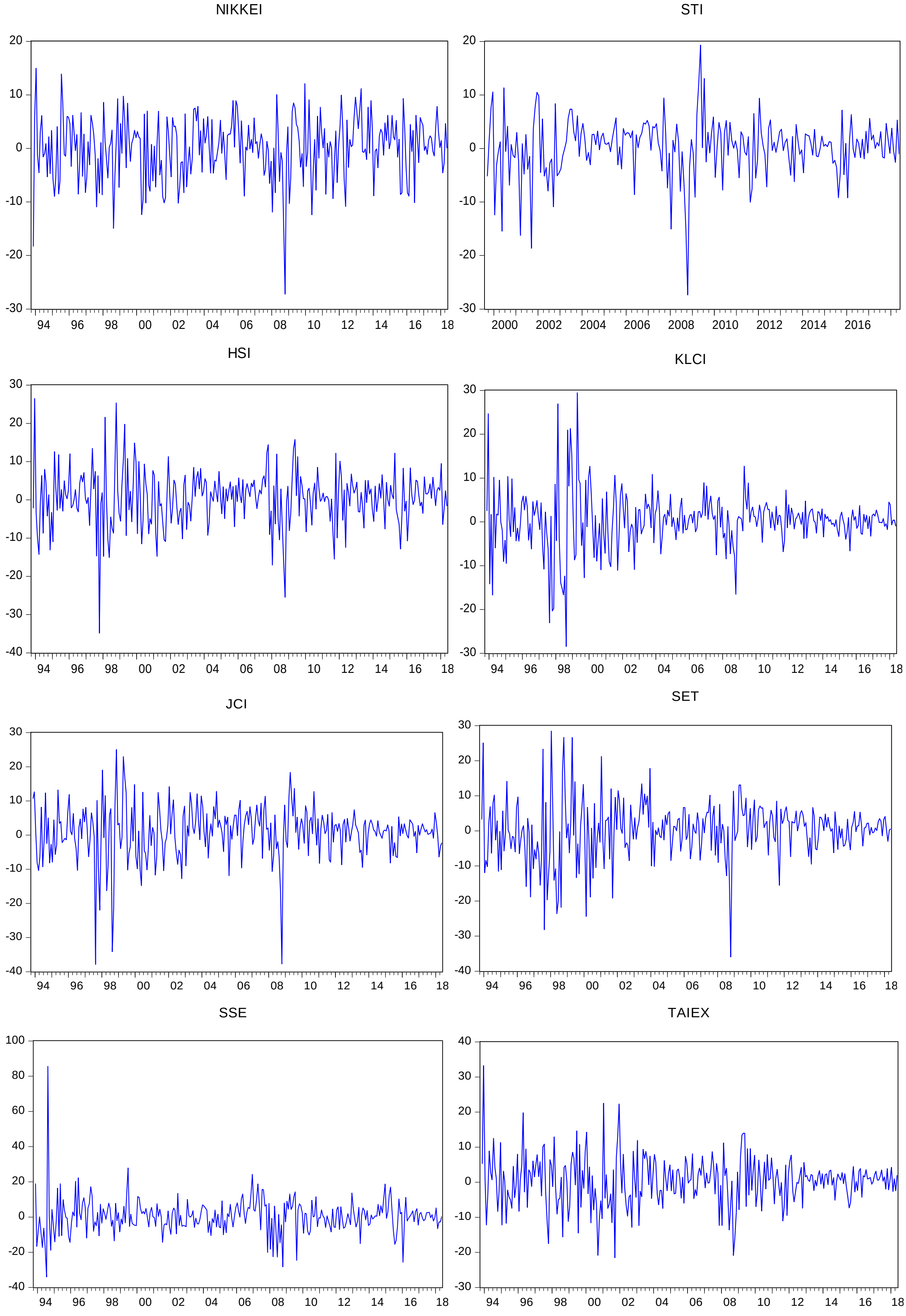


Figure A.5: Monthly Log Returns



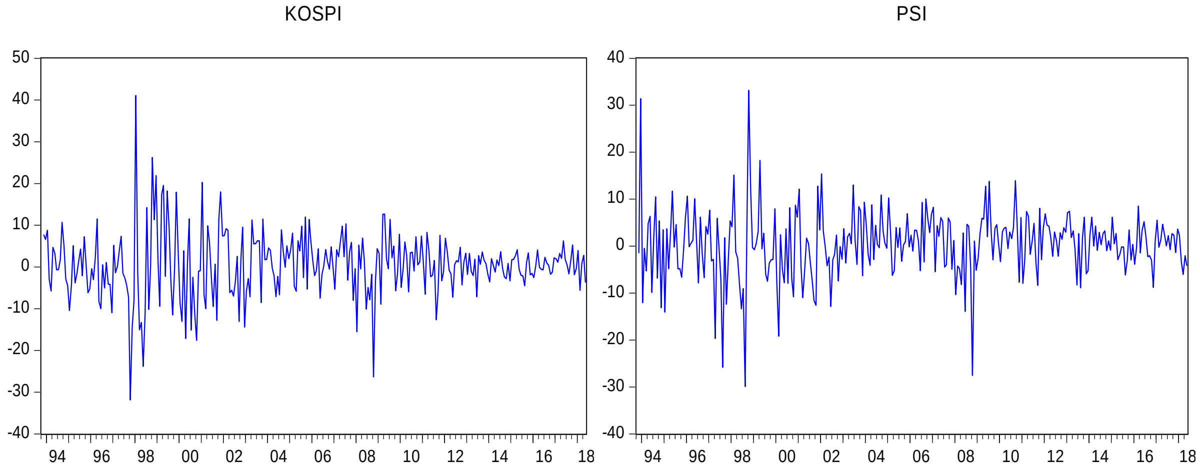
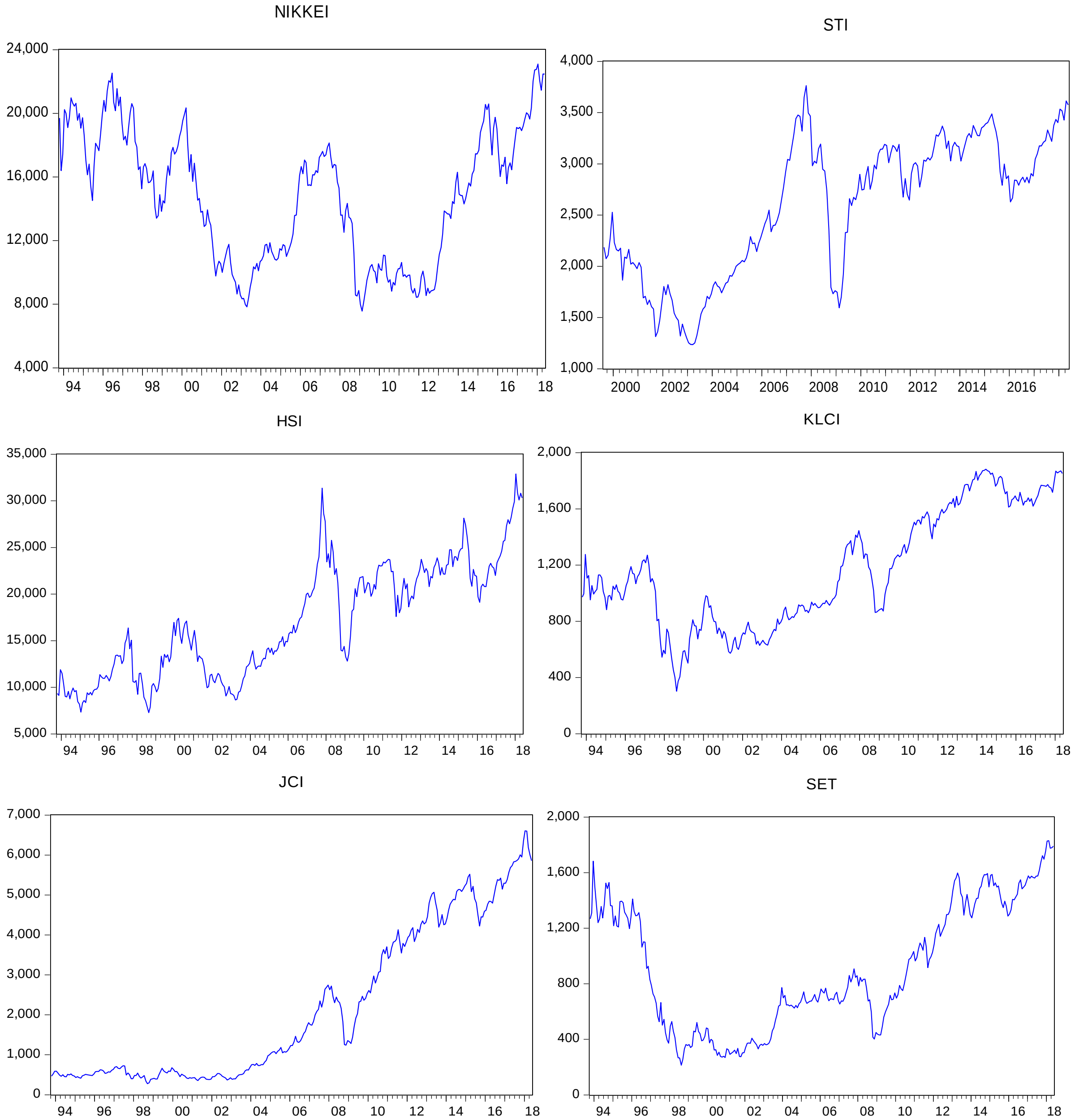
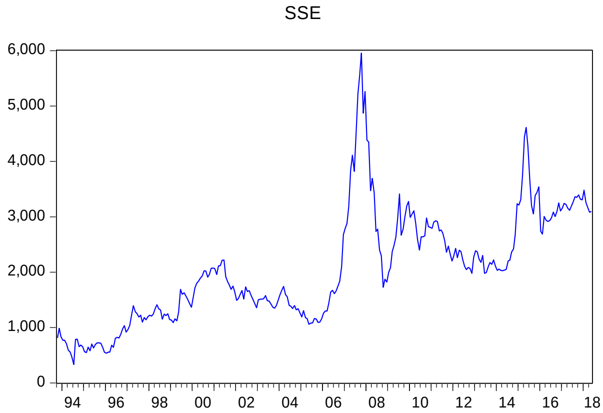


Figure A.6: Monthly Closing Prices

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3,000
2,000
1,000
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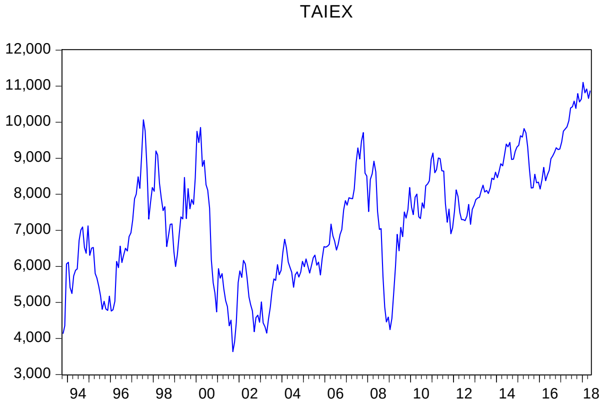
TAIEX
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11,000
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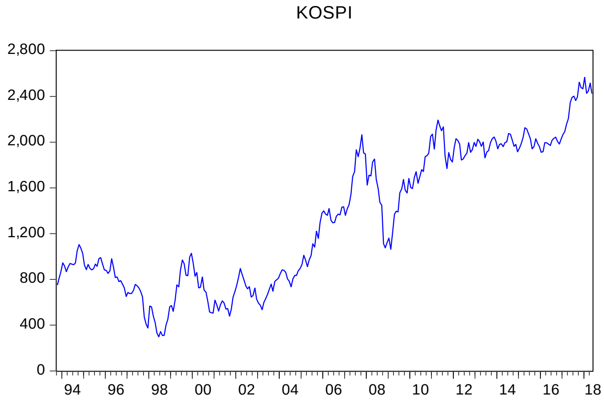
8,000
7,000
6,000
5,000
4,000
3,000
94 96 98 00 02 04 06 08 10 12 14 16 18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800
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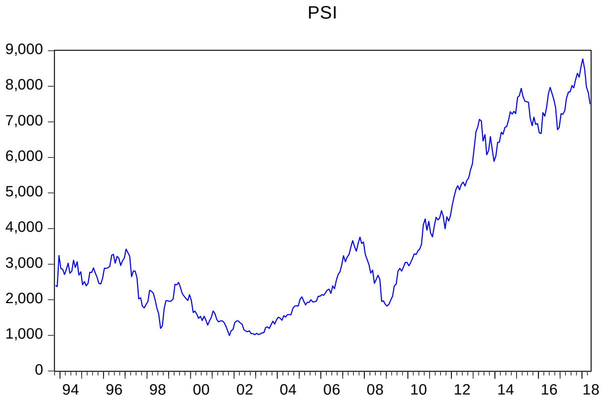
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3,000
2,000
1,000
0
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APPENDIX B

Table B.1: DM Test statistics and *p*-values for NIKKEI Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
	Recursive Daily								**Rolling Window Daily**							
GARCH vs EGARCH	4.9749	0.0000	1.0000	0.0000	0.4536	0.6502	0.6749	0.3251	5.4186	0.0000	1.0000	0.0000	0.8386	0.4018	0.7991	0.2009
GARCH vs TGARCH	0.5074	0.6119	0.6940	0.3060	1.3588	0.1743	0.9128	0.0872	1.0137	0.3108	0.8446	0.1554	1.5337	0.1252	0.9374	0.0626
GARCH vs MGARCH	5.1672	0.0000	1.0000	0.0000	-0.2520	0.8011	0.4005	0.5995	3.0167	0.0026	0.9987	0.0013	-0.6530	0.5138	0.2569	0.7431
GARCH vs PGARCH	3.6168	0.0003	0.9998	0.0002	0.7550	0.4503	0.7748	0.2252	2.7372	0.0062	0.9969	0.0031	0.8376	0.4023	0.7988	0.2012
EGARCH vs TGARCH	-4.2163	0.0000	0.0000	0.0000	0.6318	0.5276	0.7362	0.2638	-4.7943	0.0000	0.0000	1.0000	0.3104	0.7562	0.6219	0.3781
EGARCH vs MGARCH	-4.9436	0.0000	0.0000	0.0000	-0.4551	0.6490	0.3245	0.6755	-5.3951	0.0000	0.0000	1.0000	-0.8458	0.3977	0.1989	0.8011
EGARCH vs PGARCH	-3.0604	0.0022	0.0011	0.9989	0.2336	0.8153	0.5923	0.4077	-4.2289	0.0000	0.0000	1.0000	-0.5114	0.6091	0.3045	0.6955
TGARCH vs MGARCH	-0.4372	0.6620	0.3310	0.6690	-1.3515	0.1766	0.0883	0.9117	-0.9531	0.3406	0.1703	0.8297	-1.5231	0.1278	0.0639	0.9361
TGARCH vs PGARCH	2.9876	0.0028	0.9986	0.0014	-0.7352	0.4623	0.2311	0.7689	2.0369	0.0418	0.9791	0.0209	-0.7262	0.4678	0.2339	0.7661
MGARCH vs PGARCH	3.5715	0.0004	0.9998	0.0002	0.7557	0.4499	0.7750	0.2250	2.7020	0.0069	0.9965	0.0035	0.8452	0.3981	0.8010	0.1990
	Recursive Weekly								**Rolling Window Weekly**							
GARCH vs EGARCH	1.4580	0.1454	0.9273	0.0727	0.2791	0.7803	0.6099	0.3901	0.7815	0.4348	0.7826	0.2174	0.2971	0.7665	0.6168	0.3832
GARCH vs TGARCH	0.1565	0.8757	0.5621	0.4379	-0.4182	0.6759	0.3380	0.6620	0.2404	0.8101	0.5950	0.4050	-0.3150	0.7529	0.3764	0.6236
GARCH vs MGARCH	0.2526	0.8007	0.5997	0.4003	0.0604	0.9518	0.5241	0.4759	NA	NA	NA	NA	NA	NA	NA	NA
GARCH vs PGARCH	0.4682	0.6398	0.6801	0.3199	-0.3393	0.7345	0.3673	0.6327	0.3219	0.7476	0.6262	0.3738	-0.7486	0.4544	0.2272	0.7728
EGARCH vs TGARCH	-0.8759	0.3814	0.1907	0.8093	-0.4154	0.6780	0.3390	0.6610	-0.3859	0.6997	0.3499	0.6501	-0.3588	0.7199	0.3599	0.6401
EGARCH vs MGARCH	-1.4580	0.1454	0.0727	0.9273	-0.2791	0.7803	0.3901	0.6099	NA	NA	NA	NA	NA	NA	NA	NA
EGARCH vs PGARCH	-0.8960	0.3706	0.1853	0.8147	-0.3509	0.7258	0.3629	0.6371	-0.2987	0.7653	0.3826	0.6174	-0.6108	0.5416	0.2708	0.7292
TGARCH vs MGARCH	-0.1565	0.8757	0.4379	0.5621	0.4182	0.6759	0.6620	0.3380	NA	NA	NA	NA	NA	NA	NA	NA
TGARCH vs PGARCH	0.3580	0.7205	0.6398	0.3602	0.4799	0.6315	0.6843	0.3157	0.3052	0.7603	0.6199	0.3801	-1.3085	0.1912	0.0956	0.9044
MGARCH vs PGARCH	0.4682	0.6398	0.6801	0.3199	-0.3393	0.7345	0.3673	0.6327	NA	NA	NA	NA	NA	NA	NA	NA
	Recursive Monthly								**Rolling Window Monthly**							
GARCH vs EGARCH	2.6604	0.0088	0.9956	0.0044	1.5994	0.1121	0.9439	0.0561	0.2203	0.8259	0.5870	0.4130	1.1821	0.2392	0.8804	0.1196
GARCH vs TGARCH	-0.3078	0.7587	0.3793	0.6207	-1.0520	0.2946	0.1473	0.8527	-0.7750	0.4396	0.2198	0.7802	-0.9053	0.3668	0.1834	0.8166
GARCH vs MGARCH	0.6667	0.5060	0.7470	0.2530	1.1985	0.2327	0.8837	0.1163	-1.0005	0.3187	0.1594	0.8406	-1.0000	0.3190	0.1595	0.8405
GARCH vs PGARCH	-3.3190	0.0011	0.0006	0.9994	-1.2023	0.2312	0.1156	0.8844	-4.3606	0.0000	0.0000	1.0000	-1.5573	0.1216	0.0608	0.9392
EGARCH vs TGARCH	-2.1601	0.0326	0.0163	0.9837	-1.4754	0.1425	0.0712	0.9288	-0.8382	0.4033	0.2017	0.7983	-1.3415	0.1819	0.0910	0.9090
EGARCH vs MGARCH	-2.6577	0.0088	0.0044	0.9956	-1.5289	0.1287	0.0643	0.9357	-1.0005	0.3188	0.1594	0.8406	-1.0000	0.3190	0.1595	0.8405
EGARCH vs PGARCH	-3.5115	0.0006	0.0003	0.9997	-1.2710	0.2059	0.1030	0.8970	-4.2538	0.0000	0.0000	1.0000	-1.6875	0.0937	0.0469	0.9531
TGARCH vs MGARCH	0.3300	0.7419	0.6291	0.3709	1.2090	0.2286	0.8857	0.1143	-1.0005	0.3187	0.1594	0.8406	-1.0000	0.3190	0.1595	0.8405
TGARCH vs PGARCH	-3.2408	0.0015	0.0007	0.9993	-1.1771	0.2411	0.1205	0.8795	-4.3562	0.0000	0.0000	1.0000	-1.7234	0.0870	0.0435	0.9565
MGARCH vs PGARCH	-3.3163	0.0012	0.0006	0.9994	-1.2241	0.2229	0.1114	0.8886	1.0005	0.3187	0.8406	0.1594	1.0000	0.3190	0.8405	0.1595

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.2: DM Test statistics and *p*-values for STI Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
	Recursive Daily								**Rolling Window Daily**							
GARCH vs EGARCH	0.3525	0.7245	0.6377	0.3623	0.1201	0.9044	0.5478	0.4522	0.4491	0.6534	0.6733	0.3267	-0.0945	0.9247	0.4624	0.5376
GARCH vs TGARCH	-1.4827	0.1383	0.0691	0.3060	-0.2078	0.8354	0.4177	0.5823	-0.0585	0.9534	0.4767	0.5233	-0.0585	0.9534	0.4767	0.5233
GARCH vs MGARCH	-1.0608	0.2889	0.1444	0.8556	-0.9189	0.3582	0.1791	0.8209	0.6141	0.5392	0.7304	0.2696	-0.4847	0.6279	0.3140	0.6860
GARCH vs PGARCH	-3.7518	0.0002	0.0001	0.9999	-1.5502	0.1212	0.0606	0.9394	-2.6969	0.0070	0.0035	0.9965	-1.0686	0.2854	0.1427	0.8573
EGARCH vs TGARCH	-2.3466	0.0190	0.0095	0.9905	-0.7116	0.4768	0.2384	0.7616	-0.8121	0.4168	0.2084	0.7916	0.4150	0.6782	0.6609	0.3391
EGARCH vs MGARCH	-0.3780	0.7054	0.3527	0.6473	-0.1460	0.8839	0.4420	0.5580	-0.3957	0.6924	0.3462	0.6538	0.0732	0.9416	0.5292	0.4708
EGARCH vs PGARCH	-4.3895	0.0000	0.0000	1.0000	-1.8886	0.0591	0.0295	0.9705	-3.7728	0.0002	0.0001	0.9999	-2.0674	0.0388	0.0194	0.9806
TGARCH vs MGARCH	1.4168	0.1567	0.9217	0.0783	0.1603	0.8727	0.5637	0.4363	0.1099	0.9125	0.5438	0.4562	-0.1165	0.9073	0.4536	0.5464
TGARCH vs PGARCH	-2.9375	0.0033	0.0017	0.9983	-1.8105	0.0704	0.0352	0.9648	-3.2226	0.0013	0.0006	0.9994	-2.5626	0.0104	0.0052	0.9948
MGARCH vs PGARCH	-3.6890	0.0002	0.0001	0.9999	-1.4817	0.1385	0.0693	0.9307	-2.7073	0.0068	0.0034	0.9966	-1.0102	0.3125	0.1563	0.8437
	Recursive Weekly								**Rolling Window Weekly**							
GARCH vs EGARCH	3.5782	0.0004	0.9998	0.0002	0.9864	0.3244	0.8378	0.1622	3.1445	0.0018	0.9991	0.0009	0.8500	0.3957	0.8021	0.1979
GARCH vs TGARCH	4.5686	0.0000	1.0000	0.0000	0.9733	0.3309	0.8346	0.1654	4.2335	0.0000	1.0000	0.0000	0.8965	0.3704	0.8148	0.1852
GARCH vs MGARCH	2.2573	0.0244	0.9878	0.0122	1.3761	0.1694	0.9153	0.0847	1.3569	0.1754	0.9123	0.0877	0.7902	0.4298	0.7851	0.2149
GARCH vs PGARCH	3.9430	0.0001	1.0000	0.0000	0.9035	0.3667	0.8166	0.1834	3.3647	0.0008	0.9996	0.0004	0.8062	0.4205	0.7897	0.2103
EGARCH vs TGARCH	1.5739	0.1162	0.9419	0.0581	-0.3291	0.7423	0.3711	0.6289	3.1282	0.0019	0.9991	0.0009	0.5204	0.6031	0.6985	0.3015
EGARCH vs MGARCH	-3.5338	0.0004	0.0002	0.9998	-0.9694	0.3328	0.1664	0.8336	-3.1143	0.0020	0.0010	0.9990	-0.8404	0.4011	0.2005	0.7995
EGARCH vs PGARCH	0.4972	0.6193	0.6903	0.3097	-0.7285	0.4667	0.2333	0.7667	0.7660	0.4440	0.7780	0.2220	-0.1513	0.8798	0.4399	0.5601
TGARCH vs MGARCH	-4.5163	0.0000	0.0000	1.0000	-0.9552	0.3399	0.1700	0.8300	-4.2010	0.0000	0.0000	1.0000	-0.8871	0.3755	0.1877	0.8123
TGARCH vs PGARCH	-1.9641	0.0501	0.0250	0.9750	-0.5849	0.5589	0.2794	0.7206	-3.6698	0.0003	0.0001	0.9999	-1.4721	0.1417	0.0708	0.9292
MGARCH vs PGARCH	3.8935	0.0001	0.9999	0.0001	0.8864	0.3758	0.8121	0.1879	3.3341	0.0009	0.9995	0.0005	0.7966	0.4261	0.7870	0.2130
	Recursive Monthly								**Rolling Window Monthly**							
GARCH vs EGARCH	1.1500	0.2526	0.8737	0.1263	0.8651	0.3889	0.8056	0.1944	0.9552	0.3415	0.8292	0.1708	0.3530	0.7247	0.6376	0.3624
GARCH vs TGARCH	1.6585	0.1000	0.9500	0.0500	1.2515	0.2134	0.8933	0.1067	1.6524	0.1013	0.9494	0.0506	1.3344	0.1848	0.9076	0.0924
GARCH vs MGARCH	0.0109	0.9913	0.5043	0.4957	0.0475	0.9622	0.5189	0.4811	0.0645	0.9487	0.5257	0.4743	-0.7654	0.4457	0.2228	0.7772
GARCH vs PGARCH	-0.7764	0.4392	0.2196	0.7804	-1.0363	0.3023	0.1512	0.8488	0.2429	0.8086	0.5957	0.4043	-0.1384	0.8902	0.4451	0.5549
EGARCH vs TGARCH	-0.4819	0.6308	0.3154	0.6846	-0.4300	0.6681	0.3340	0.6660	0.5031	0.6159	0.6921	0.3079	0.6753	0.5009	0.7495	0.2505
EGARCH vs MGARCH	-1.0997	0.2738	0.1369	0.8631	-0.8436	0.4007	0.2004	0.7996	-0.9150	0.3622	0.1811	0.8189	-0.4591	0.6470	0.3235	0.6765
EGARCH vs PGARCH	-1.7992	0.0747	0.0374	0.9626	-1.8376	0.0688	0.0344	0.9656	-1.2471	0.2150	0.1075	0.8925	-1.6301	0.1059	0.0530	0.9470
TGARCH vs MGARCH	-1.1880	0.2374	0.1187	0.8813	-0.8063	0.4218	0.2109	0.7891	-1.4341	0.1544	0.0772	0.9228	-1.3391	0.1833	0.0916	0.9084
TGARCH vs PGARCH	-2.2605	0.0257	0.0129	0.9871	-1.8509	0.0668	0.0334	0.9666	-1.8609	0.0654	0.0327	0.9673	-1.4788	0.1420	0.0710	0.9290
MGARCH vs PGARCH	-0.6760	0.5005	0.2502	0.7498	-0.9522	0.3431	0.1715	0.8285	0.2101	0.8339	0.5830	0.4170	-0.0308	0.9755	0.4878	0.5122

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.3: DM Test statistics and *p*-values for Hang Seng Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
	Recursive Daily								**Rolling Window Daily**							
GARCH vs EGARCH	3.0324	0.0024	0.9988	0.0012	2.9417	0.0033	0.9984	0.0016	4.3739	0.0000	1.0000	0.0000	2.6013	0.0093	0.9953	0.0047
GARCH vs TGARCH	2.7157	0.0067	0.9967	0.0033	2.7030	0.0069	0.9965	0.0035	4.2016	0.0000	1.0000	0.0000	2.5941	0.0095	0.9952	0.0048
GARCH vs MGARCH	2.8790	0.0040	0.9980	0.0020	2.0756	0.0380	0.9810	0.0190	2.5799	0.0099	0.9950	0.0050	1.9687	0.0491	0.9755	0.0245
GARCH vs PGARCH	1.3262	0.1849	0.0924	0.9076	2.3201	0.0204	0.9898	0.0102	4.9956	0.0000	1.0000	0.0000	2.7382	0.0062	0.9969	0.0031
EGARCH vs TGARCH	-2.1728	0.0299	0.0149	0.9851	-0.3778	0.7056	0.3528	0.6472	-2.6507	0.0081	0.0040	0.9960	0.4495	0.6531	0.6735	0.3265
EGARCH vs MGARCH	-2.9816	0.0029	0.0014	0.9986	2.8960	0.0038	0.0019	0.9981	-4.3056	0.0000	0.0000	1.0000	-2.4366	0.0149	0.0074	0.9926
EGARCH vs PGARCH	-4.6601	0.0000	0.0000	1.0000	-0.4472	0.6548	0.3274	0.6726	-1.5784	0.1146	0.0573	0.9427	0.9052	0.3654	0.8173	0.1827
TGARCH vs MGARCH	-2.6658	0.0077	0.0039	0.9961	-2.7333	0.0063	0.0032	0.9968	-4.2264	0.0000	0.0000	1.0000	-2.6452	0.0082	0.0041	0.9959
TGARCH vs PGARCH	-4.1398	0.0000	0.0000	1.0000	-0.1207	0.9039	0.4520	0.5480	3.8265	0.0001	0.9999	0.0001	1.0876	0.2768	0.8616	0.1384
MGARCH vs PGARCH	-1.4398	0.1500	0.0750	0.9250	2.3249	0.0201	0.9899	0.0101	5.0187	0.0000	1.0000	0.0000	-2.0712	0.0401	0.0201	0.9799
	Recursive Weekly								**Rolling Window Weekly**							
GARCH vs EGARCH	-0.1119	0.9109	0.4555	0.5445	0.8167	0.4144	0.7928	0.2072	1.9166	0.0557	0.9721	0.0279	1.8144	0.0701	0.9649	0.0351
GARCH vs TGARCH	0.4565	0.6482	0.6759	0.3241	0.7167	0.4738	0.7631	0.2369	0.8489	0.3962	0.8019	0.1981	0.4251	0.6709	0.6646	0.3354
GARCH vs MGARCH	0.6868	0.4925	0.7538	0.2462	-0.9090	0.3637	0.1819	0.8181	1.0858	0.2780	0.8610	0.1390	-0.6518	0.5148	0.2574	0.7426
GARCH vs PGARCH	-0.7148	0.4750	0.2375	0.7625	0.5762	0.5647	0.7177	0.2823	1.4296	0.1533	0.9233	0.0767	0.9379	0.3487	0.8257	0.1743
EGARCH vs TGARCH	0.6174	0.5372	0.7314	0.2686	0.0188	0.9850	0.5075	0.4925	-1.0178	0.3092	0.1546	0.8454	-1.2000	0.2306	0.1153	0.8847
EGARCH vs MGARCH	0.1460	0.8840	0.5580	0.4420	-0.8448	0.3986	0.1993	0.8007	-1.7850	0.0748	0.0374	0.9626	-1.7448	0.0815	0.0408	0.9592
EGARCH vs PGARCH	-0.6858	0.4931	0.2465	0.7535	-0.3421	0.7324	0.3662	0.6338	-0.6897	0.4906	0.2453	0.7547	-1.7083	0.0881	0.0440	0.9560
TGARCH vs MGARCH	-0.4060	0.6849	0.3424	0.6576	-0.7293	0.4661	0.2330	0.7670	-0.7593	0.4480	0.2240	0.7760	-0.4383	0.6614	0.3307	0.6693
TGARCH vs PGARCH	-1.8396	0.0663	0.0332	0.9668	-0.6736	0.5008	0.2504	0.7496	1.2211	0.2225	0.8887	0.1113	0.7193	0.4722	0.7639	0.2361
MGARCH vs PGARCH	-0.7251	0.4686	0.2343	0.7657	0.6012	0.5479	0.7260	0.2740	1.3015	0.1936	0.9032	0.0968	0.9210	0.3574	0.8213	0.1787
	Recursive Monthly								**Rolling Window Monthly**							
GARCH vs EGARCH	-0.4607	0.6457	0.3228	0.6772	0.2938	0.7693	0.6153	0.3847	0.0560	0.9554	0.5223	0.4777	0.1413	0.8879	0.5561	0.4439
GARCH vs TGARCH	-1.4661	0.1448	0.0724	0.9276	-1.5497	0.1234	0.0617	0.9383	-1.3420	0.1817	0.0908	0.9092	-0.2086	0.8351	0.4175	0.5825
GARCH vs MGARCH	0.3688	0.7128	0.6436	0.3564	0.3154	0.7529	0.6236	0.3764	0.8793	0.3807	0.8097	0.1903	0.5993	0.5499	0.7250	0.2750
GARCH vs PGARCH	-5.5805	0.0000	0.0000	1.0000	-1.6891	0.0933	0.0467	0.9533	-2.6023	0.0102	0.0051	0.9949	-0.3151	0.7531	0.3766	0.6234
EGARCH vs TGARCH	-0.4175	0.6770	0.3385	0.6615	-0.9016	0.3688	0.1844	0.8156	-0.5901	0.5561	0.2780	0.7220	-0.3050	0.7608	0.3804	0.6196
EGARCH vs MGARCH	0.8798	0.3804	0.8098	0.1902	-0.2286	0.8195	0.4098	0.5902	0.1205	0.9042	0.5479	0.4521	0.0169	0.9865	0.5067	0.4933
EGARCH vs PGARCH	-5.9298	0.0000	0.0000	1.0000	-2.4547	0.0153	0.0076	0.9924	-3.5160	0.0006	0.0003	0.9997	-0.9427	0.3474	0.1737	0.8263
TGARCH vs MGARCH	1.5346	0.1270	0.9365	0.0635	1.3650	0.1744	0.9128	0.0872	2.4064	0.0174	0.9913	0.0087	1.6194	0.1075	0.9462	0.0538
TGARCH vs PGARCH	-5.4040	0.0000	0.0000	1.0000	-1.5732	0.1178	0.0589	0.9411	-2.4339	0.0161	0.0081	0.9919	-0.3384	0.7355	0.3678	0.6322
MGARCH vs PGARCH	-5.8743	0.0000	0.0000	1.0000	-2.0712	0.0401	0.0201	0.9799	-3.0209	0.0030	0.0015	0.9985	-0.6271	0.5316	0.2658	0.7342

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.4: DM Test statistics and *p*-values for KLCI Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
				Recursive Daily								**Rolling Window Daily**				
GARCH vs EGARCH	1.6920	0.0908	0.9546	0.0454	3.8457	0.0001	0.9999	0.0001	1.0746	0.2827	0.8587	0.1413	3.3640	0.0008	0.9996	0.0004
GARCH vs TGARCH	-2.5575	0.0106	0.0053	0.9947	-2.3716	0.0178	0.0089	0.9911	-3.1592	0.0016	0.0008	0.9992	-2.3482	0.0189	0.0095	0.9905
GARCH vs MGARCH	5.4386	0.0000	1.0000	0.0000	5.1603	0.0000	1.0000	0.0000	1.6167	0.1061	0.9470	0.0530	1.7572	0.0790	0.9605	0.0395
GARCH vs PGARCH	-1.0970	0.2727	0.1364	0.8636	0.0569	0.9546	0.5227	0.4773	-0.1708	0.8644	0.4322	0.5678	1.1112	0.2666	0.8667	0.1333
EGARCH vs TGARCH	-3.9444	0.0001	0.0000	1.0000	-4.1053	0.0000	0.0000	1.0000	-3.6244	0.0003	0.0001	0.9999	-3.5201	0.0004	0.0002	0.9998
EGARCH vs MGARCH	3.5273	0.0004	0.9998	0.0002	-1.9035	0.0571	0.0285	0.9715	-0.0450	0.9641	0.4821	0.5179	-3.0579	0.0022	0.0011	0.9989
EGARCH vs PGARCH	-2.3182	0.0205	0.0103	0.9897	-2.7972	0.0052	0.0026	0.9974	-0.7727	0.4398	0.2199	0.7801	-0.7646	0.4446	0.2223	0.7777
TGARCH vs MGARCH	7.1346	0.0000	1.0000	0.0000	4.2056	0.0000	1.0000	0.0000	4.5381	0.0000	1.0000	0.0000	2.7490	0.0060	0.9970	0.0030
TGARCH vs PGARCH	0.6354	0.5252	0.7374	0.2626	1.3333	0.1825	0.9087	0.0913	1.4892	0.1365	0.9317	0.0683	1.9536	0.0508	0.9746	0.0254
MGARCH vs PGARCH	-3.7378	0.0002	0.0001	0.9999	-1.1408	0.2540	0.1270	0.8730	-0.6745	0.5000	0.2500	0.7500	0.8916	0.3727	0.8137	0.1863
				Recursive Weekly								**Rolling Window Weekly**				
GARCH vs EGARCH	-3.7872	0.0002	0.0001	0.9999	-1.8320	0.0674	0.0337	0.9663	-2.6560	0.0081	0.0041	0.9959	-0.3183	0.7503	0.3752	0.6248
GARCH vs TGARCH	-4.4596	0.0000	0.0000	1.0000	-0.8078	0.4195	0.2097	0.7903	-2.6850	0.0075	0.0037	0.9963	-1.7576	0.0793	0.0397	0.9603
GARCH vs MGARCH	4.5911	0.0000	1.0000	0.0000	0.9803	0.3273	0.8363	0.1637	2.9218	0.0036	0.9982	0.0018	1.7701	0.0772	0.9614	0.0386
GARCH vs PGARCH	-4.2314	0.0000	0.0000	1.0000	-3.8256	0.0001	0.0001	0.9999	-2.3895	0.0172	0.0086	0.9914	-1.4218	0.1556	0.0778	0.9222
EGARCH vs TGARCH	2.1113	0.0351	0.9824	0.0176	1.5948	0.1113	0.9444	0.0556	-0.3884	0.6979	0.3489	0.6511	-1.3408	0.1805	0.0902	0.9098
EGARCH vs MGARCH	3.8511	0.0001	0.9999	0.0001	1.8619	0.0631	0.9684	0.0316	2.7839	0.0055	0.9972	0.0028	0.3618	0.7176	0.6412	0.3588
EGARCH vs PGARCH	-3.0717	0.0022	0.0011	0.9989	-3.5171	0.0005	0.0002	0.9998	-1.3731	0.1702	0.0851	0.9149	-1.4200	0.1561	0.0781	0.9219
TGARCH vs MGARCH	4.6261	0.0000	1.0000	0.0000	0.8418	0.4002	0.7999	0.2001	2.7846	0.0055	0.9972	0.0028	1.7961	0.0730	0.9635	0.0365
TGARCH vs PGARCH	-3.7208	0.0002	0.0001	0.9999	-3.7552	0.0002	0.0001	0.9999	-0.7426	0.4580	0.2290	0.7710	-0.5382	0.5906	0.2953	0.7047
MGARCH vs PGARCH	-4.2491	0.0000	0.0000	1.0000	-3.8301	0.0001	0.0001	0.9999	-2.4554	0.0144	0.0072	0.9928	-1.4421	0.1498	0.0749	0.9251
				Recursive Monthly								**Rolling Window Monthly**				
GARCH vs EGARCH	0.0779	0.9380	0.5310	0.4690	0.3963	0.6925	0.6538	0.3462	-0.3002	0.7644	0.3822	0.6178	0.1045	0.9169	0.5415	0.4585
GARCH vs TGARCH	-1.1408	0.2558	0.1279	0.8721	-0.4164	0.6777	0.3389	0.6611	-1.9259	0.0561	0.0280	0.9720	-0.9190	0.3596	0.1798	0.8202
GARCH vs MGARCH	3.4150	0.0008	0.9996	0.0004	1.0826	0.2808	0.8596	0.1404	NA	NA	NA	NA	NA	NA	NA	NA
GARCH vs PGARCH	-1.2298	0.2208	0.1104	0.8896	-1.0321	0.3038	0.1519	0.8481	-7.6736	0.0000	0.0000	1.0000	-3.8744	0.0002	0.0001	0.9999
EGARCH vs TGARCH	-1.2221	0.2237	0.1118	0.8882	-1.3104	0.1921	0.0961	0.9039	-2.0996	0.0375	0.0187	0.9813	-1.6452	0.1021	0.0510	0.9490
EGARCH vs MGARCH	0.0266	0.9788	0.5106	0.4894	-0.3774	0.7064	0.3532	0.6468	NA	NA	NA	NA	NA	NA	NA	NA
EGARCH vs PGARCH	-1.2448	0.2152	0.1076	0.8924	-1.5891	0.1142	0.0571	0.9429	-8.6373	0.0000	0.0000	1.0000	-4.3230	0.0000	0.0000	1.0000
TGARCH vs MGARCH	1.2762	0.2039	0.8981	0.1019	0.4347	0.6644	0.6678	0.3322	NA	NA	NA	NA	NA	NA	NA	NA
TGARCH vs PGARCH	-0.4622	0.6446	0.3223	0.6777	-1.5585	0.1213	0.0606	0.9394	-7.3712	0.0000	0.0000	1.0000	-4.8036	0.0000	0.0000	1.0000
MGARCH vs PGARCH	-1.3595	0.1761	0.0880	0.9120	-1.0419	0.2992	0.1496	0.8504	NA	NA	NA	NA	NA	NA	NA	NA

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.5: DM Test statistics and *p*-values for JCI Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
				Recursive Daily								**Rolling Window Daily**				
GARCH vs EGARCH	4.6370	0.0000	1.0000	0.0000	2.6396	0.0083	0.9958	0.0042	3.4684	0.0005	0.9997	0.0003	2.8227	0.0048	0.9976	0.0024
GARCH vs TGARCH	0.5832	0.5598	0.7201	0.2799	0.7078	0.4791	0.7604	0.2396	-0.4036	0.6865	0.3433	0.6567	0.6048	0.5453	0.7273	0.2727
GARCH vs MGARCH	0.9560	0.3392	0.8304	0.1696	0.9949	0.3199	0.8401	0.1599	-2.2341	0.0256	0.0128	0.9872	-2.1377	0.0326	0.0163	0.9837
GARCH vs PGARCH	0.2000	0.8415	0.5792	0.4208	1.1065	0.2686	0.8657	0.1343	0.9110	0.3624	0.8188	0.1812	1.0952	0.2735	0.8632	0.1368
EGARCH vs TGARCH	-3.0237	0.0025	0.0013	0.9987	-0.6463	0.5181	0.2591	0.7409	-3.0742	0.0021	0.0011	0.9989	-0.6270	0.5307	0.2654	0.7346
EGARCH vs MGARCH	-4.5683	0.0000	0.0000	1.0000	-2.4357	0.0149	0.0075	0.9925	-3.7418	0.0002	0.0001	0.9999	-2.9682	0.0030	0.0015	0.9985
EGARCH vs PGARCH	-3.8168	0.0001	0.0001	0.9999	-1.2144	0.2247	0.1124	0.8876	-2.3661	0.0180	0.0090	0.9910	-0.5570	0.5775	0.2888	0.7112
TGARCH vs MGARCH	-0.5485	0.5834	0.2917	0.7083	-0.6874	0.4919	0.2460	0.7540	0.1339	0.8935	0.5533	0.4467	-0.6670	0.5048	0.2524	0.7476
TGARCH vs PGARCH	-0.4343	0.6641	0.3320	0.6680	-0.1352	0.8925	0.4462	0.5538	2.2327	0.0256	0.9872	0.0128	0.6630	0.5074	0.7463	0.2537
MGARCH vs PGARCH	0.1428	0.8864	0.5568	0.4432	1.0901	0.2758	0.8621	0.1379	1.1724	0.2411	0.8794	0.1206	1.1589	0.2466	0.8767	0.1233
				Recursive Weekly								**Rolling Window Weekly**				
GARCH vs EGARCH	0.5757	0.5650	0.7175	0.2825	1.1574	0.2476	0.8762	0.1238	0.4608	0.6451	0.6775	0.3225	1.4358	0.1516	0.9242	0.0758
GARCH vs TGARCH	-3.3100	0.0010	0.0005	0.9995	-1.1492	0.2509	0.1255	0.8745	-3.5921	0.0004	0.0002	0.9998	-0.5874	0.5571	0.2786	0.7214
GARCH vs MGARCH	2.2249	0.0265	0.9868	0.0132	0.9873	0.3239	0.8380	0.1620	-0.9667	0.3341	0.1671	0.8329	0.1195	0.9049	0.5476	0.4524
GARCH vs PGARCH	-3.8382	0.0001	0.0001	0.9999	-1.3643	0.1730	0.0865	0.9135	-5.0858	0.0000	0.0000	1.0000	-1.2250	0.2210	0.1105	0.8895
EGARCH vs TGARCH	-3.8979	0.0001	0.0001	0.9999	-2.1643	0.0308	0.0154	0.9846	-4.2839	0.0000	0.0000	1.0000	-2.7713	0.0058	0.0029	0.9971
EGARCH vs MGARCH	-0.4096	0.6822	0.3411	0.6589	-1.0785	0.2812	0.1406	0.8594	-0.6169	0.5376	0.2688	0.7312	-1.3753	0.1695	0.0848	0.9152
EGARCH vs PGARCH	-4.2608	0.0000	0.0000	1.0000	-2.2708	0.0235	0.0118	0.9882	-5.3594	0.0000	0.0000	1.0000	-3.2480	0.0012	0.0006	0.9994
TGARCH vs MGARCH	3.3459	0.0009	0.9996	0.0004	1.1734	0.2411	0.8794	0.1206	3.2812	0.0011	0.9995	0.0005	0.5715	0.5679	0.7161	0.2839
TGARCH vs PGARCH	-2.0985	0.0363	0.0181	0.9819	-1.5081	0.1321	0.0660	0.9340	-2.4205	0.0158	0.0079	0.9921	-1.7576	0.0793	0.0397	0.9603
MGARCH vs PGARCH	0.5757	0.5650	0.7175	0.2825	1.1574	0.2476	0.8762	0.1238	-4.7785	0.0000	0.0000	1.0000	-1.1632	0.2452	0.1226	0.8774
				Recursive Monthly								**Rolling Window Monthly**				
GARCH vs EGARCH	-3.9896	0.0001	0.0001	0.9999	-2.9315	0.0039	0.0020	0.9980	0.5628	0.5744	0.7128	0.2872	1.3262	0.1869	0.9065	0.0935
GARCH vs TGARCH	-3.8280	0.0002	0.0001	0.9999	-2.5648	0.0113	0.0057	0.9943	-1.5331	0.1274	0.0637	0.9363	-1.0423	0.2990	0.1495	0.8505
GARCH vs MGARCH	1.5076	0.1338	0.9331	0.0669	-0.2530	0.8006	0.4003	0.5997	-4.0777	0.0001	0.0000	1.0000	-3.7775	0.0002	0.0001	0.9999
GARCH vs PGARCH	-2.2652	0.0250	0.0125	0.9875	-2.1852	0.0305	0.0152	0.9848	-2.0589	0.0413	0.0206	0.9794	-2.0946	0.0379	0.0190	0.9810
EGARCH vs TGARCH	2.0662	0.0406	0.9797	0.0203	1.5945	0.1130	0.9435	0.0565	-1.2940	0.1978	0.0989	0.9011	-1.8435	0.0674	0.0337	0.9663
EGARCH vs MGARCH	4.0244	0.0001	1.0000	0.0000	2.9349	0.0039	0.9981	0.0019	-0.9810	0.3283	0.1642	0.8358	-1.4297	0.1550	0.0775	0.9225
EGARCH vs PGARCH	1.4036	0.1626	0.9187	0.0813	-0.4481	0.6548	0.3274	0.6726	-1.4909	0.1382	0.0691	0.9309	-1.9045	0.0589	0.0294	0.9706
TGARCH vs MGARCH	3.9616	0.0001	0.9999	0.0001	2.6077	0.0101	0.9950	0.0050	1.1712	0.2434	0.8783	0.1217	0.9461	0.3457	0.8272	0.1728
TGARCH vs PGARCH	-0.5048	0.6144	0.3072	0.6928	-1.9459	0.0536	0.0268	0.9732	-1.8788	0.0623	0.0311	0.9689	-2.2280	0.0274	0.0137	0.9863
MGARCH vs PGARCH	-2.3181	0.0218	0.0109	0.9891	-2.1936	0.0298	0.0149	0.9851	-1.8281	0.0696	0.0348	0.9652	-2.0594	0.0412	0.0206	0.9794

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.6: DM Test statistics and *p*-values for SET Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
				Recursive Daily									**Rolling Window Daily**			
GARCH vs EGARCH	1.8401	0.0659	0.9671	0.0329	0.2096	0.8340	0.5830	0.4170	1.3697	0.1709	0.9146	0.0854	0.0151	0.9880	0.5060	0.4940
GARCH vs TGARCH	1.1774	0.2391	0.8804	0.1196	0.7933	0.4277	0.7862	0.2138	-0.2330	0.8158	0.4079	0.5921	0.6644	0.5065	0.7468	0.2532
GARCH vs MGARCH	3.2638	0.0011	0.9994	0.0006	2.2313	0.0257	0.9871	0.0129	1.8260	0.0680	0.9660	0.0340	-0.2714	0.7861	0.3930	0.6070
GARCH vs PGARCH	-2.2789	0.0227	0.0114	0.9886	-0.3759	0.7070	0.3535	0.6465	-0.9638	0.3352	0.1676	0.8324	-0.2701	0.7871	0.3936	0.6064
EGARCH vs TGARCH	-1.5811	0.1140	0.0570	0.9430	-0.0031	0.9975	0.4988	0.5012	-1.6009	0.1095	0.0548	0.9452	0.1804	0.8569	0.5716	0.4284
EGARCH vs MGARCH	-1.2593	0.2080	0.1040	0.8960	-0.1820	0.8556	0.4278	0.5722	-1.0930	0.2745	0.1373	0.8627	-0.0201	0.9840	0.4920	0.5080
EGARCH vs PGARCH	-4.1522	0.0000	0.0000	1.0000	-0.7027	0.4823	0.2411	0.7589	-2.5849	0.0098	0.0049	0.9951	-0.2655	0.7907	0.3953	0.6047
TGARCH vs MGARCH	0.6023	0.5470	0.7265	0.2735	-0.6802	0.4964	0.2482	0.7518	1.1132	0.2657	0.8671	0.1329	-0.6713	0.5021	0.2510	0.7490
TGARCH vs PGARCH	-3.6526	0.0003	0.0001	0.9999	-1.2850	0.1989	0.0994	0.9006	-1.2258	0.2204	0.1102	0.8898	-0.9572	0.3386	0.1693	0.8307
MGARCH vs PGARCH	-3.2538	0.0012	0.0006	0.9994	-0.4282	0.6685	0.3343	0.6657	-1.4867	0.1372	0.0686	0.9314	-0.2597	0.7951	0.3976	0.6024
				Recursive Weekly									**Rolling Window Weekly**			
GARCH vs EGARCH	1.7184	0.0862	0.9569	0.0431	1.8496	0.0649	0.9676	0.0324	3.1809	0.0015	0.9992	0.0008	2.2923	0.0222	0.9889	0.0111
GARCH vs TGARCH	-3.5077	0.0005	0.0002	0.9998	-2.2648	0.0239	0.0119	0.9881	-5.0915	0.0000	0.0000	1.0000	-3.1833	0.0015	0.0008	0.9992
GARCH vs MGARCH	1.3468	0.1786	0.9107	0.0893	0.5541	0.5797	0.7101	0.2899	1.0870	0.2775	0.8613	0.1387	1.4277	0.1539	0.9231	0.0769
GARCH vs PGARCH	3.5073	0.0005	0.9998	0.0002	2.1377	0.0329	0.9835	0.0165	1.8654	0.0626	0.9687	0.0313	0.6397	0.5226	0.7387	0.2613
EGARCH vs TGARCH	-3.0162	0.0027	0.0013	0.9987	-2.6556	0.0081	0.0041	0.9959	-4.8865	0.0000	0.0000	1.0000	-2.9168	0.0037	0.0018	0.9982
EGARCH vs MGARCH	-1.7051	0.0887	0.0443	0.9557	-1.8589	0.0635	0.0318	0.9682	-3.2595	0.0012	0.0006	0.9994	-2.3443	0.0194	0.0097	0.9903
EGARCH vs PGARCH	2.3682	0.0182	0.9909	0.0091	2.2113	0.0274	0.9863	0.0137	-2.2572	0.0244	0.0122	0.9878	-0.9131	0.3615	0.1808	0.8192
TGARCH vs MGARCH	3.5124	0.0005	0.9998	0.0002	2.2448	0.0251	0.9874	0.0126	4.8982	0.0000	1.0000	0.0000	3.0405	0.0025	0.9988	0.0012
TGARCH vs PGARCH	3.9982	0.0001	1.0000	0.0000	2.8171	0.0050	0.9975	0.0025	4.0357	0.0001	1.0000	0.0000	1.9582	0.0507	0.9747	0.0253
MGARCH vs PGARCH	3.5129	0.0005	0.9998	0.0002	2.1495	0.0320	0.9840	0.0160	1.8352	0.0670	0.9665	0.0335	0.4979	0.6188	0.6906	0.3094
				Recursive Monthly									**Rolling Window Monthly**			
GARCH vs EGARCH	-3.0459	0.0028	0.0014	0.9986	-0.7511	0.4538	0.2269	0.7731	-1.4844	0.1399	0.0699	0.9301	1.1940	0.2344	0.8828	0.1172
GARCH vs TGARCH	-2.0352	0.0436	0.0218	0.9782	-1.4371	0.1528	0.0764	0.9236	-1.3491	0.1794	0.0897	0.9103	-1.3875	0.1674	0.0837	0.9163
GARCH vs MGARCH	-2.6308	0.0094	0.0047	0.9953	-0.1857	0.8529	0.4265	0.5735	-0.7057	0.4815	0.2407	0.7593	1.1633	0.2466	0.8767	0.1233
GARCH vs PGARCH	0.1651	0.8691	0.5655	0.4345	-0.3418	0.7330	0.3665	0.6335	1.7418	0.0837	0.9582	0.0418	1.3631	0.1750	0.9125	0.0875
EGARCH vs TGARCH	2.2479	0.0261	0.9870	0.0130	-0.2145	0.8305	0.4152	0.5848	1.0953	0.2752	0.8624	0.1376	-1.2868	0.2002	0.1001	0.8999
EGARCH vs MGARCH	2.8724	0.0047	0.9977	0.0023	0.7171	0.4745	0.7628	0.2372	1.4497	0.1493	0.9254	0.0746	-1.1209	0.2642	0.1321	0.8679
EGARCH vs PGARCH	2.7235	0.0073	0.9964	0.0036	0.0248	0.9802	0.5099	0.4901	3.8434	0.0002	0.9999	0.0001	1.2211	0.2240	0.8880	0.1120
TGARCH vs MGARCH	1.4309	0.1546	0.9227	0.0773	1.4390	0.1523	0.9239	0.0761	0.5003	0.6176	0.6912	0.3088	1.5056	0.1343	0.9328	0.0672
TGARCH vs PGARCH	0.9966	0.3206	0.8397	0.1603	0.2389	0.8115	0.5942	0.4058	1.7561	0.0812	0.9594	0.0406	1.3801	0.1697	0.9152	0.0848
MGARCH vs PGARCH	0.4163	0.6778	0.6611	0.3389	-0.3222	0.7478	0.3739	0.6261	1.9483	0.0533	0.9733	0.0267	1.3081	0.1929	0.9036	0.0964

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.7: DM Test statistics and *p*-values for SSE Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
Recursive Daily									**Rolling Window Daily**							
GARCH vs EGARCH	2.0171	0.0438	0.9781	0.0219	1.4789	0.1393	0.9304	0.0696	3.8382	0.0001	0.9999	0.0001	0.7217	0.4705	0.7647	0.2353
GARCH vs TGARCH	-0.6216	0.5343	0.2671	0.7329	0.4923	0.6225	0.6887	0.3113	2.1992	0.0279	0.9860	0.0140	-0.6527	0.5140	0.2570	0.7430
GARCH vs MGARCH	3.8078	0.0001	0.9999	0.0001	2.9873	0.0028	0.9986	0.0014	-1.9501	0.0513	0.0256	0.9744	0.5668	0.5709	0.7146	0.2854
GARCH vs PGARCH	-1.5902	0.1119	0.0560	0.9440	-0.7477	0.4547	0.2274	0.7726	-0.6951	0.4870	0.2435	0.7565	-0.6174	0.5370	0.2685	0.7315
EGARCH vs TGARCH	-3.1050	0.0019	0.0010	0.9990	-0.8878	0.3747	0.1874	0.8126	-3.7318	0.0002	0.0001	0.9999	-0.7939	0.4273	0.2137	0.7863
EGARCH vs MGARCH	0.7751	0.4384	0.7808	0.2192	-0.3977	0.6909	0.3454	0.6546	-3.8602	0.0001	0.0001	0.9999	-0.7081	0.4789	0.2395	0.7605
EGARCH vs PGARCH	-7.4058	0.0000	0.0000	1.0000	-4.1153	0.0000	0.0000	1.0000	-8.8025	0.0000	0.0000	1.0000	-2.3312	0.0198	0.0099	0.9901
TGARCH vs MGARCH	5.6427	0.0000	1.0000	0.0000	0.7656	0.4440	0.7780	0.2220	-2.2387	0.0253	0.0126	0.9874	0.6550	0.5125	0.7437	0.2563
TGARCH vs PGARCH	-1.3623	0.1732	0.0866	0.9134	-1.2095	0.2266	0.1133	0.8867	-0.8841	0.3767	0.1884	0.8116	-0.5559	0.5783	0.2892	0.7108
MGARCH vs PGARCH	-5.1290	0.0000	0.0000	1.0000	-1.7660	0.0775	0.0388	0.9612	-0.6635	0.5071	0.2535	0.7465	-0.6305	0.5284	0.2642	0.7358
Recursive Weekly									**Rolling Window Weekly**							
GARCH vs EGARCH	3.2787	0.0011	0.9994	0.0006	2.2949	0.0221	0.9890	0.0110	3.7391	0.0002	0.9999	0.0001	1.7114	0.0875	0.9562	0.0438
GARCH vs TGARCH	-1.9441	0.0524	0.0262	0.9738	-1.1746	0.2406	0.1203	0.8797	2.7886	0.0055	0.9973	0.0027	0.5899	0.5555	0.7223	0.2777
GARCH vs MGARCH	-2.2902	0.0224	0.0112	0.9888	-1.1805	0.2383	0.1191	0.8809	0.0909	0.9276	0.5362	0.4638	0.8265	0.4089	0.7956	0.2044
GARCH vs PGARCH	-3.5254	0.0005	0.0002	0.9998	-2.4534	0.0144	0.0072	0.9928	0.4385	0.6612	0.6694	0.3306	-0.8229	0.4109	0.2054	0.7946
EGARCH vs TGARCH	-3.9137	0.0001	0.0001	0.9999	-2.4048	0.0165	0.0082	0.9918	-3.1482	0.0017	0.0009	0.9991	-1.9540	0.0512	0.0256	0.9744
EGARCH vs MGARCH	-3.8074	0.0002	0.0001	0.9999	-2.3921	0.0171	0.0085	0.9915	-3.4459	0.0006	0.0003	0.9997	-1.1785	0.2391	0.1195	0.8805
EGARCH vs PGARCH	-3.8389	0.0001	0.0001	0.9999	-2.5957	0.0097	0.0048	0.9952	-2.9484	0.0033	0.0017	0.9983	-1.6622	0.0970	0.0485	0.9515
TGARCH vs MGARCH	0.2828	0.7775	0.6113	0.3887	0.5203	0.6030	0.6985	0.3015	-2.3065	0.0214	0.0107	0.9893	0.2070	0.8361	0.5820	0.4180
TGARCH vs PGARCH	-3.3522	0.0009	0.0004	0.9996	-2.5591	0.0107	0.0054	0.9946	-1.2916	0.1970	0.0985	0.9015	-0.8829	0.3777	0.1888	0.8112
MGARCH vs PGARCH	-3.2364	0.0013	0.0006	0.9994	-2.4623	0.0141	0.0070	0.9930	0.3185	0.7502	0.6249	0.3751	-0.9746	0.3302	0.1651	0.8349
Recursive Monthly									**Rolling Window Monthly**							
GARCH vs EGARCH	0.8134	0.4173	0.7913	0.2087	0.9893	0.3242	0.8379	0.1621	-0.2385	0.8118	0.4059	0.5941	-0.1030	0.9181	0.4591	0.5409
GARCH vs TGARCH	-1.7492	0.0823	0.0412	0.9588	-1.7283	0.0861	0.0430	0.9570	1.5589	0.1212	0.9394	0.0606	-0.0598	0.9524	0.4762	0.5238
GARCH vs MGARCH	1.4013	0.1633	0.9184	0.0816	-0.0312	0.9752	0.4876	0.5124	-1.0000	0.3190	0.1595	0.8405	-1.0000	0.3190	0.1595	0.8405
GARCH vs PGARCH	-2.0286	0.0443	0.0222	0.9778	-2.4331	0.0162	0.0081	0.9919	1.5773	0.1169	0.9416	0.0584	1.1237	0.2630	0.8685	0.1315
EGARCH vs TGARCH	-2.7957	0.0059	0.0029	0.9971	-3.1673	0.0019	0.0009	0.9991	1.4634	0.1455	0.9272	0.0728	0.6148	0.5397	0.7302	0.2698
EGARCH vs MGARCH	0.4754	0.6352	0.6824	0.3176	-0.8618	0.3902	0.1951	0.8049	-1.0000	0.3190	0.1595	0.8405	-1.0000	0.3190	0.1595	0.8405
EGARCH vs PGARCH	-2.2892	0.0235	0.0118	0.9882	-2.7546	0.0066	0.0033	0.9967	1.4564	0.1474	0.9263	0.0737	1.1459	0.2537	0.8731	0.1269
TGARCH vs MGARCH	2.4147	0.0170	0.9915	0.0085	1.6522	0.1006	0.9497	0.0503	-1.0000	0.3190	0.1595	0.8405	-1.0000	0.3190	0.1595	0.8405
TGARCH vs PGARCH	-0.9356	0.3510	0.1755	0.8245	-1.7381	0.0843	0.0422	0.9578	0.1711	0.8644	0.5678	0.4322	1.1141	0.2671	0.8665	0.1335
MGARCH vs PGARCH	-2.5218	0.0127	0.0064	0.9936	-2.2786	0.0241	0.0121	0.9879	1.0000	0.3190	0.8405	0.1595	1.0000	0.3190	0.8405	0.1595

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.8: DM Test statistics and *p*-values for TAIEX Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
			Recursive Daily									**Rolling Window Daily**				
GARCH vs EGARCH	0.9645	0.3349	0.8326	0.1674	1.2098	0.2264	0.8868	0.1132	1.1910	0.2338	0.8831	0.1169	0.4381	0.6614	0.6693	0.3307
GARCH vs TGARCH	-4.7049	0.0000	0.0000	1.0000	0.2317	0.8168	0.5916	0.4084	-4.7427	0.0000	0.0000	1.0000	0.2323	0.8164	0.5918	0.4082
GARCH vs MGARCH	-0.0351	0.9720	0.4860	0.5140	1.6573	0.0976	0.9512	0.0488	2.6383	0.0084	0.9958	0.0042	1.7935	0.0730	0.9635	0.0365
GARCH vs PGARCH	-4.2499	0.0000	0.0000	1.0000	-1.5768	0.1149	0.0575	0.9425	-3.3243	0.0009	0.0004	0.9996	-0.9642	0.3350	0.1675	0.8325
EGARCH vs TGARCH	-6.1942	0.0000	0.0000	1.0000	-1.4699	0.1417	0.0708	0.9292	-6.3921	0.0000	0.0000	1.0000	-0.2688	0.7881	0.3941	0.6059
EGARCH vs MGARCH	-0.9759	0.3292	0.1646	0.8354	-1.1807	0.2378	0.1189	0.8811	-1.1499	0.2503	0.1251	0.8749	-0.4080	0.6833	0.3417	0.6583
EGARCH vs PGARCH	-5.8275	0.0000	0.0000	1.0000	-4.5383	0.0000	0.0000	1.0000	-4.8912	0.0000	0.0000	1.0000	-1.3343	0.1822	0.0911	0.9089
TGARCH vs MGARCH	4.7689	0.0000	1.0000	0.0000	-0.1816	0.8559	0.4280	0.5720	4.8260	0.0000	1.0000	0.0000	-0.1938	0.8463	0.4232	0.5768
TGARCH vs PGARCH	-1.5109	0.1309	0.0655	0.9345	-2.6643	0.0078	0.0039	0.9961	-0.3739	0.7085	0.3542	0.6458	-1.6736	0.0943	0.0472	0.9528
MGARCH vs PGARCH	-4.2731	0.0000	0.0000	1.0000	-1.6390	0.1013	0.0507	0.9493	-3.3668	0.0008	0.0004	0.9996	-1.0045	0.3152	0.1576	0.8424
			Recursive Weekly									**Rolling Window Weekly**				
GARCH vs EGARCH	-2.0911	0.0369	0.0185	0.9815	-0.8522	0.3944	0.1972	0.8028	-0.2957	0.7676	0.3838	0.6162	0.1417	0.8874	0.5563	0.4437
GARCH vs TGARCH	-0.7275	0.4672	0.2336	0.7664	1.3618	0.1738	0.9131	0.0869	0.4796	0.6317	0.6842	0.3158	1.1983	0.2313	0.8844	0.1156
GARCH vs MGARCH	-3.1372	0.0018	0.0009	0.9991	-1.9617	0.0503	0.0251	0.9749	-1.4777	0.1400	0.0700	0.9300	-0.9252	0.3552	0.1776	0.8224
GARCH vs PGARCH	-1.8639	0.0628	0.0314	0.9686	-2.0191	0.0439	0.0220	0.9780	-2.5127	0.0122	0.0061	0.9939	-1.9215	0.0551	0.0276	0.9724
EGARCH vs TGARCH	1.2962	0.1954	0.9023	0.0977	2.1000	0.0361	0.9819	0.0181	0.7093	0.4784	0.7608	0.2392	1.0279	0.3044	0.8478	0.1522
EGARCH vs MGARCH	1.6081	0.1083	0.9458	0.0542	0.4465	0.6554	0.6723	0.3277	0.0136	0.9891	0.5054	0.4946	-0.3452	0.7300	0.3650	0.6350
EGARCH vs PGARCH	-0.6826	0.4951	0.2476	0.7524	-1.8506	0.0647	0.0324	0.9676	-2.7285	0.0065	0.0033	0.9967	-2.0978	0.0363	0.0182	0.9818
TGARCH vs MGARCH	0.2598	0.7951	0.6024	0.3976	-1.4781	0.1399	0.0699	0.9301	-0.6864	0.4927	0.2464	0.7536	-1.2048	0.2287	0.1144	0.8856
TGARCH vs PGARCH	-1.2256	0.2208	0.1104	0.8896	-2.0462	0.0412	0.0206	0.9794	-2.4601	0.0142	0.0071	0.9929	-1.9862	0.0475	0.0237	0.9763
MGARCH vs PGARCH	-1.6316	0.1033	0.0516	0.9484	-1.9564	0.0509	0.0254	0.9746	-2.4393	0.0150	0.0075	0.9925	-1.9212	0.0552	0.0276	0.9724
			Recursive Monthly									**Rolling Window Monthly**				
GARCH vs EGARCH	-9.7431	0.0000	0.0000	1.0000	-6.8476	0.0000	0.0000	1.0000	-3.4547	0.0007	0.0004	0.9996	-1.4641	0.1453	0.0727	0.9273
GARCH vs TGARCH	-2.5822	0.0108	0.0054	0.9946	-0.3941	0.6941	0.3470	0.6530	-0.7993	0.4254	0.2127	0.7873	0.2942	0.7691	0.6155	0.3845
GARCH vs MGARCH	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
GARCH vs PGARCH	-3.2389	0.0015	0.0007	0.9993	-1.8523	0.0660	0.0330	0.9670	0.6402	0.5231	0.7385	0.2615	0.6768	0.4997	0.7502	0.2498
EGARCH vs TGARCH	8.9016	0.0000	1.0000	0.0000	4.9588	0.0000	1.0000	0.0000	3.0196	0.0030	0.9985	0.0015	2.2357	0.0269	0.9865	0.0135
EGARCH vs MGARCH	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
EGARCH vs PGARCH	9.2551	0.0000	1.0000	0.0000	4.6488	0.0000	1.0000	0.0000	4.2142	0.0000	1.0000	0.0000	2.6629	0.0087	0.9957	0.0043
TGARCH vs MGARCH	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
TGARCH vs PGARCH	-1.4070	0.1616	0.0808	0.9192	-1.2948	0.1974	0.0987	0.9013	1.6472	0.1018	0.9491	0.0509	0.6958	0.4877	0.7561	0.2439
MGARCH vs PGARCH	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

Table B.9: DM Test statistics and *p*-values for KOSPI Index

Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
				Recursive Daily								**Rolling Window Daily**				
GARCH vs EGARCH	2.5370	0.0112	0.9944	0.0056	2.6951	0.0071	0.9965	0.0035	0.8975	0.3695	0.8152	0.1848	2.8137	0.0049	0.9975	0.0025
GARCH vs TGARCH	-0.4477	0.6544	0.3272	0.6728	1.0465	0.2954	0.8523	0.1477	-2.9034	0.0037	0.0019	0.9981	0.9763	0.3290	0.8355	0.1645
GARCH vs MGARCH	6.9437	0.0000	1.0000	0.0000	2.5426	0.0111	0.9945	0.0055	-0.9051	0.3655	0.1828	0.8172	-1.5928	0.1113	0.0557	0.9443
GARCH vs PGARCH	-3.1087	0.0019	0.0009	0.9991	0.3646	0.7155	0.6423	0.3577	-4.2694	0.0000	0.0000	1.0000	0.4151	0.6781	0.6609	0.3391
EGARCH vs TGARCH	-6.1942	0.0000	0.0000	1.0000	-1.4699	0.1417	0.0708	0.9292	-3.2004	0.0014	0.0007	0.9993	-1.1363	0.2559	0.1280	0.8720
EGARCH vs MGARCH	-2.8100	0.0050	0.0025	0.9975	-0.7476	0.4548	0.2274	0.7726	-0.9122	0.3618	0.1809	0.8191	-2.7897	0.0053	0.0027	0.9973
EGARCH vs PGARCH	-4.6720	0.0000	0.0000	1.0000	-2.2567	0.0241	0.0120	0.9880	-5.1593	0.0000	0.0000	1.0000	-3.2145	0.0013	0.0007	0.9993
TGARCH vs MGARCH	0.5306	0.5958	0.7021	0.2979	-1.0405	0.2982	0.1491	0.8509	2.8164	0.0049	0.9976	0.0024	-1.0038	0.3156	0.1578	0.8422
TGARCH vs PGARCH	-3.1346	0.0017	0.0009	0.9991	-2.2352	0.0255	0.0127	0.9873	-2.7679	0.0057	0.0028	0.9972	-1.2428	0.2141	0.1070	0.8930
MGARCH vs PGARCH	-3.1497	0.0017	0.0008	0.9992	0.3575	0.7207	0.6396	0.3604	-4.2243	0.0000	0.0000	1.0000	0.4808	0.6307	0.6847	0.3153
				Recursive Weekly								**Rolling Window Weekly**				
GARCH vs EGARCH	1.2952	0.1958	0.9021	0.0979	-0.3591	0.7196	0.3598	0.6402	0.9247	0.3555	0.8223	0.1777	2.0549	0.0403	0.9798	0.0202
GARCH vs TGARCH	-1.9267	0.0545	0.0272	0.9728	1.0130	0.3114	0.8443	0.1557	-3.2808	0.0011	0.0005	0.9995	0.8787	0.3799	0.8100	0.1900
GARCH vs MGARCH	5.6476	0.0000	1.0000	0.0000	2.4140	0.0161	0.9920	0.0080	2.6984	0.0072	0.9964	0.0036	-1.2630	0.2071	0.1035	0.8965
GARCH vs PGARCH	3.0623	0.0023	0.9989	0.0011	2.2790	0.0230	0.9885	0.0115	-2.2789	0.0230	0.0115	0.9885	2.4720	0.0137	0.9931	0.0069
EGARCH vs TGARCH	-1.5052	0.1328	0.0664	0.9336	0.4789	0.6321	0.6839	0.3161	-2.4766	0.0135	0.0068	0.9932	-0.8198	0.4127	0.2063	0.7937
EGARCH vs MGARCH	-1.1622	0.2456	0.1228	0.8772	0.3859	0.6997	0.6502	0.3498	-0.7943	0.4273	0.2137	0.7863	-2.1124	0.0351	0.0175	0.9825
EGARCH vs PGARCH	-0.8259	0.4092	0.2046	0.7954	0.5661	0.5716	0.7142	0.2858	-4.1083	0.0000	0.0000	1.0000	-1.2130	0.2256	0.1128	0.8872
TGARCH vs MGARCH	2.6595	0.0080	0.9960	0.0040	-0.8986	0.3692	0.1846	0.8154	3.4569	0.0006	0.9997	0.0003	-0.8951	0.3711	0.1855	0.8145
TGARCH vs PGARCH	5.1003	0.0000	1.0000	0.0000	0.3783	0.7054	0.6473	0.3527	0.6380	0.5237	0.7382	0.2618	0.5014	0.6163	0.6919	0.3081
MGARCH vs PGARCH	2.2885	0.0224	0.9888	0.0112	2.1930	0.0287	0.9857	0.0143	-2.4646	0.0140	0.0070	0.9930	2.4828	0.0133	0.9933	0.0067
				Recursive Monthly								**Rolling Window Monthly**				
GARCH vs EGARCH	0.4723	0.6374	0.6813	0.3187	-0.0046	0.9964	0.4982	0.5018	-2.4031	0.0175	0.0088	0.9912	-1.2907	0.1989	0.0994	0.9006
GARCH vs TGARCH	-1.7375	0.0844	0.0422	0.9578	-1.3154	0.1905	0.0952	0.9048	-1.8626	0.0645	0.0323	0.9677	-1.5522	0.1228	0.0614	0.9386
GARCH vs MGARCH	3.6192	0.0004	0.9998	0.0002	2.9323	0.0039	0.9980	0.0020	-3.8199	0.0002	0.0001	0.9999	-2.5659	0.0113	0.0056	0.9944
GARCH vs PGARCH	2.5568	0.0116	0.9942	0.0058	1.1458	0.2537	0.8731	0.1269	-0.9119	0.3633	0.1817	0.8183	-0.3895	0.6975	0.3487	0.6513
EGARCH vs TGARCH	-3.6686	0.0003	0.0002	0.9998	-2.8657	0.0048	0.0024	0.9976	0.7658	0.4450	0.7775	0.2225	-1.1962	0.2336	0.1168	0.8832
EGARCH vs MGARCH	-0.2632	0.7928	0.3964	0.6036	0.0674	0.9463	0.5268	0.4732	-3.8016	0.0002	0.0001	0.9999	-2.5656	0.0113	0.0057	0.9943
EGARCH vs PGARCH	2.7139	0.0074	0.9963	0.0037	1.4881	0.1389	0.9306	0.0694	1.1774	0.2410	0.8795	0.1205	0.8805	0.3801	0.8100	0.1900
TGARCH vs MGARCH	1.8663	0.0640	0.9680	0.0320	1.3517	0.1786	0.9107	0.0893	-3.8025	0.0002	0.0001	0.9999	-2.5655	0.0113	0.0057	0.9943
TGARCH vs PGARCH	3.3799	0.0009	0.9995	0.0005	1.9216	0.0566	0.9717	0.0283	0.6060	0.5455	0.7273	0.2727	1.1299	0.2604	0.8698	0.1302
MGARCH vs PGARCH	2.3964	0.0178	0.9911	0.0089	2.1930	0.0287	0.9857	0.0143	3.8178	0.0002	0.9999	0.0001	2.5662	0.0113	0.9944	0.0056

Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

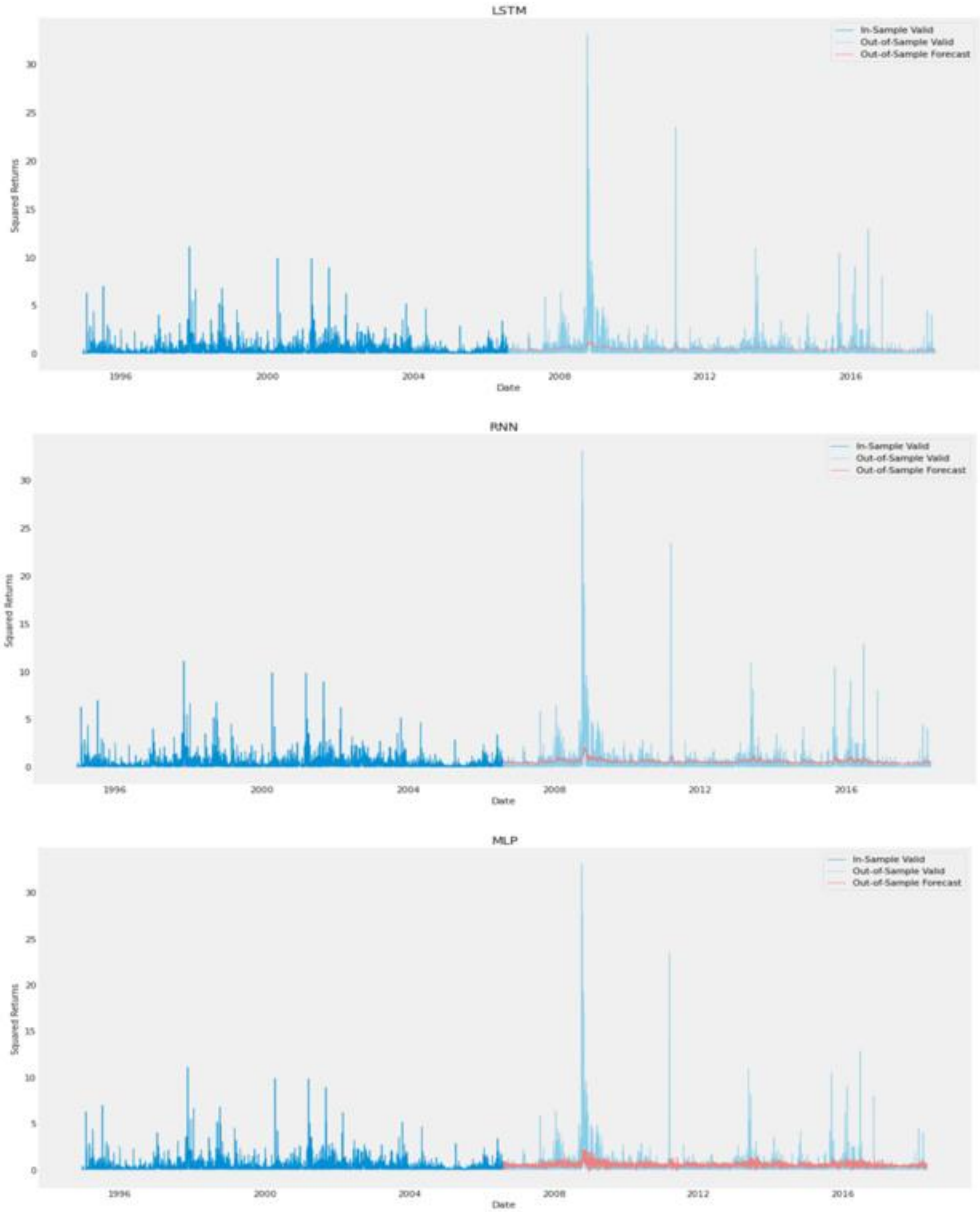
Table B.10: DM Test statistics and *p*-values for PSE Index

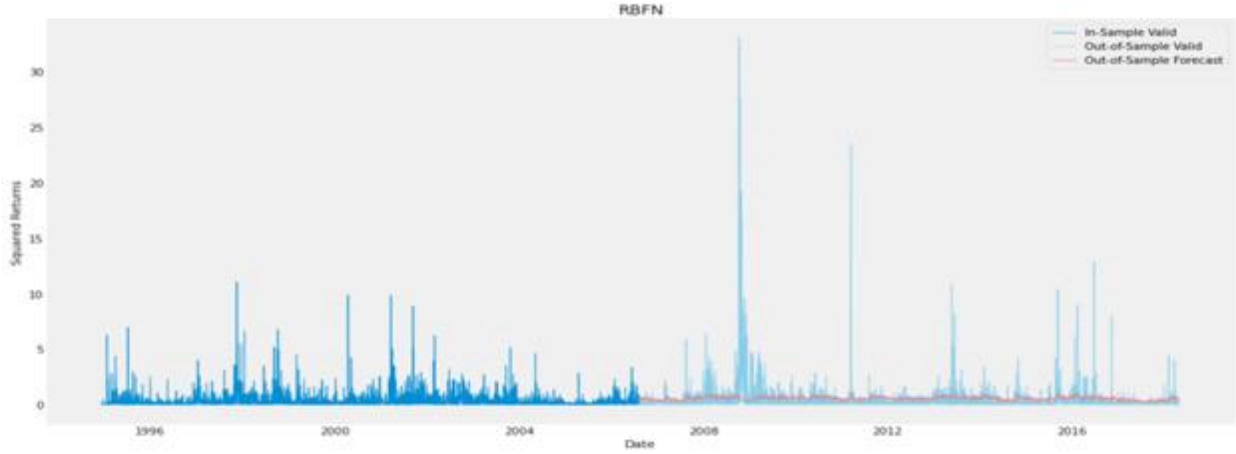
Forecast 1 vs Forecast 2	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value	DM(A)	<>P-value	>P-value	<P-value	DM(S)	<>P-value	>P-value	<P-value
				Recursive Daily								**Rolling Window Daily**				
GARCH vs EGARCH	3.6207	0.0003	0.9999	0.0001	2.8060	0.0051	0.9975	0.0025	2.8631	0.0042	0.9979	0.0021	3.5480	0.0004	0.9998	0.0002
GARCH vs TGARCH	-1.6004	0.1096	0.0548	0.9452	0.5024	0.6155	0.6923	0.3077	-0.7051	0.4808	0.2404	0.7596	0.8094	0.4184	0.7908	0.2092
GARCH vs MGARCH	-1.8889	0.0590	0.0295	0.9705	0.2083	0.8350	0.5825	0.4175	0.6201	0.5352	0.7324	0.2676	1.2869	0.1982	0.9009	0.0991
GARCH vs PGARCH	-0.3958	0.6923	0.3461	0.6539	1.6810	0.0929	0.9536	0.0464	0.4984	0.6182	0.6909	0.3091	2.0794	0.0377	0.9812	0.0188
EGARCH vs TGARCH	-3.8710	0.0001	0.0001	0.9999	-1.4905	0.1362	0.0681	0.9319	-2.8523	0.0044	0.0022	0.9978	-1.6715	0.0947	0.0474	0.9526
EGARCH vs MGARCH	-4.2562	0.0000	0.0000	1.0000	-2.8009	0.0051	0.0026	0.9974	-2.6773	0.0075	0.0037	0.9963	-3.4003	0.0007	0.0003	0.9997
EGARCH vs PGARCH	-3.7271	0.0002	0.0001	0.9999	-1.0254	0.3053	0.1526	0.8474	-2.7877	0.0053	0.0027	0.9973	-1.1960	0.2318	0.1159	0.8841
TGARCH vs MGARCH	0.5618	0.5743	0.7129	0.2871	-0.5481	0.5837	0.2918	0.7082	0.9190	0.3582	0.8209	0.1791	-0.7114	0.4769	0.2384	0.7616
TGARCH vs PGARCH	1.1472	0.2514	0.8743	0.1257	1.8135	0.0699	0.9651	0.0349	1.4103	0.1586	0.9207	0.0793	1.9219	0.0547	0.9726	0.0274
MGARCH vs PGARCH	0.5848	0.5588	0.7206	0.2794	1.9503	0.0512	0.9744	0.0256	0.3003	0.7640	0.6180	0.3820	2.1237	0.0338	0.9831	0.0169
				Recursive Weekly								**Rolling Window Weekly**				
GARCH vs EGARCH	3.9926	0.0001	1.0000	0.0000	1.8566	0.0638	0.9681	0.0319	2.8893	0.0040	0.9980	0.0020	2.1541	0.0316	0.9842	0.0158
GARCH vs TGARCH	-0.2184	0.8272	0.4136	0.5864	1.4450	0.1490	0.9255	0.0745	0.0310	0.9753	0.5123	0.4877	1.0436	0.2971	0.8515	0.1485
GARCH vs MGARCH	2.5565	0.0108	0.9946	0.0054	1.4604	0.1447	0.9277	0.0723	0.7818	0.4346	0.7827	0.2173	1.0315	0.3027	0.8486	0.1514
GARCH vs PGARCH	-0.4029	0.6871	0.3436	0.6564	0.3784	0.7053	0.6474	0.3526	-3.9597	0.0001	0.0000	1.0000	-1.7911	0.0738	0.0369	0.9631
EGARCH vs TGARCH	-4.8535	0.0000	0.0000	1.0000	-0.2795	0.7800	0.3900	0.6100	-3.3577	0.0008	0.0004	0.9996	-0.9618	0.3365	0.1683	0.8317
EGARCH vs MGARCH	-3.9551	0.0001	0.0000	1.0000	-1.8251	0.0685	0.0342	0.9658	-2.8046	0.0052	0.0026	0.9974	-1.9776	0.0484	0.0242	0.9758
EGARCH vs PGARCH	-3.5794	0.0004	0.0002	0.9998	-0.7257	0.4683	0.2342	0.7658	-5.1229	0.0000	0.0000	1.0000	-2.2819	0.0228	0.0114	0.9886
TGARCH vs MGARCH	0.3195	0.7495	0.6253	0.3747	-1.4181	0.1567	0.0783	0.9217	0.3417	0.7327	0.6336	0.3664	-0.8380	0.4023	0.2012	0.7988
TGARCH vs PGARCH	-0.1927	0.8472	0.4236	0.5764	-0.9503	0.3423	0.1712	0.8288	-4.0954	0.0000	0.0000	1.0000	-2.5462	0.0111	0.0056	0.9944
MGARCH vs PGARCH	-0.4957	0.6203	0.3102	0.6898	0.3523	0.7247	0.6376	0.3624	-4.3316	0.0000	0.0000	1.0000	-1.9407	0.0528	0.0264	0.9736
				Recursive Monthly								**Rolling Window Monthly**				
GARCH vs EGARCH	-2.0439	0.0428	0.0214	0.9786	-0.2824	0.7780	0.3890	0.6110	-3.3505	0.0010	0.0005	0.9995	-0.7561	0.4508	0.2254	0.7746
GARCH vs TGARCH	-3.4247	0.0008	0.0004	0.9996	-0.6268	0.5317	0.2659	0.7341	-3.8377	0.0002	0.0001	0.9999	-1.7552	0.0813	0.0407	0.9593
GARCH vs MGARCH	1.1143	0.2670	0.8665	0.1335	-1.2213	0.2239	0.1120	0.8880	NA	NA	NA	NA	NA	NA	NA	NA
GARCH vs PGARCH	-0.2165	0.8289	0.4145	0.5855	0.1851	0.8534	0.5733	0.4267	-4.1044	0.0001	0.0000	1.0000	-0.6650	0.5071	0.2535	0.7465
EGARCH vs TGARCH	-1.7226	0.0871	0.0435	0.9565	-0.8869	0.3766	0.1883	0.8117	-1.5519	0.1228	0.0614	0.9386	-1.5177	0.1312	0.0656	0.9344
EGARCH vs MGARCH	2.2638	0.0251	0.9875	0.0125	0.2105	0.8336	0.5832	0.4168	NA	NA	NA	NA	NA	NA	NA	NA
EGARCH vs PGARCH	3.6805	0.0003	0.9998	0.0002	1.5256	0.1293	0.9354	0.0646	-0.1721	0.8636	0.4318	0.5682	0.5006	0.6174	0.6913	0.3087
TGARCH vs MGARCH	3.7699	0.0002	0.9999	0.0001	0.5696	0.5698	0.7151	0.2849	NA	NA	NA	NA	NA	NA	NA	NA
TGARCH vs PGARCH	3.8744	0.0002	0.9999	0.0001	1.3801	0.1697	0.9152	0.0848	1.5557	0.1219	0.9390	0.0610	1.6150	0.1085	0.9458	0.0542
MGARCH vs PGARCH	-0.4011	0.6889	0.3445	0.6555	0.2793	0.7804	0.6098	0.3902	NA	NA	NA	NA	NA	NA	NA	NA

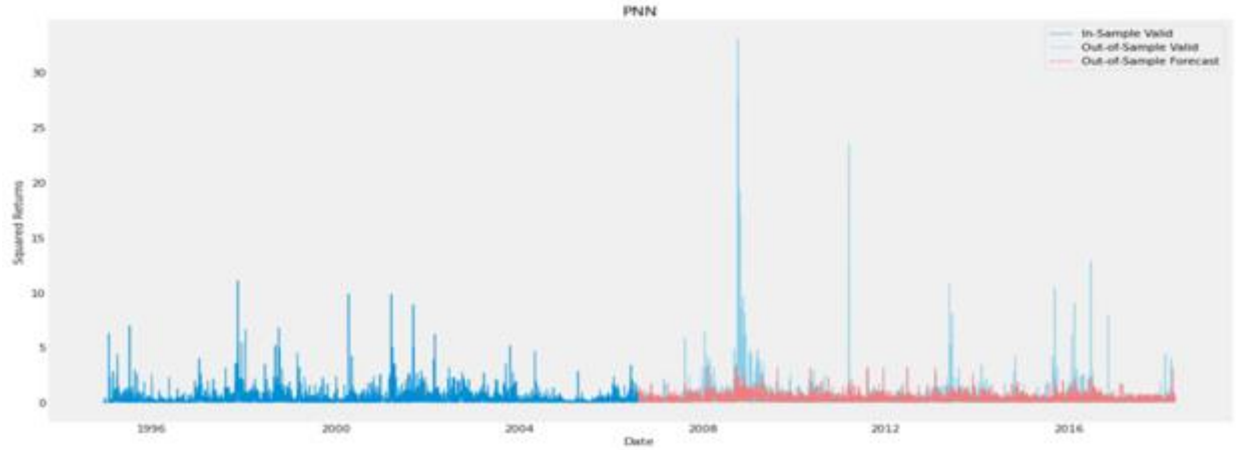
Notes: 1.The columns labelled DM(A) and DM(S) contain t-statistic based on absolute and squared prediction errors, respectively. 2. The null hypothesis of DM-test is that of equal predictive ability of the two models; a significantly positive (negative) t-statistics indicates the benchmark model is dominated by (dominates) the corresponding model.

APPENDIX C

Figure C.1: Out-of-sample performance of ANN models for NIKKEI index




RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
5
10
15
20
25
30
1996
2000
2004
2008
2012
2016
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
5
10
15
20
25
30
1996
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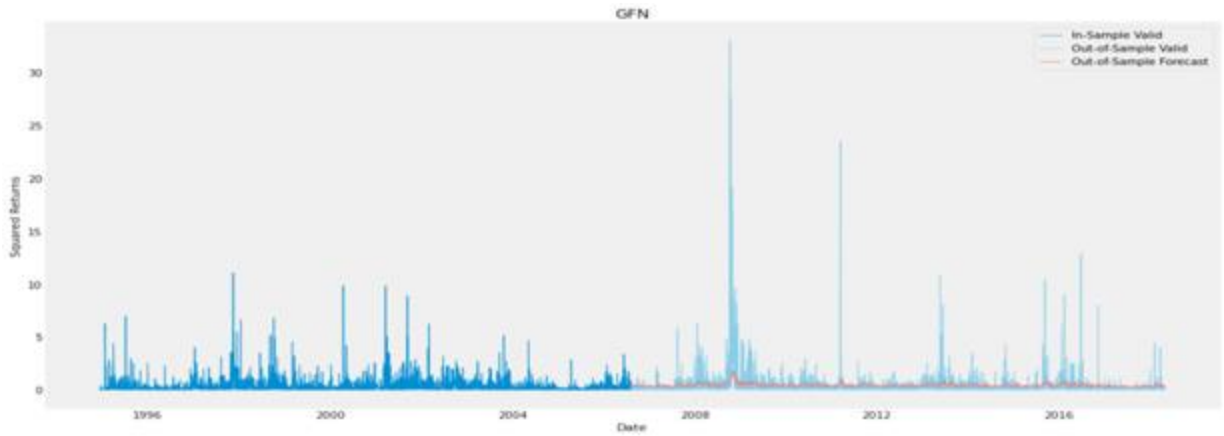
2004
2008
2012
2016
Date


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
5
10
15
20
25
30
1996
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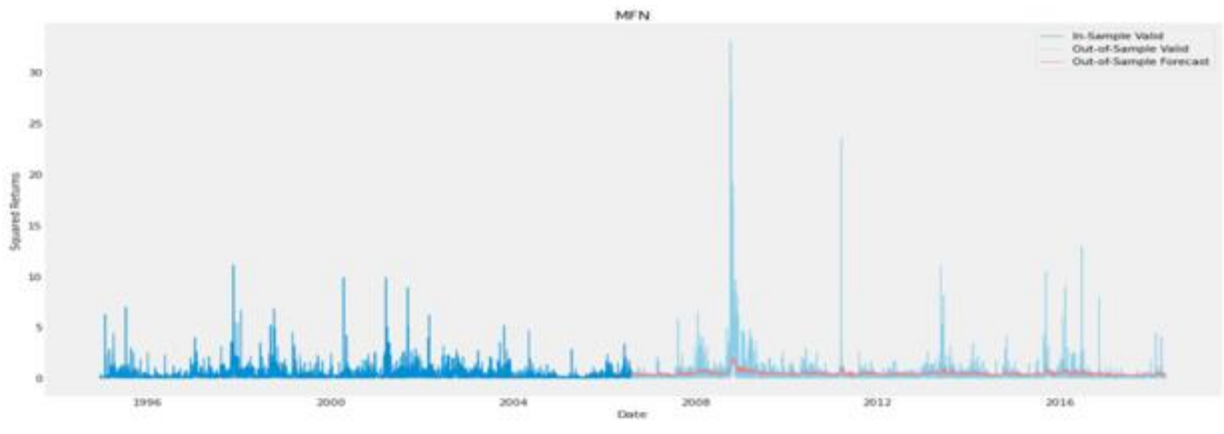
2004
2008
2012
2016
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
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10
15
20
25
30
1996
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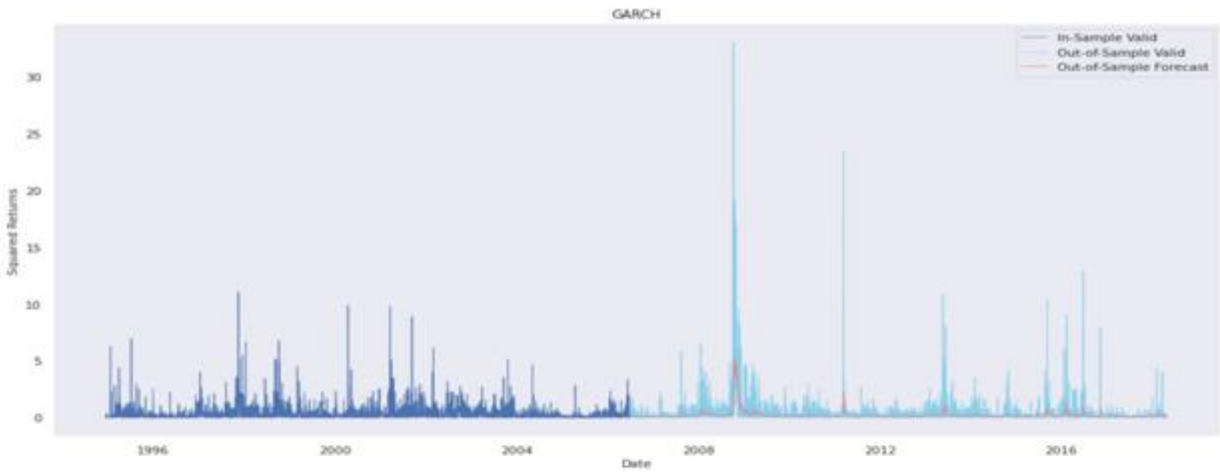
2004
2008
2012
2016
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
20
25
30
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2000
2004
2008
2012
2016

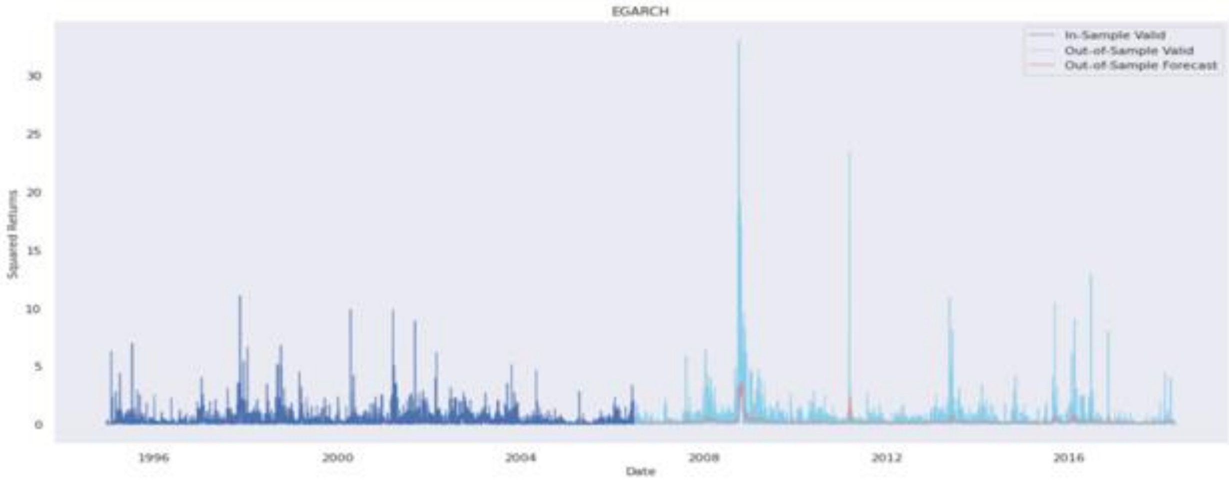
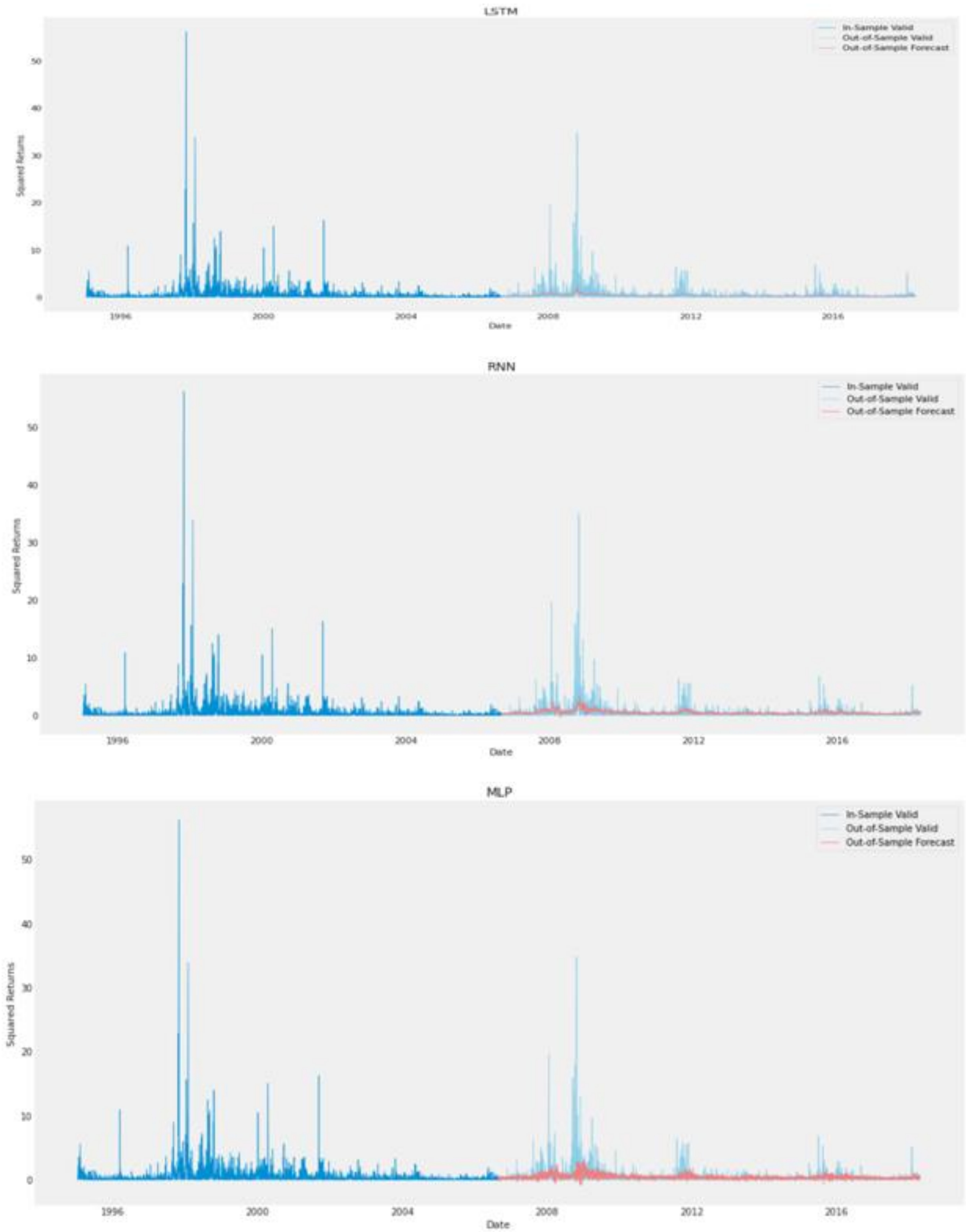
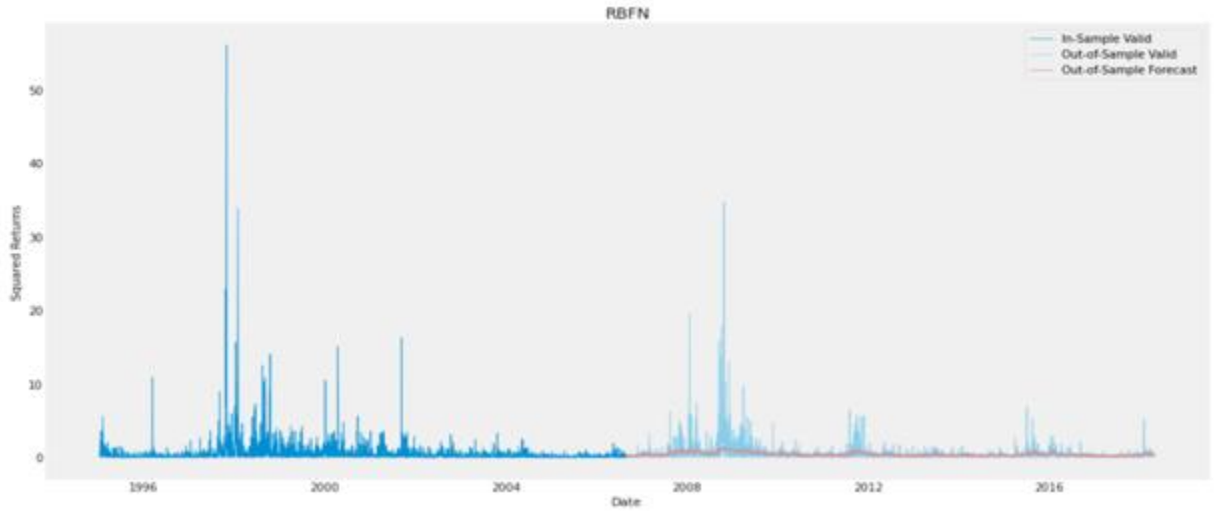
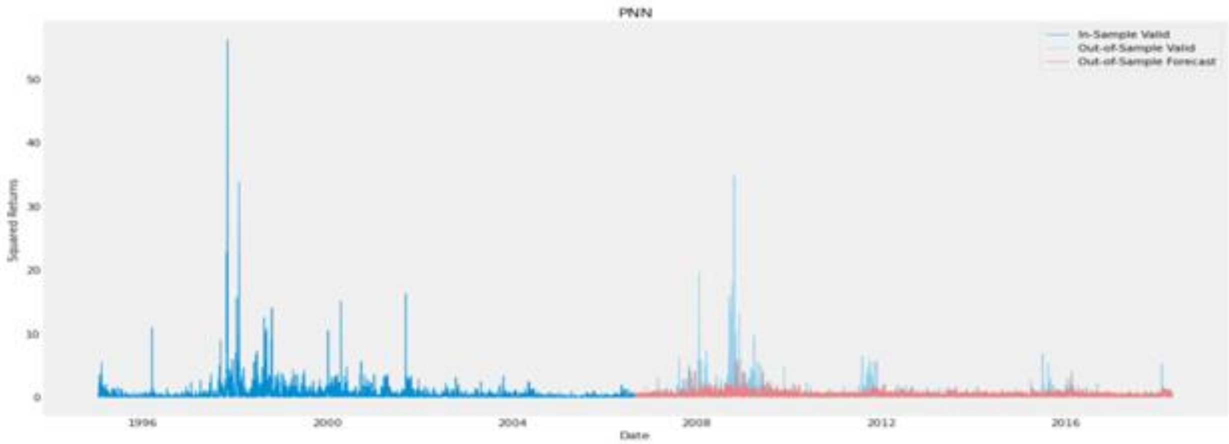
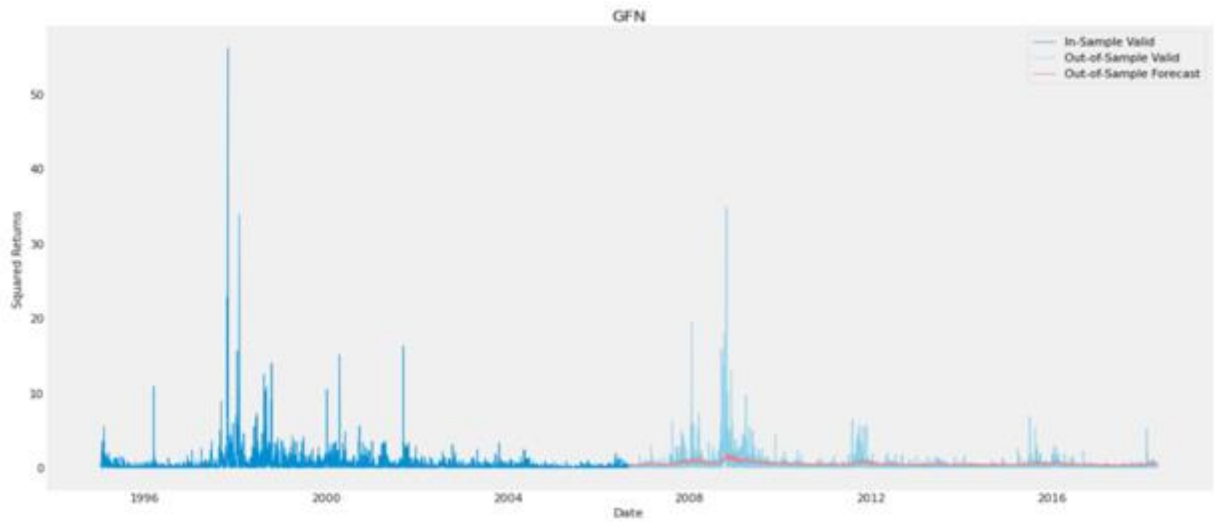

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
20
25
30
1996
2000
2004
2008
2012
2016

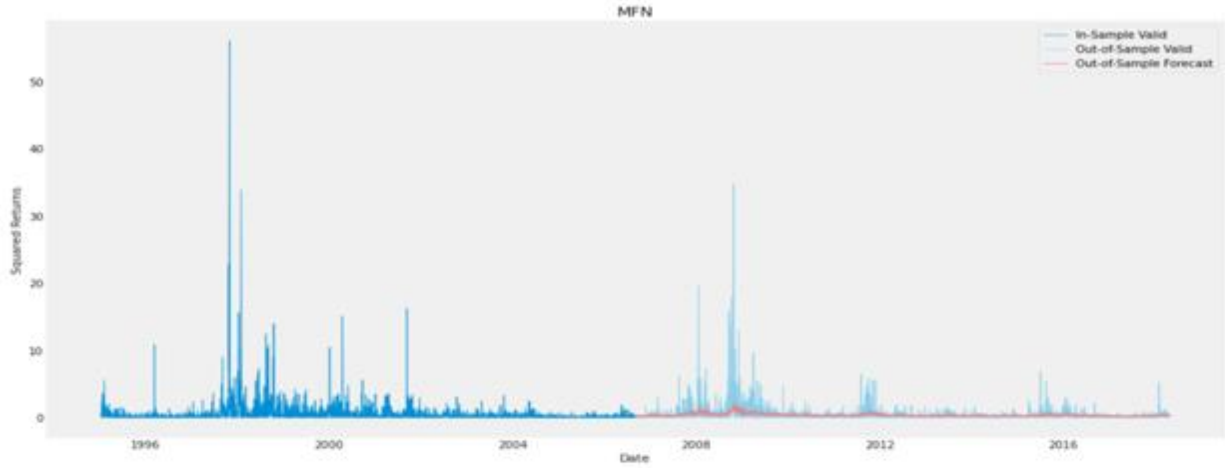
Figure C.2: Out-of-sample performance of ANN models for HANG SENG index

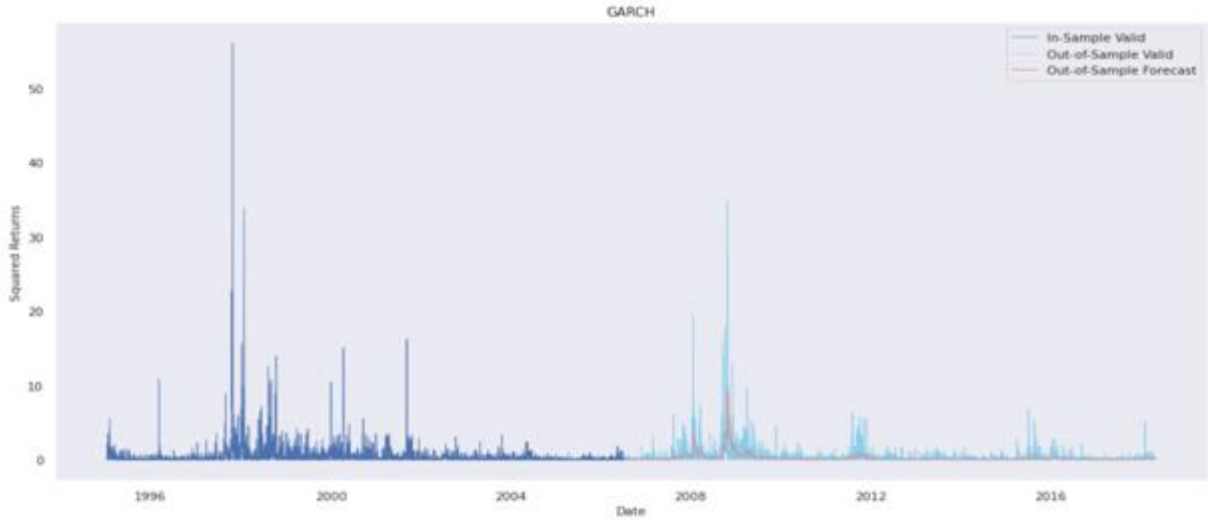



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016

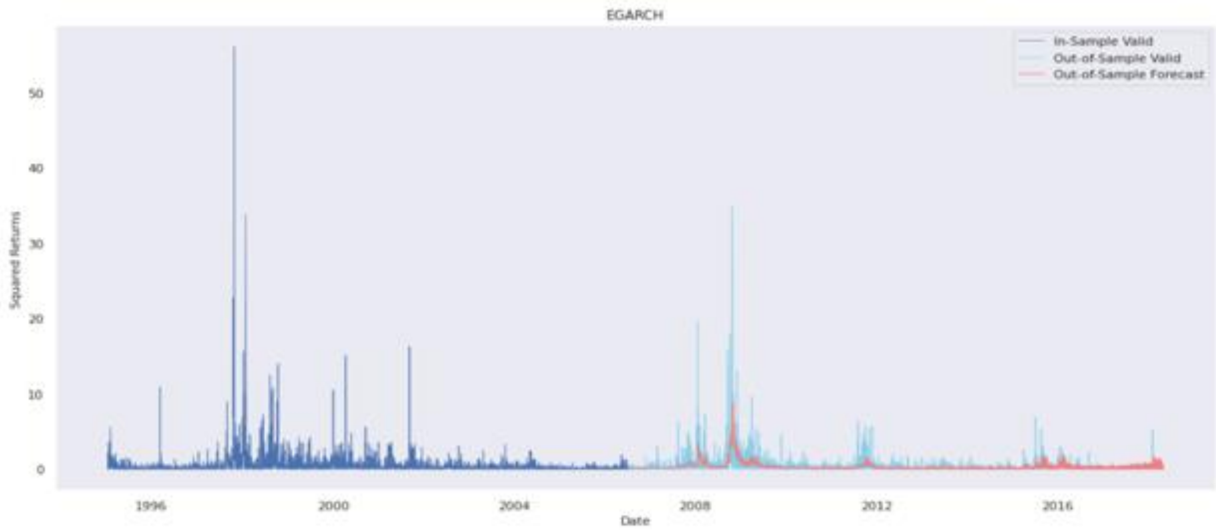
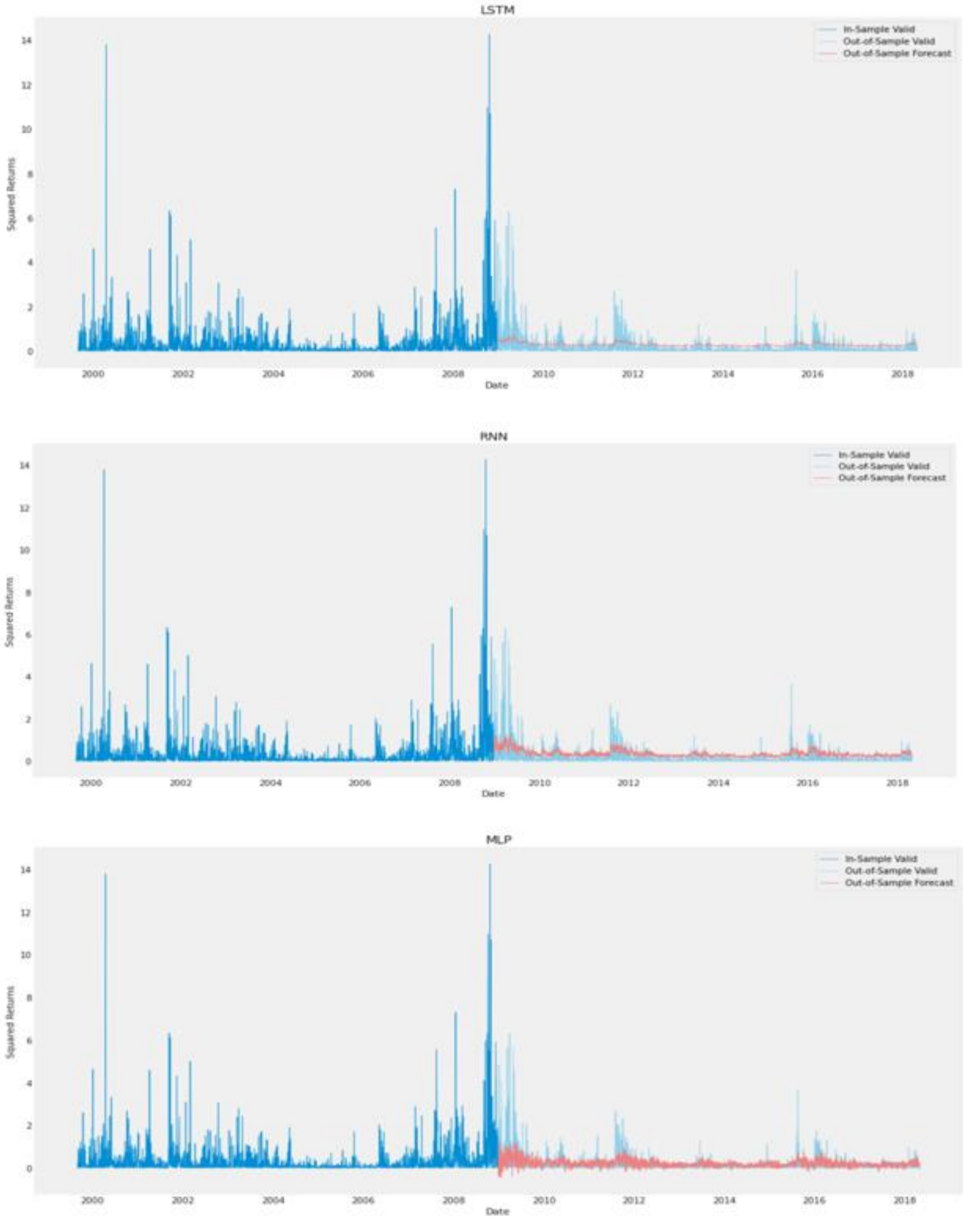
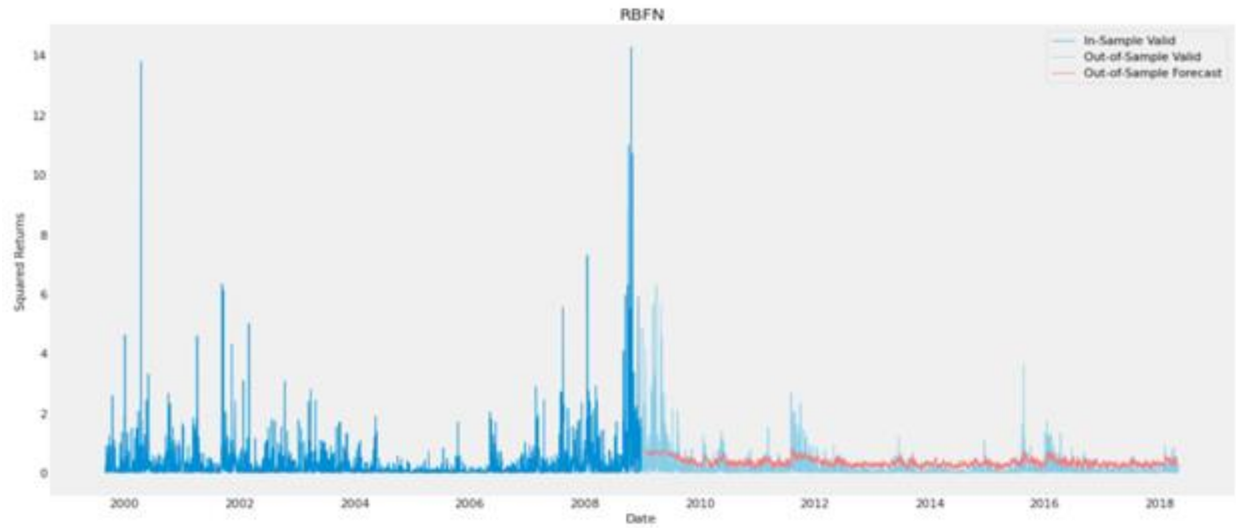
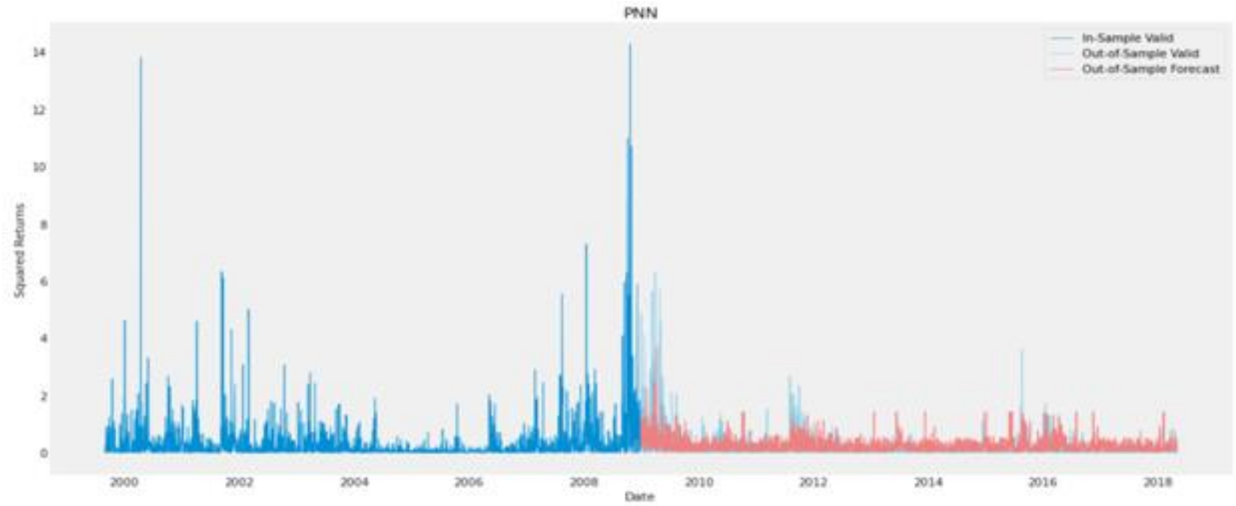
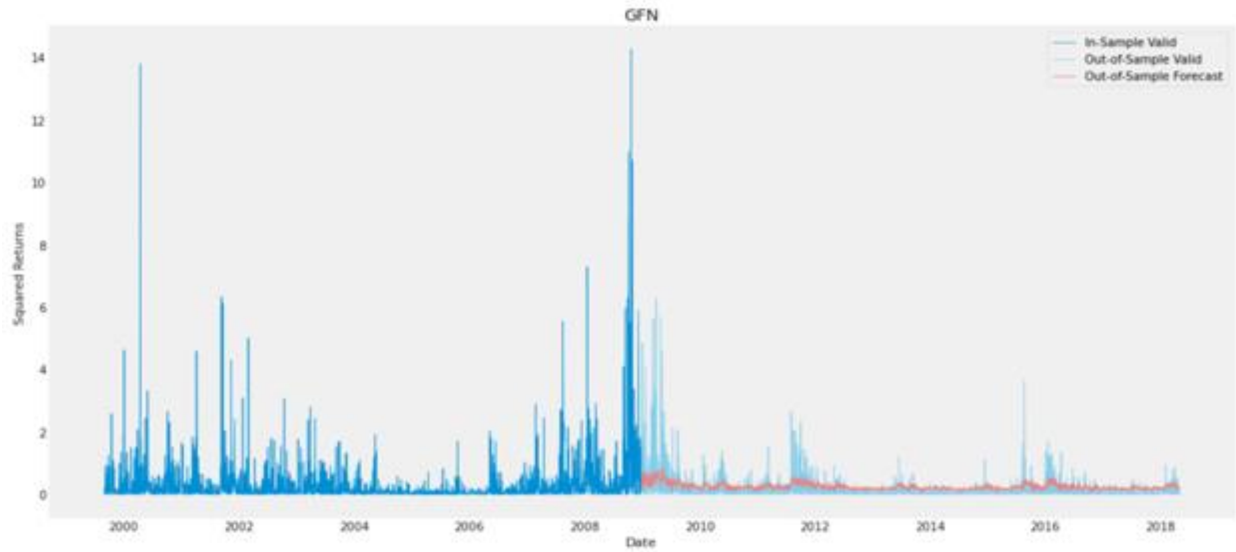

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016

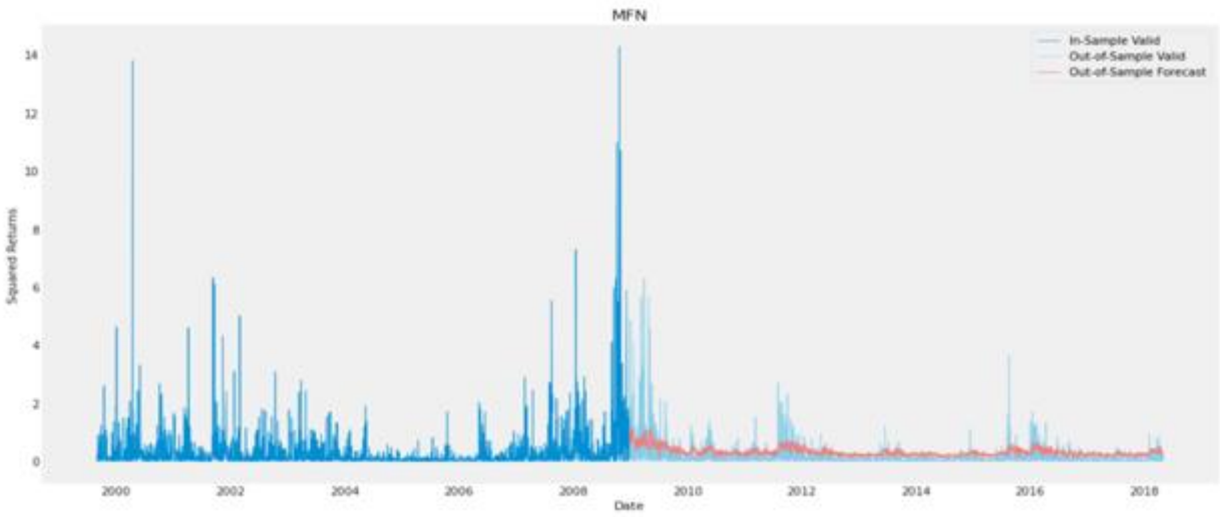
Figure C.3: Out-of-sample performance of ANN models for STI index

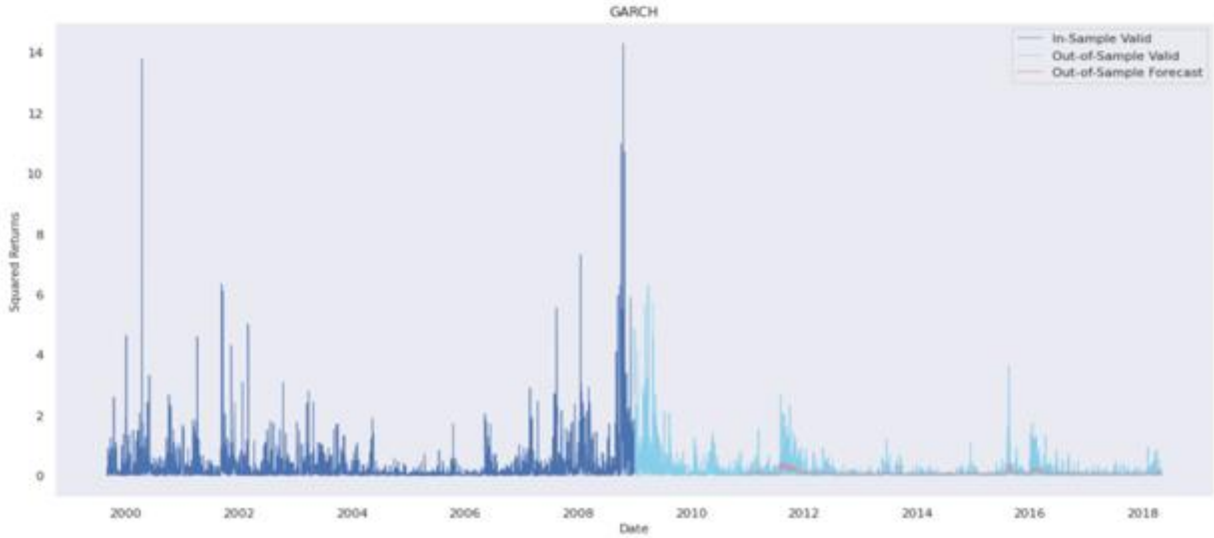



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

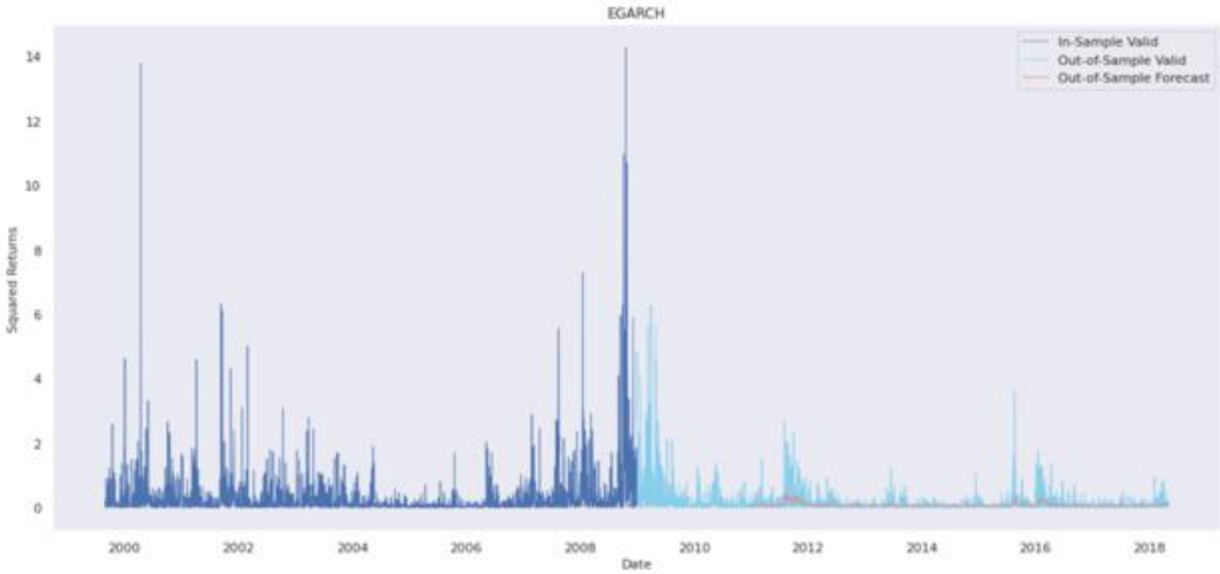
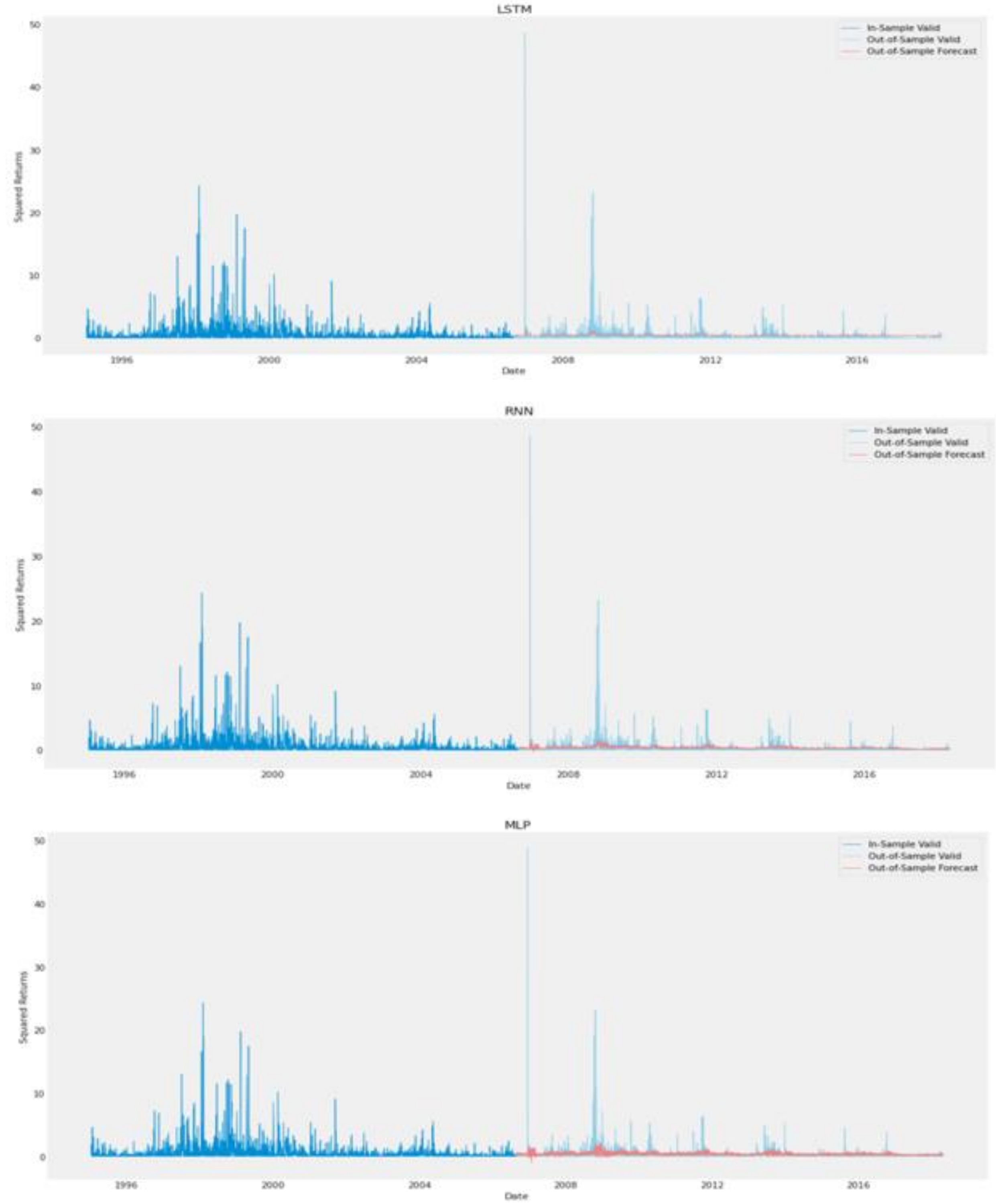
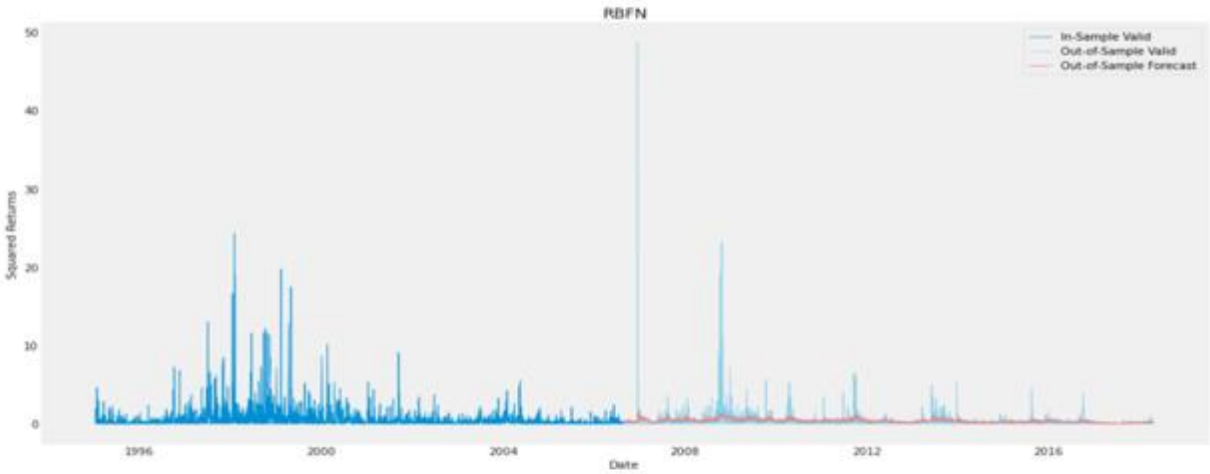
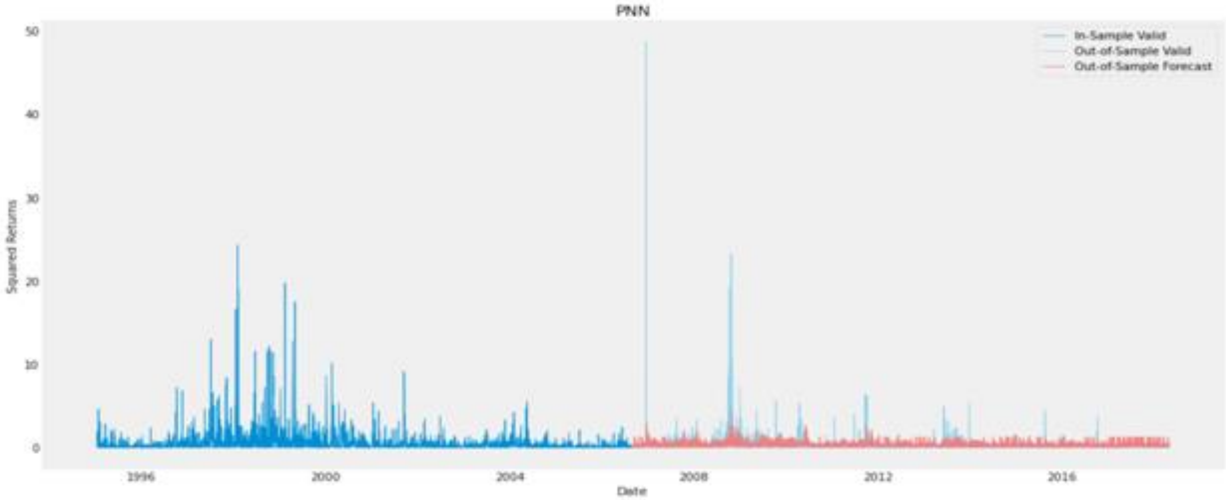
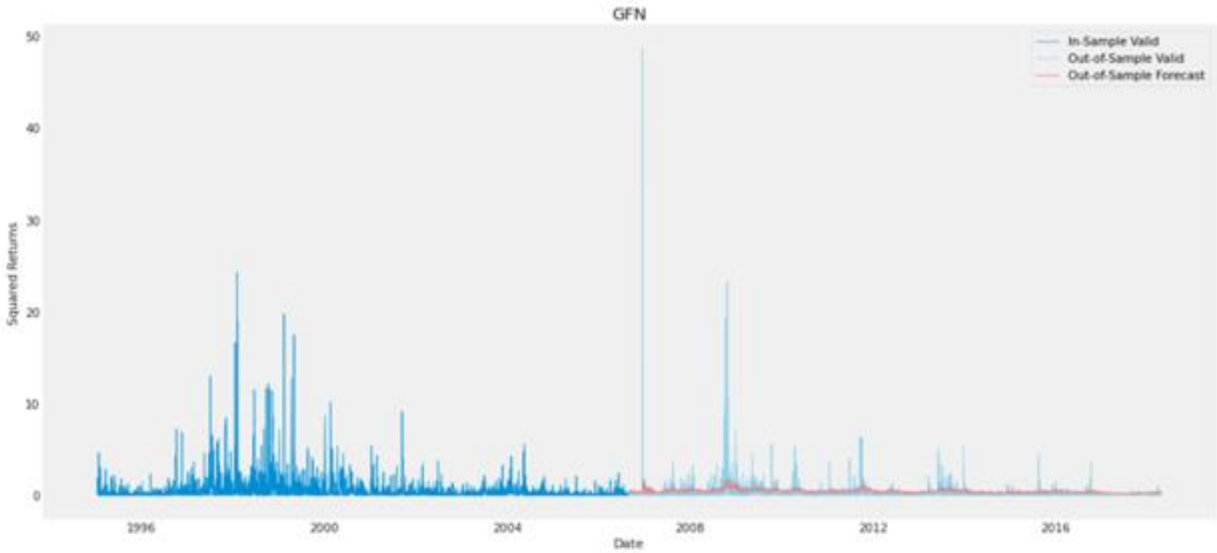

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

Figure C.4: Out-of-sample performance of ANN models for SET index




RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GFN
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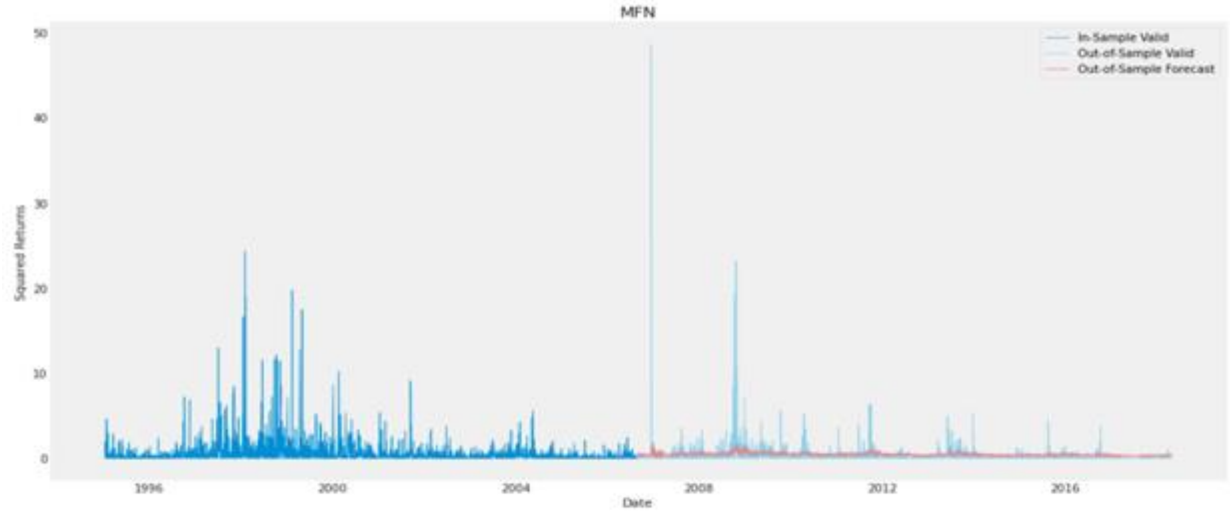
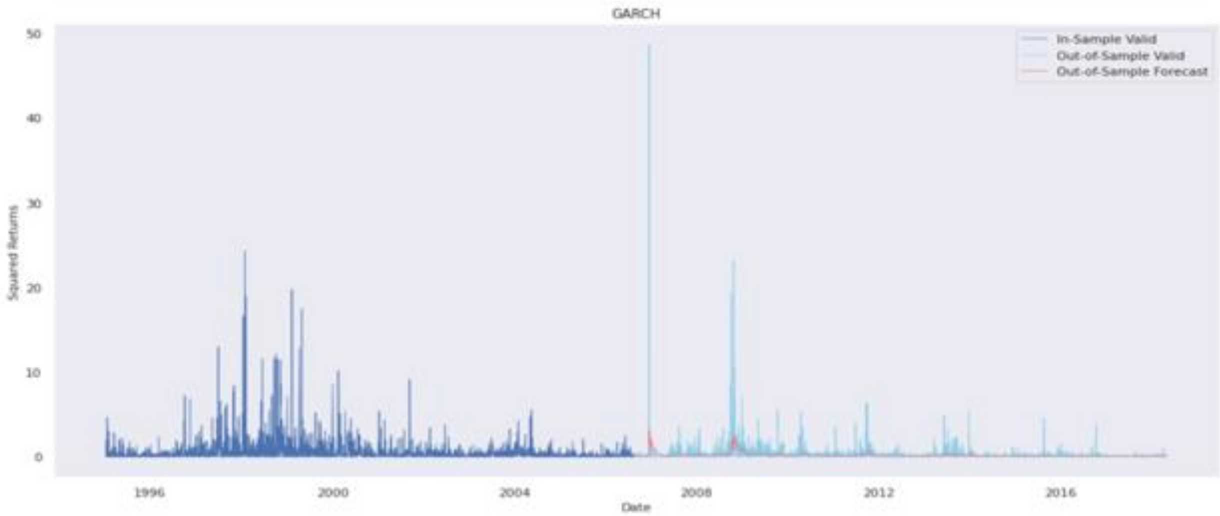
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
10
20
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40
50
1996
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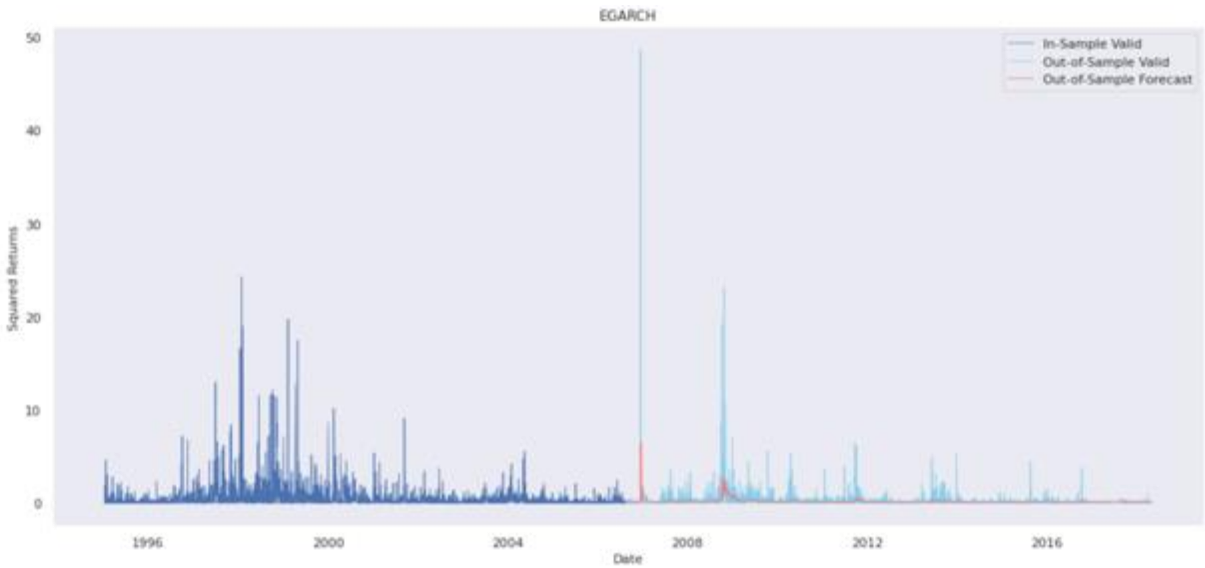
2008
2012
2016


EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
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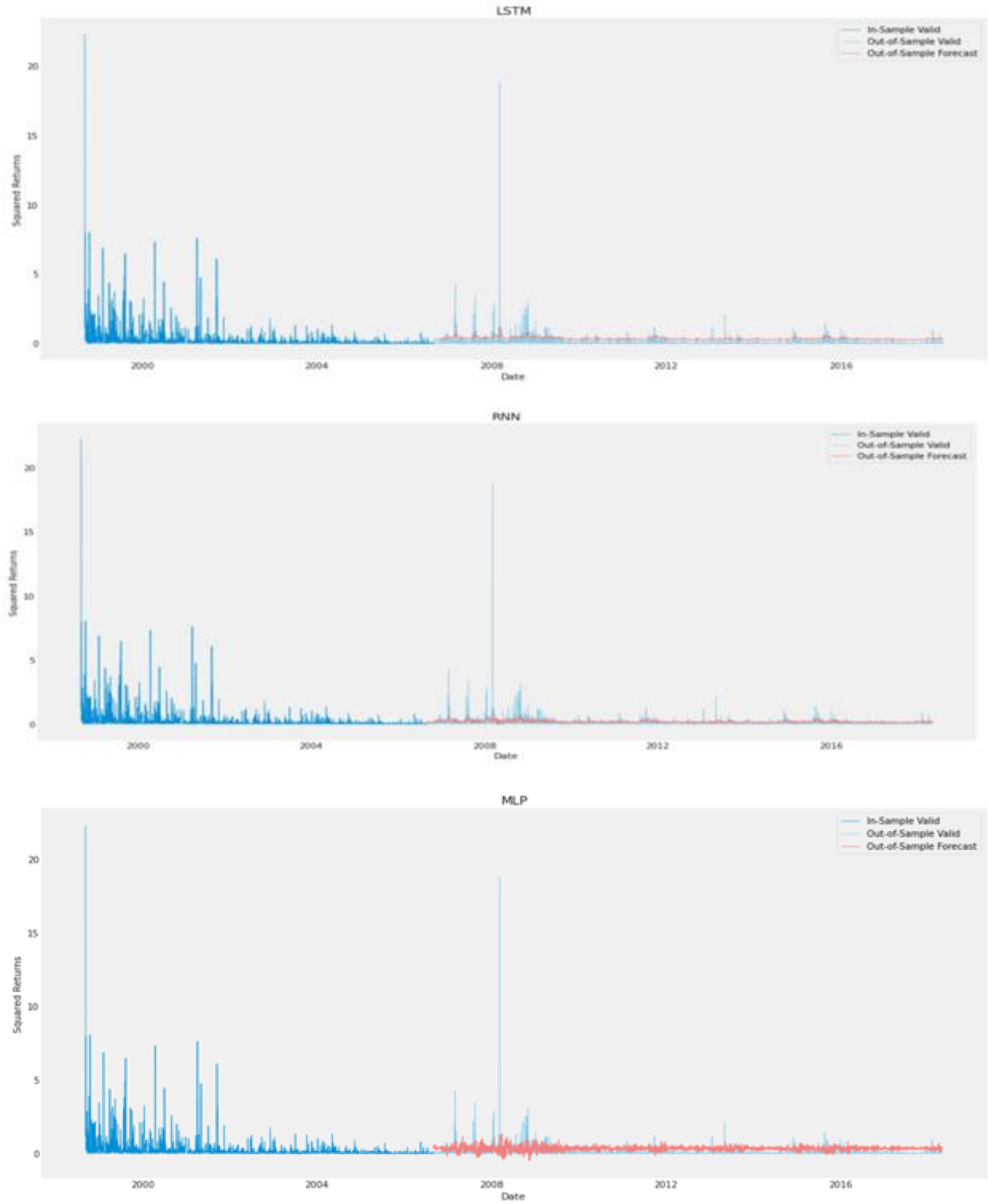
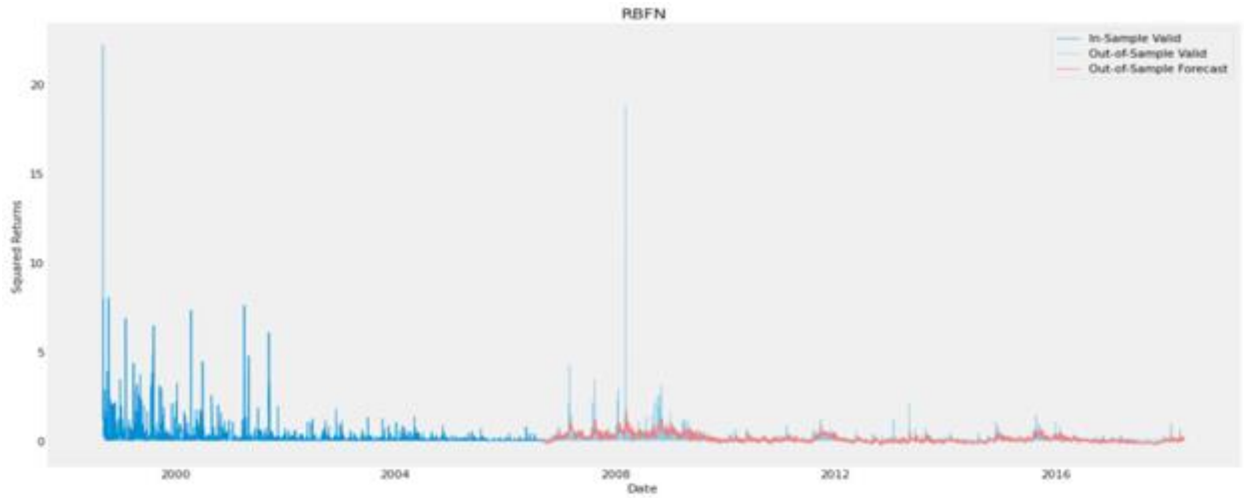
1996
2000
2004
2008
2012
2016

Figure C.5: Out-of-sample performance of ANN models for KLCI index




RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
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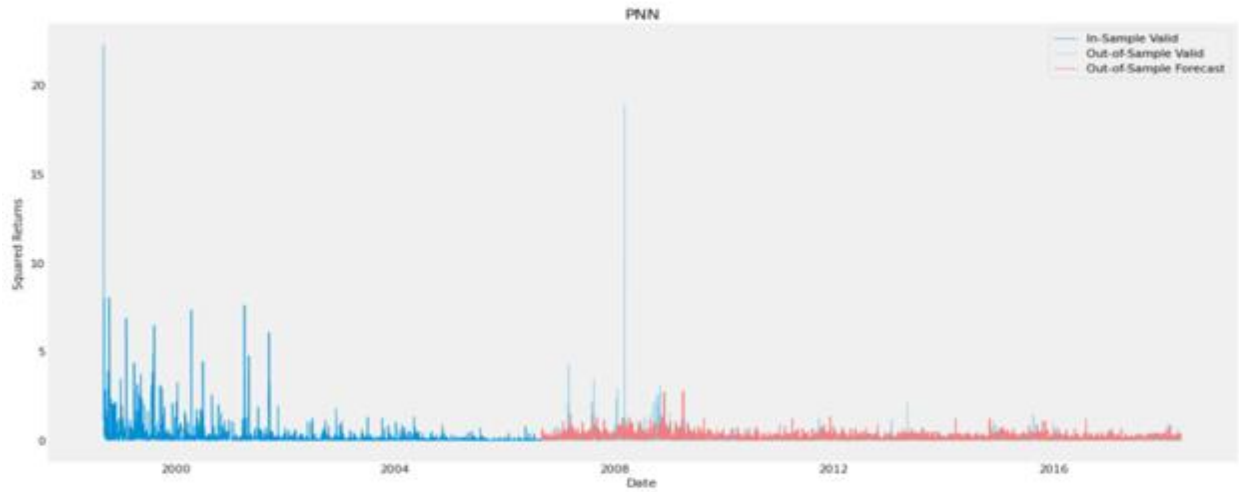
10
15
20
2000
2004
2008
2012
2016


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
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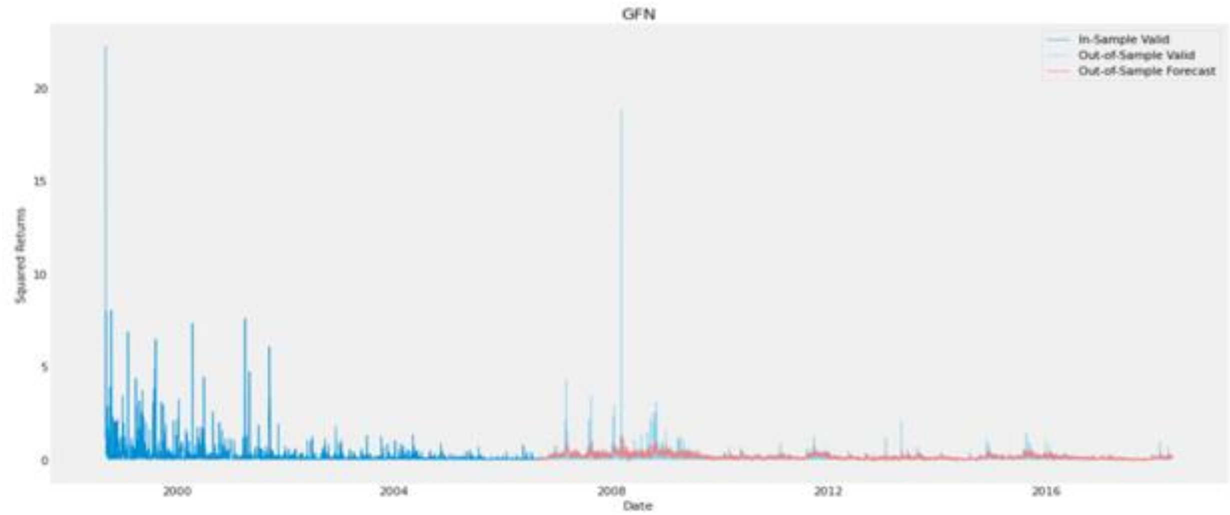
2000
2004
2008
2012
2016


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
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10
15
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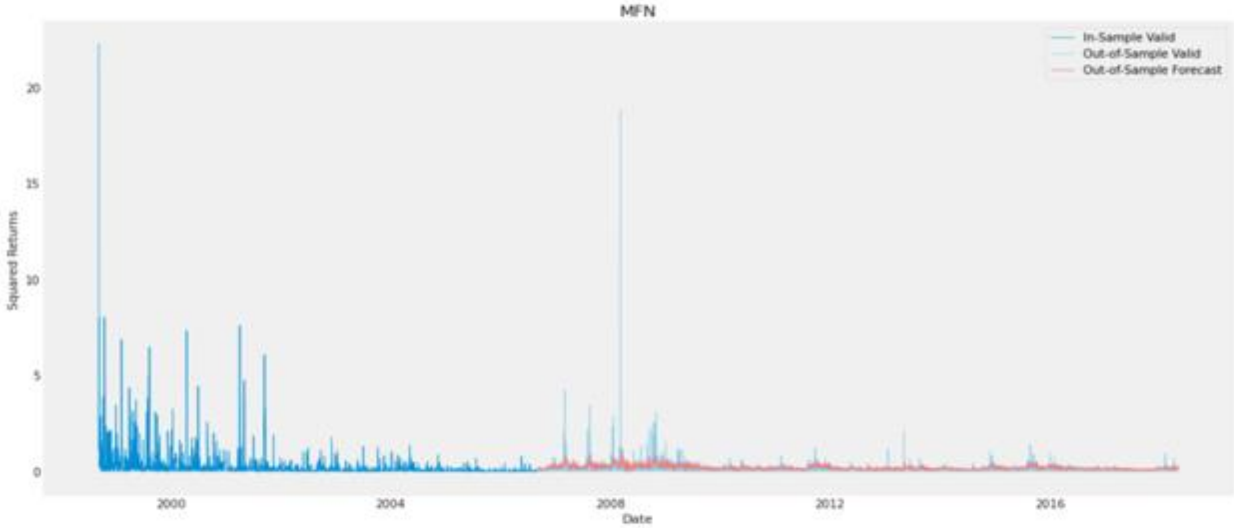
2000
2004
2008
2012
2016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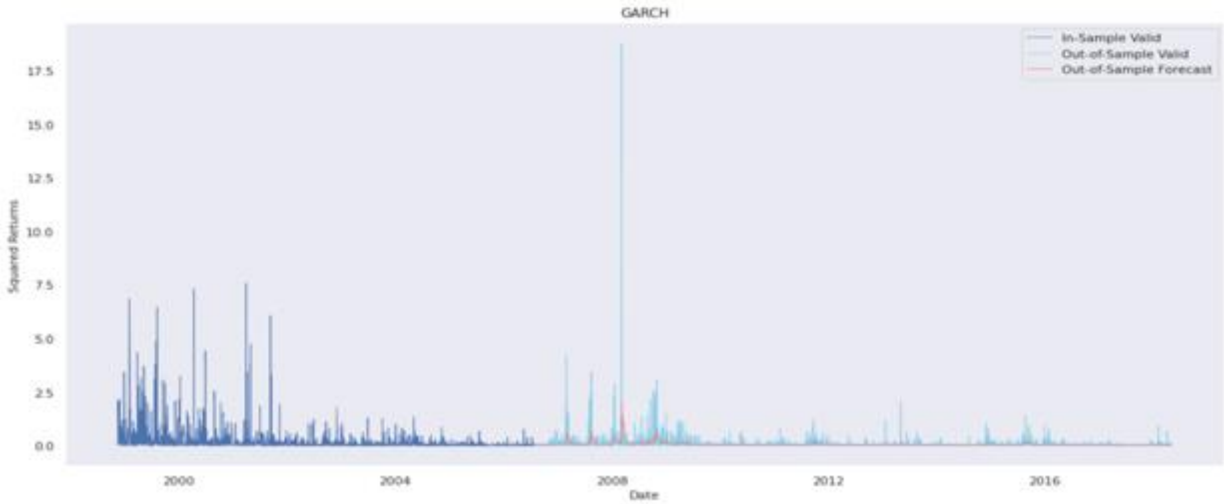
Out-of-Sample Forecast
Squared Returns
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

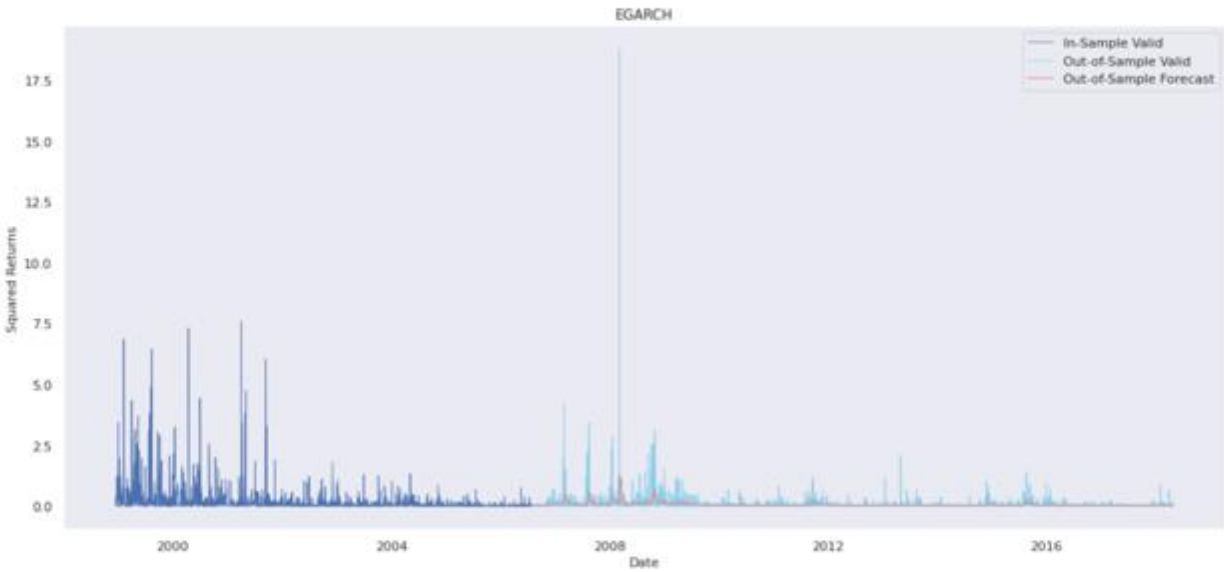
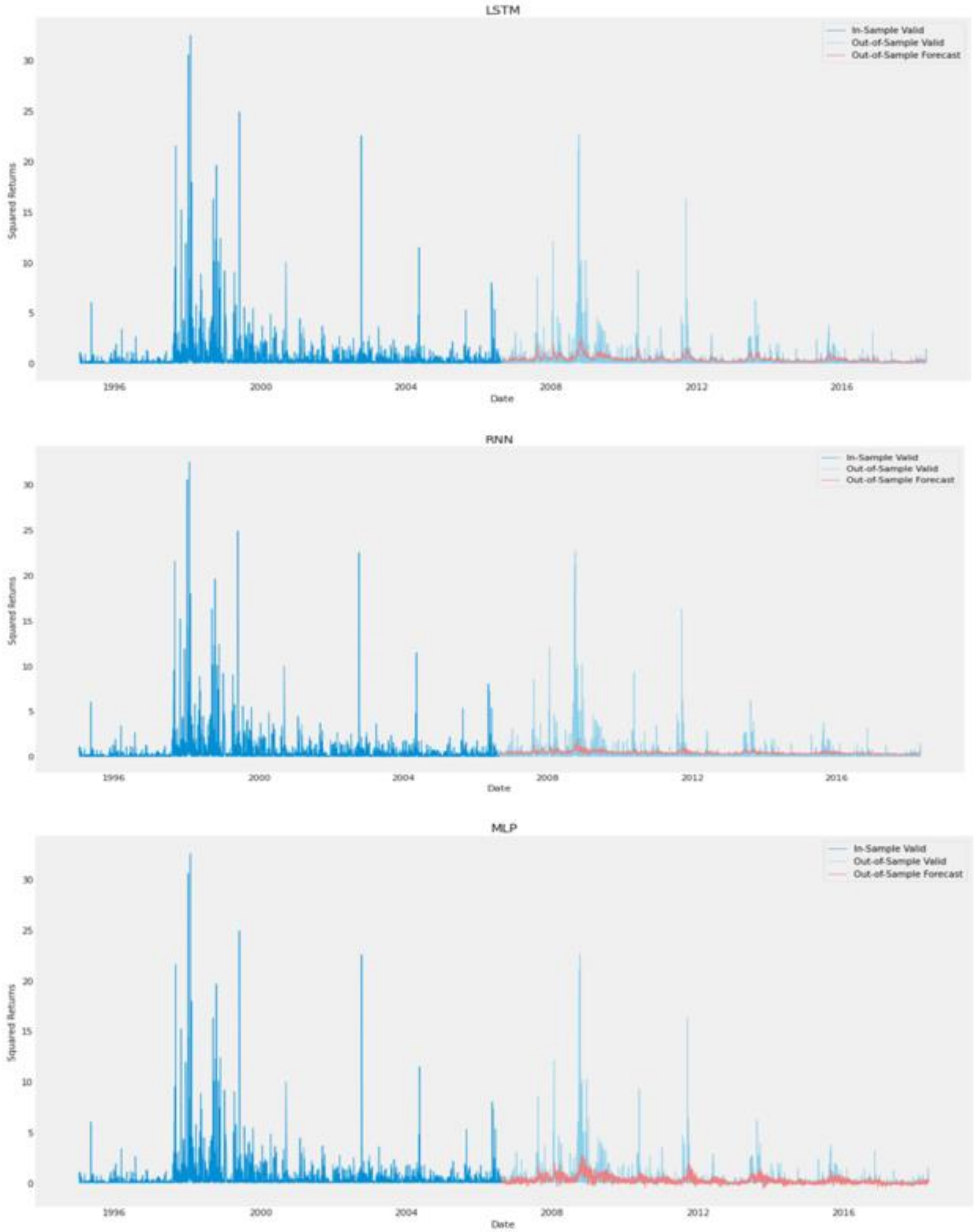
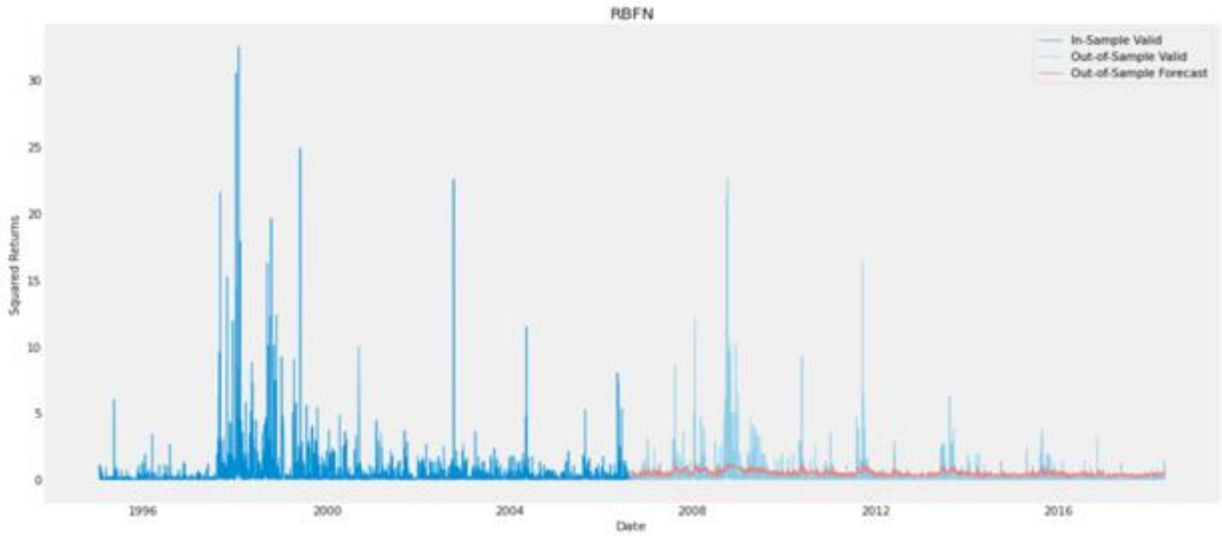
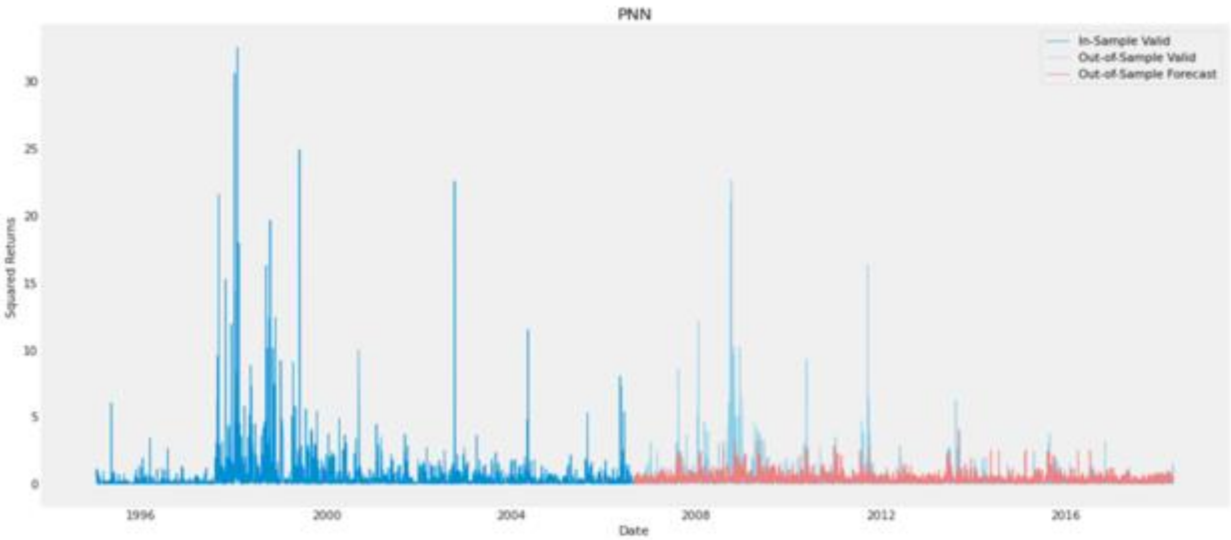
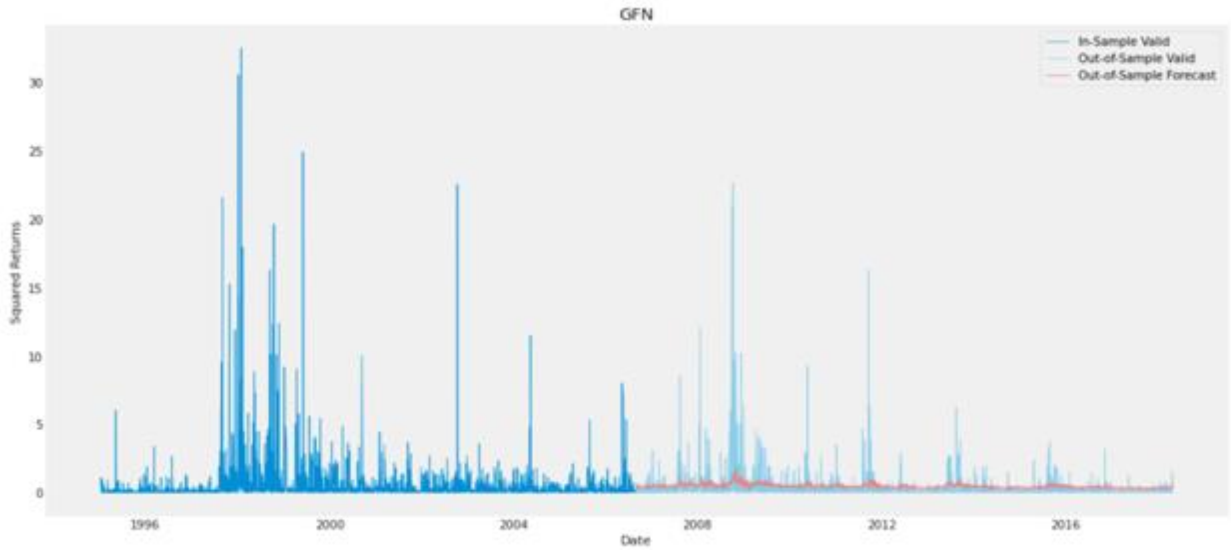

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

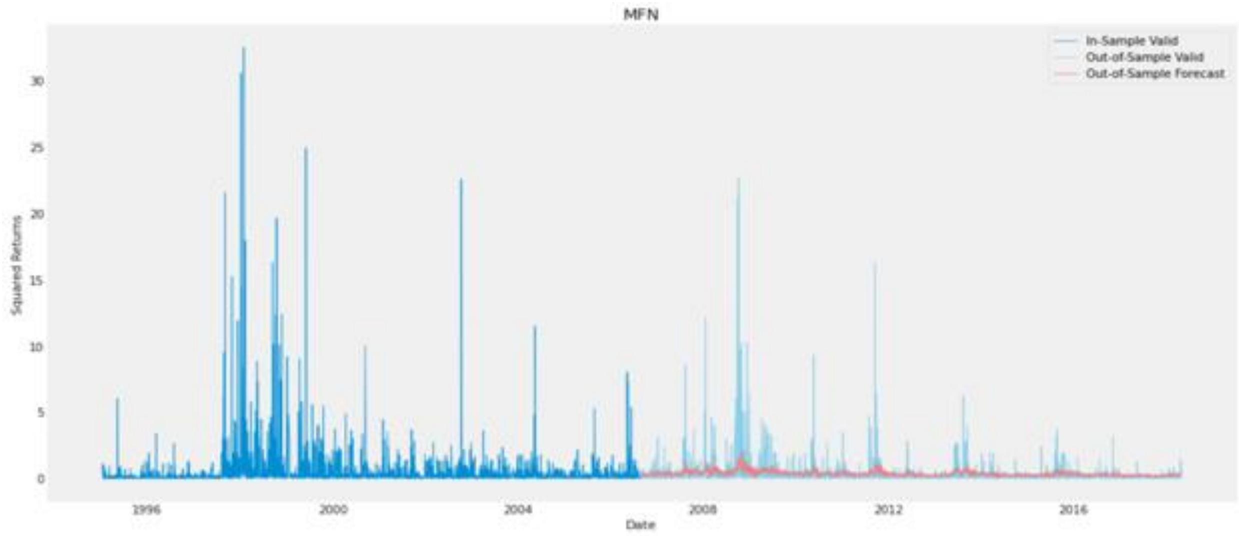
Figure C.6: Out-of-sample performance of ANN models for JCI index

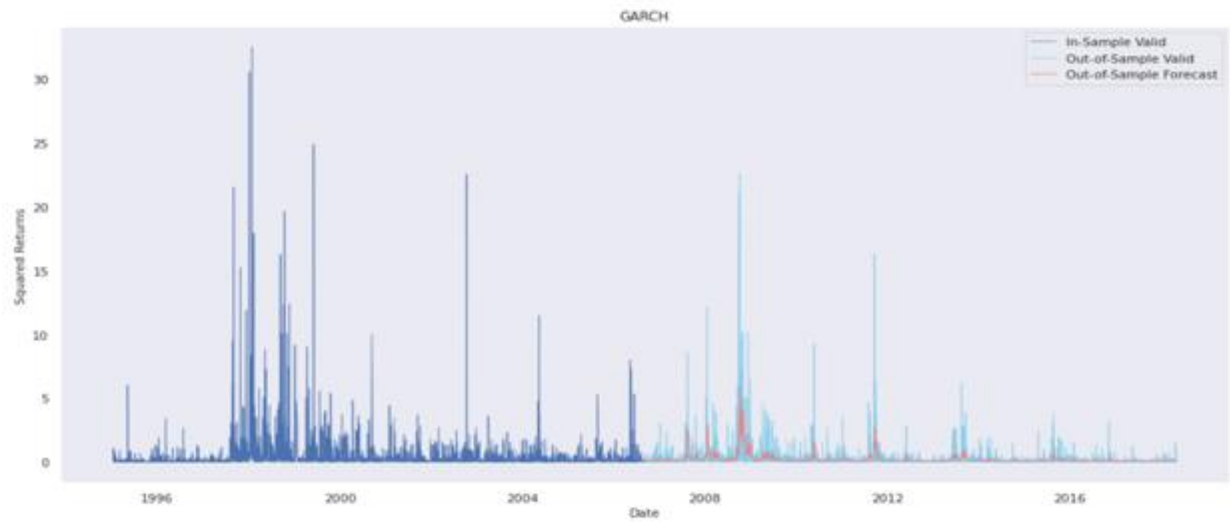



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

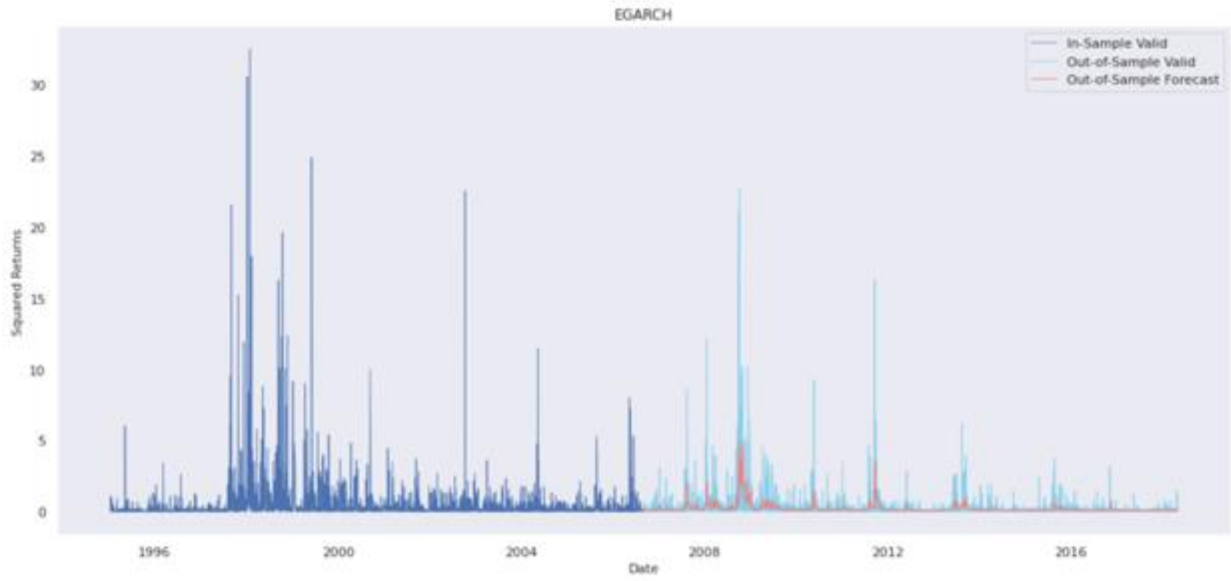
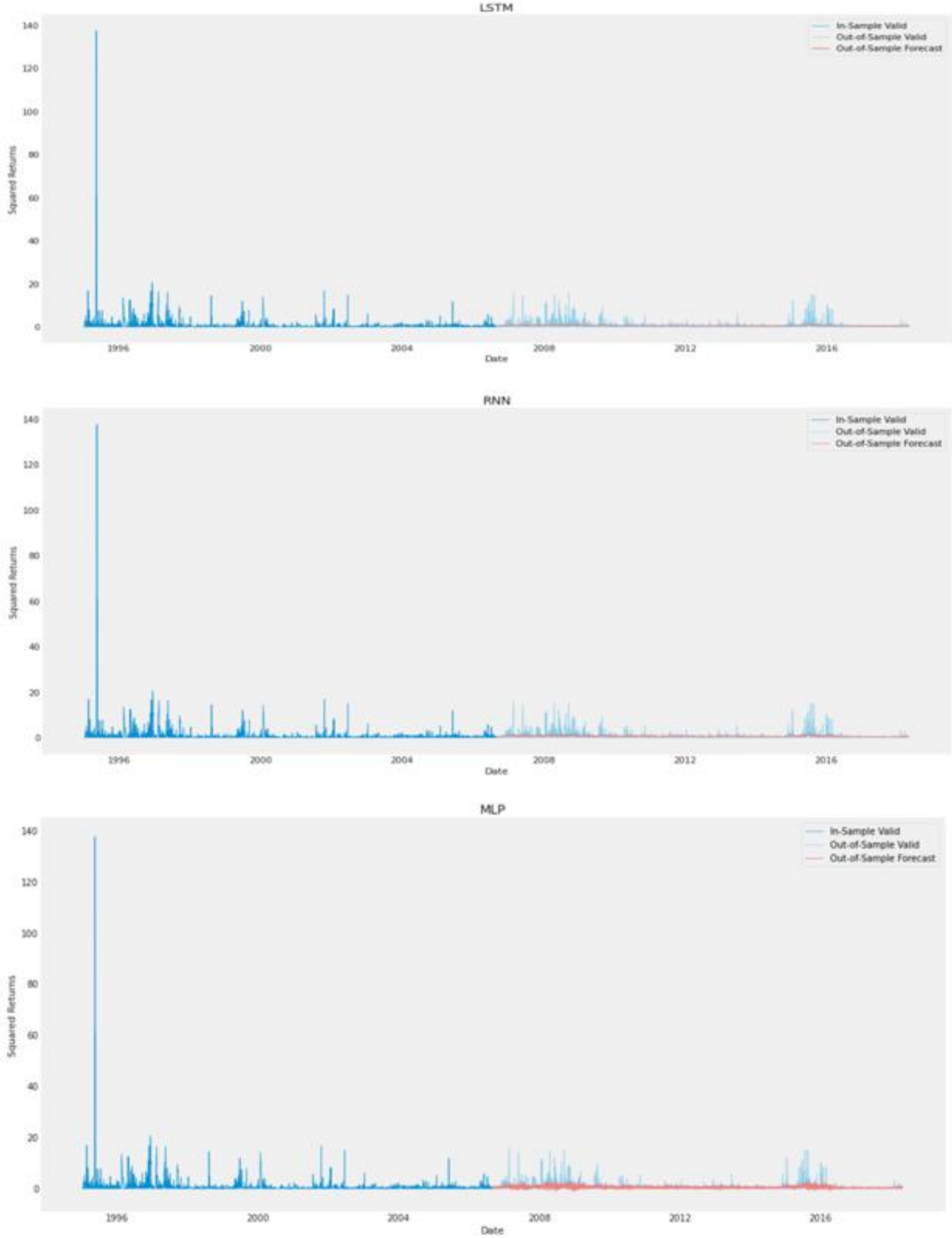
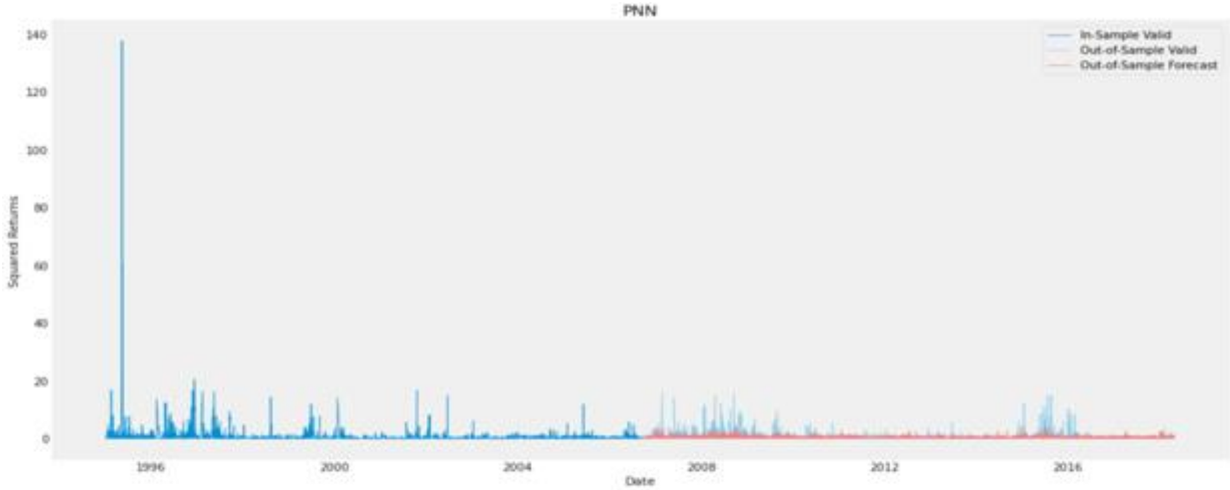

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

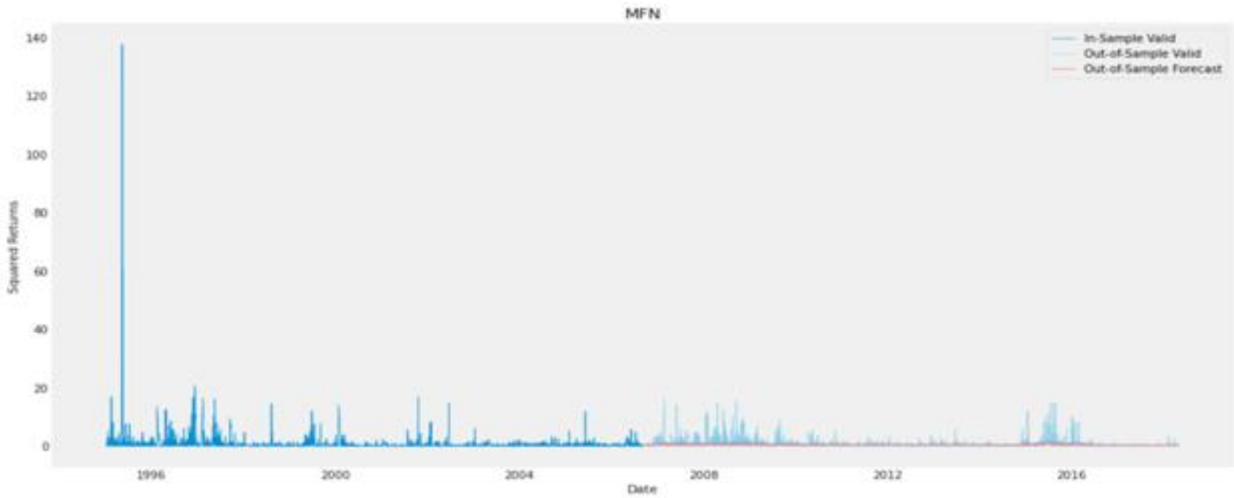
Figure C.7: Out-of-sample performance of ANN models for SSE index




RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

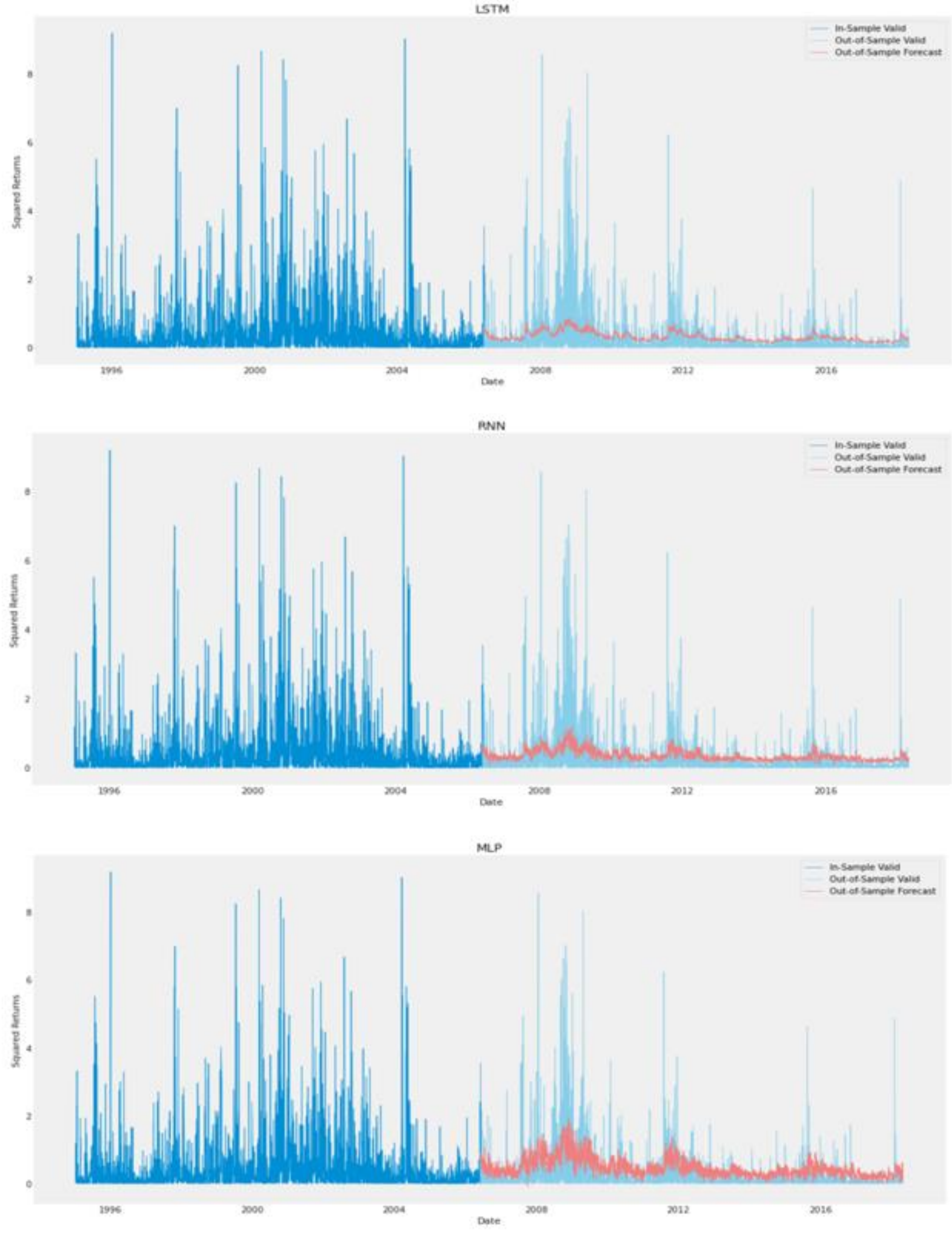

GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date

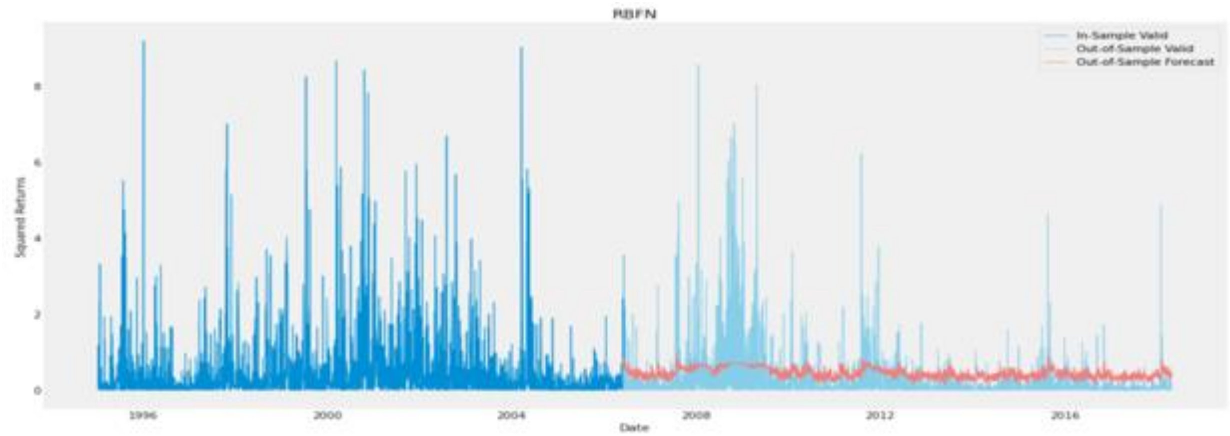

MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016

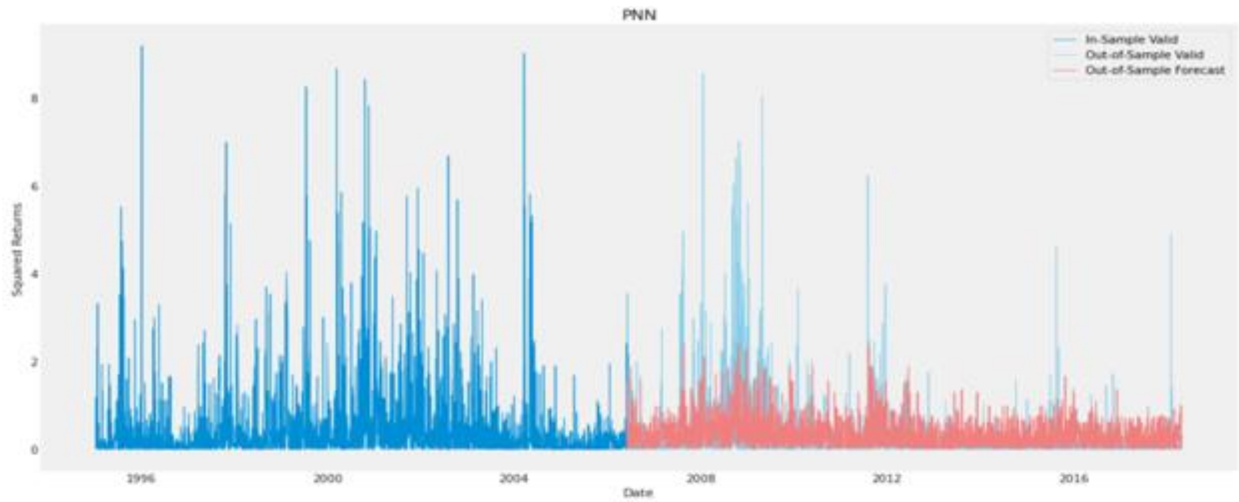

GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016

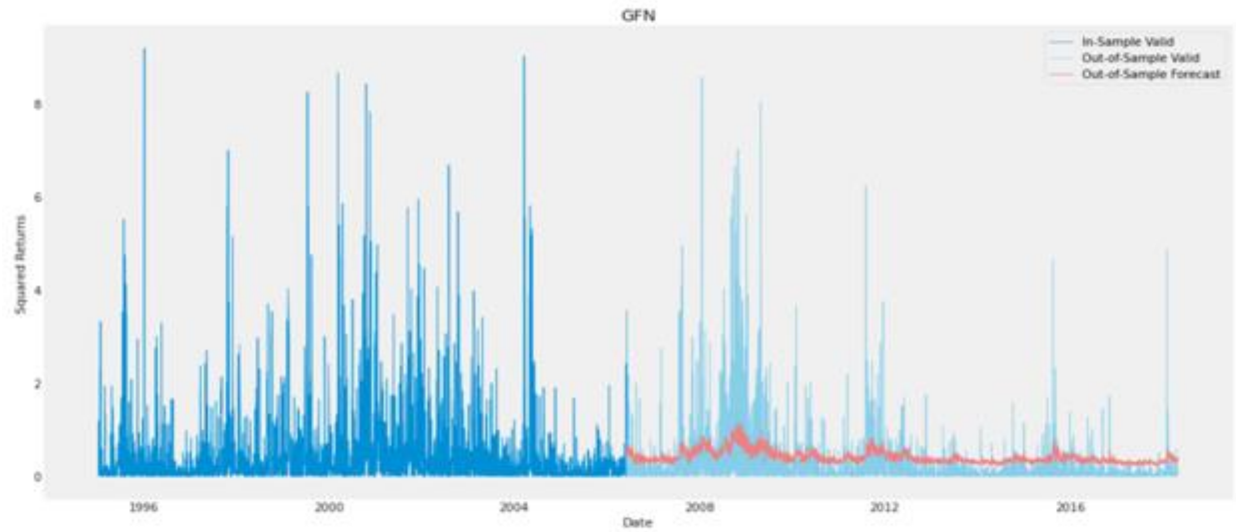

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
1996
2000
2004
2008
2012
2016

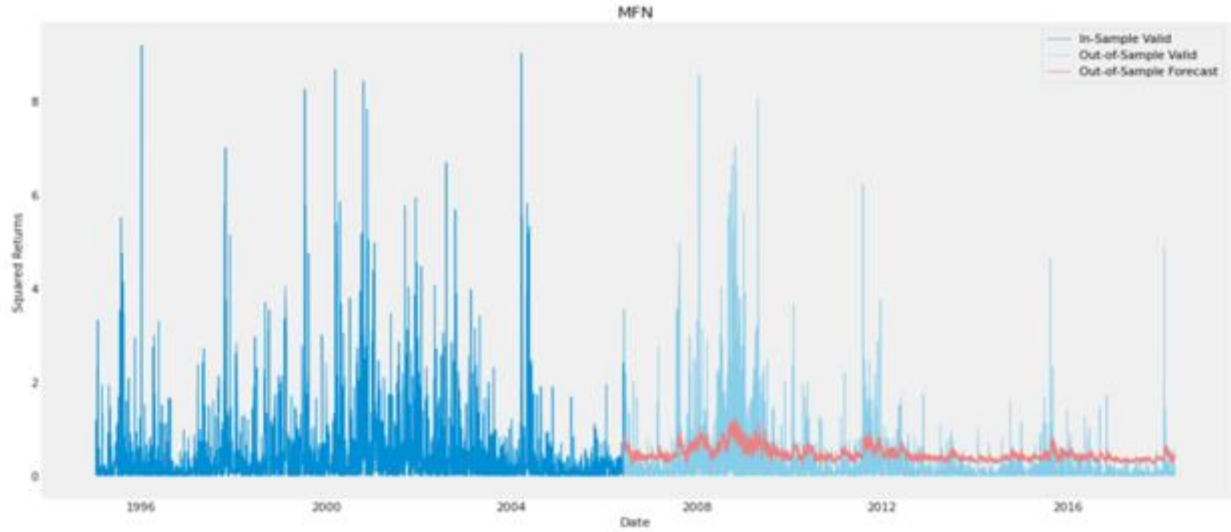
Figure C.8: Out-of-sample performance of ANN models for TAIEX index

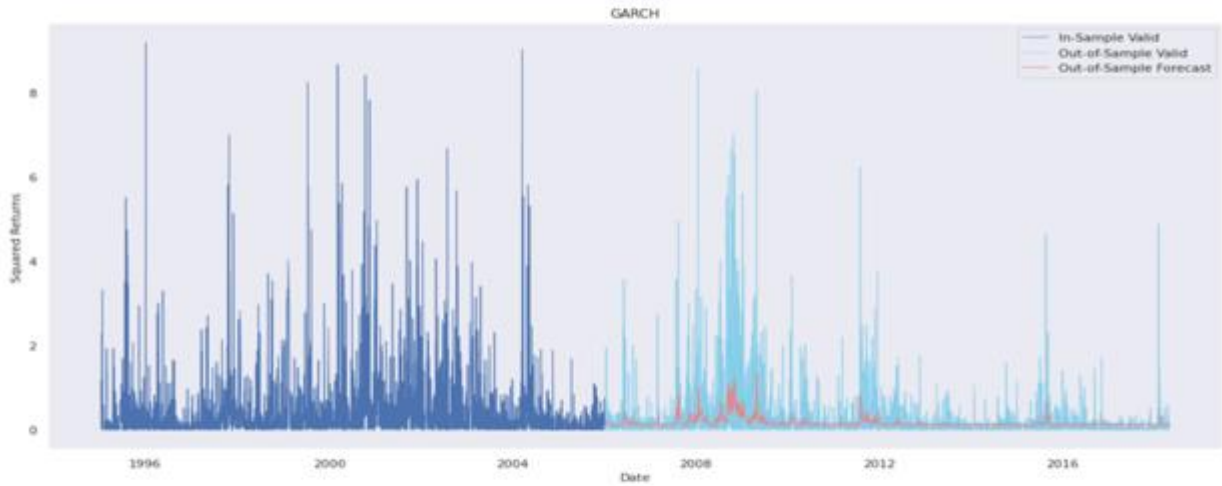



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date

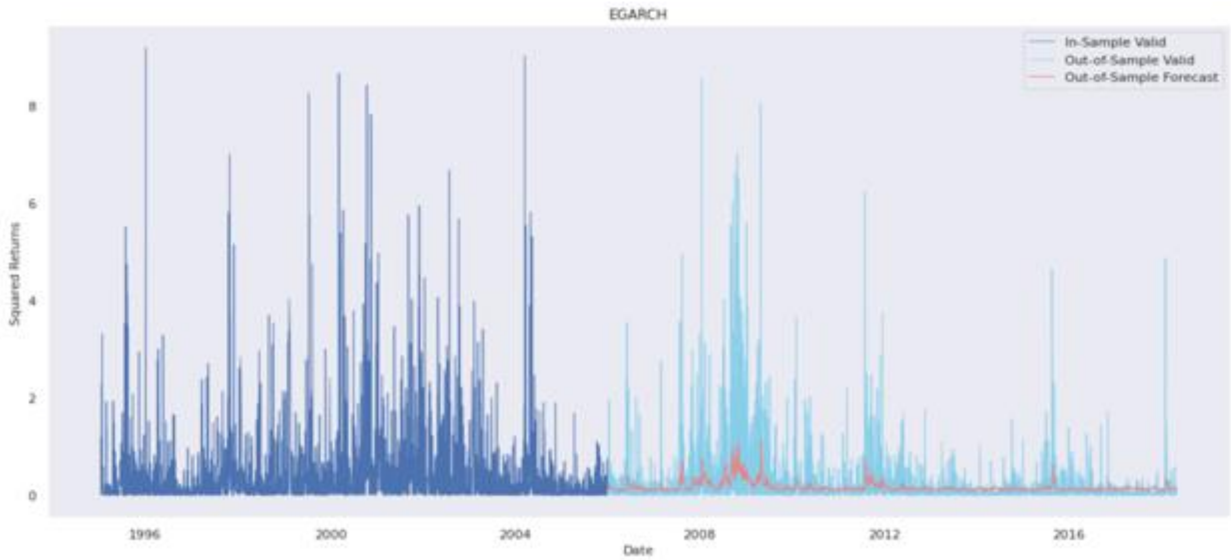
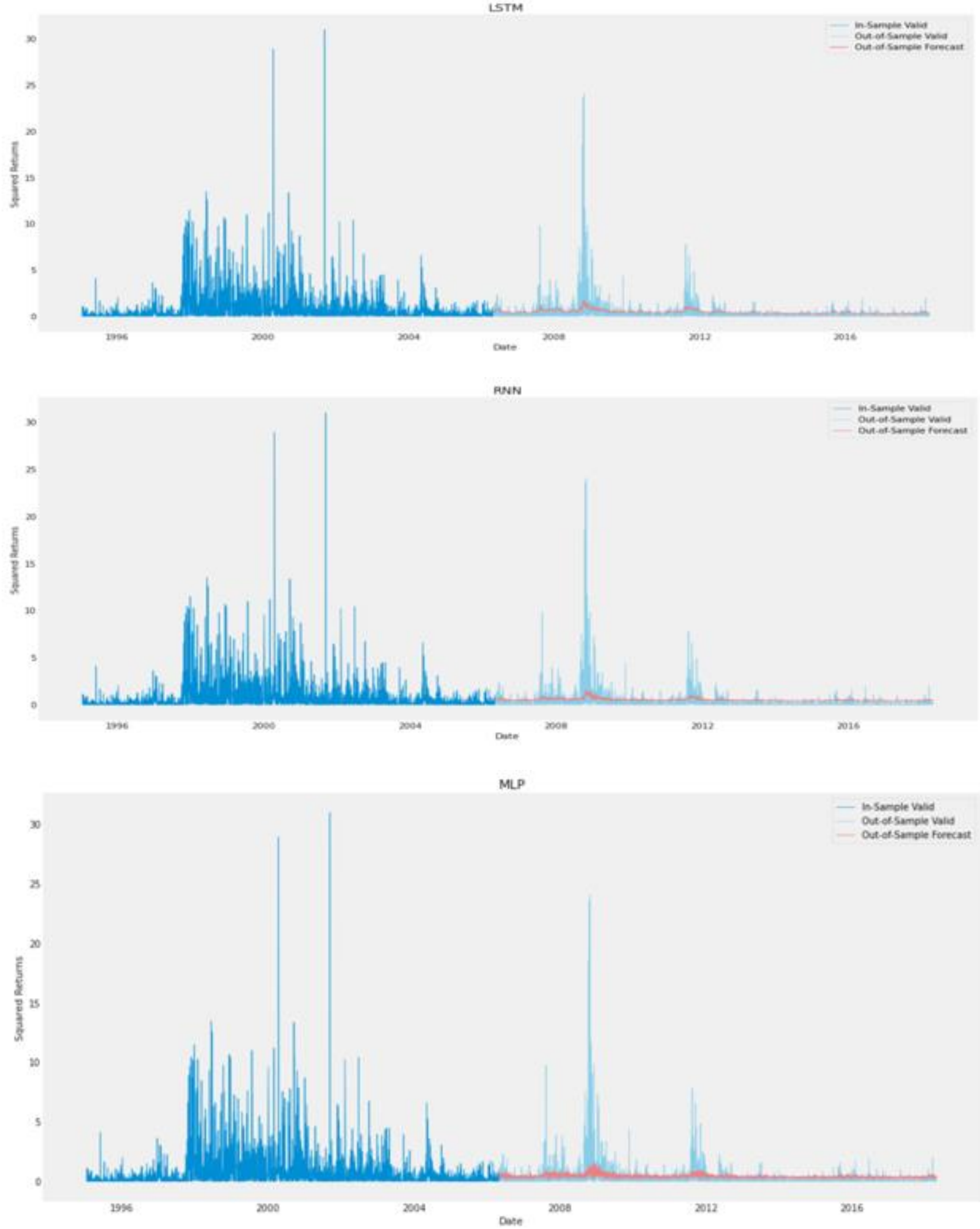
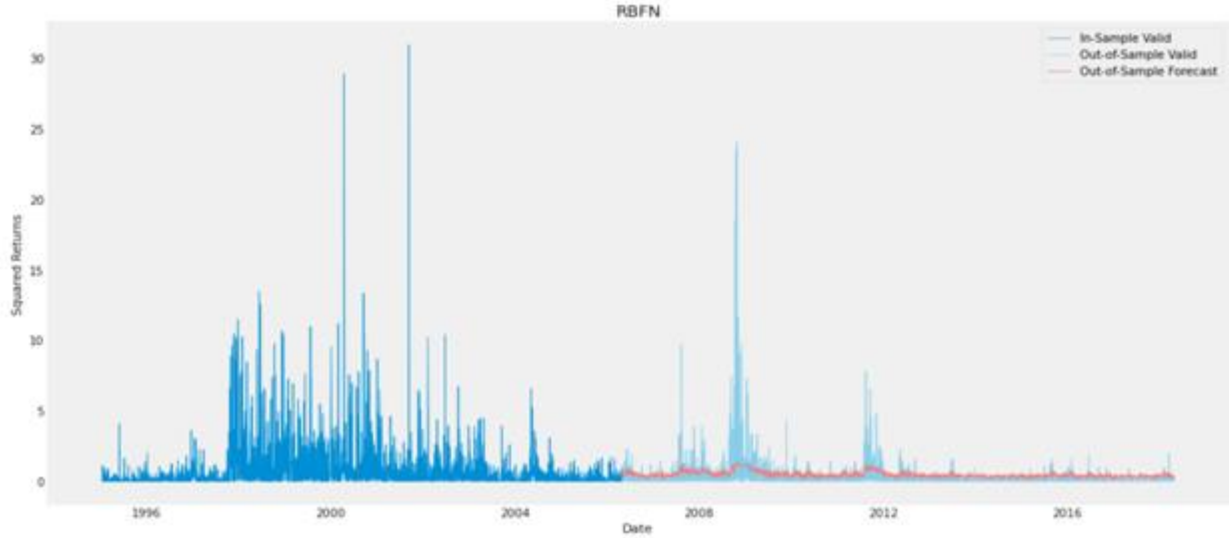
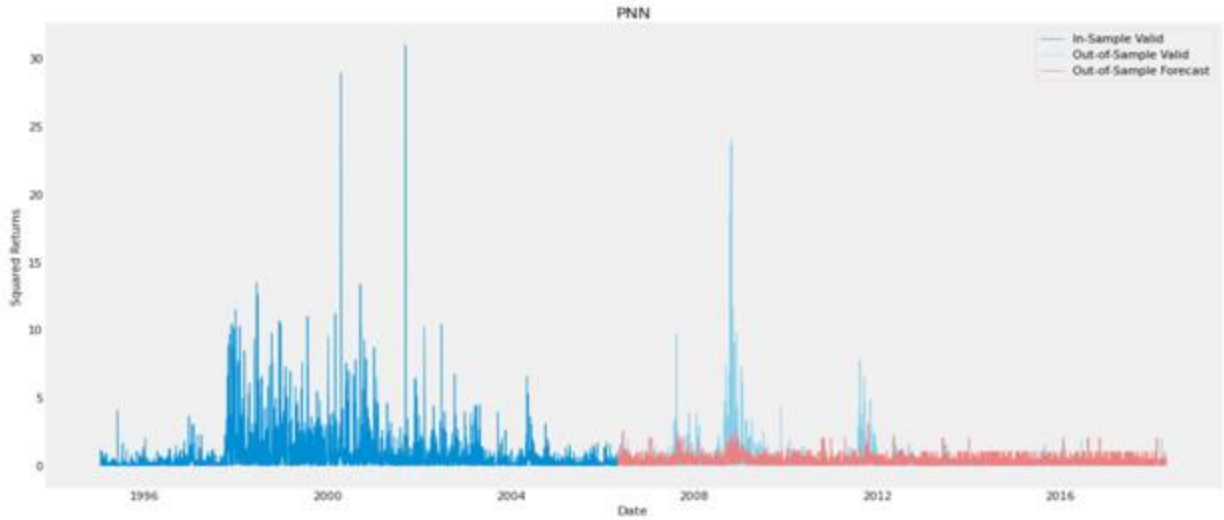
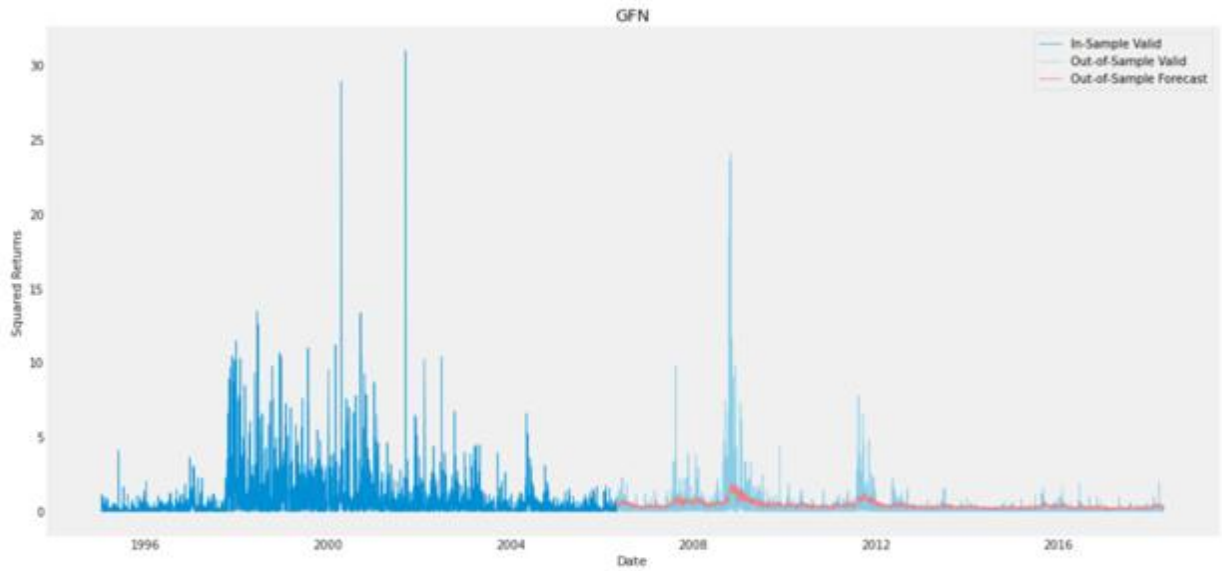

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
2
4
6
8
1996
2000
2004
2008
2012
2016
Date

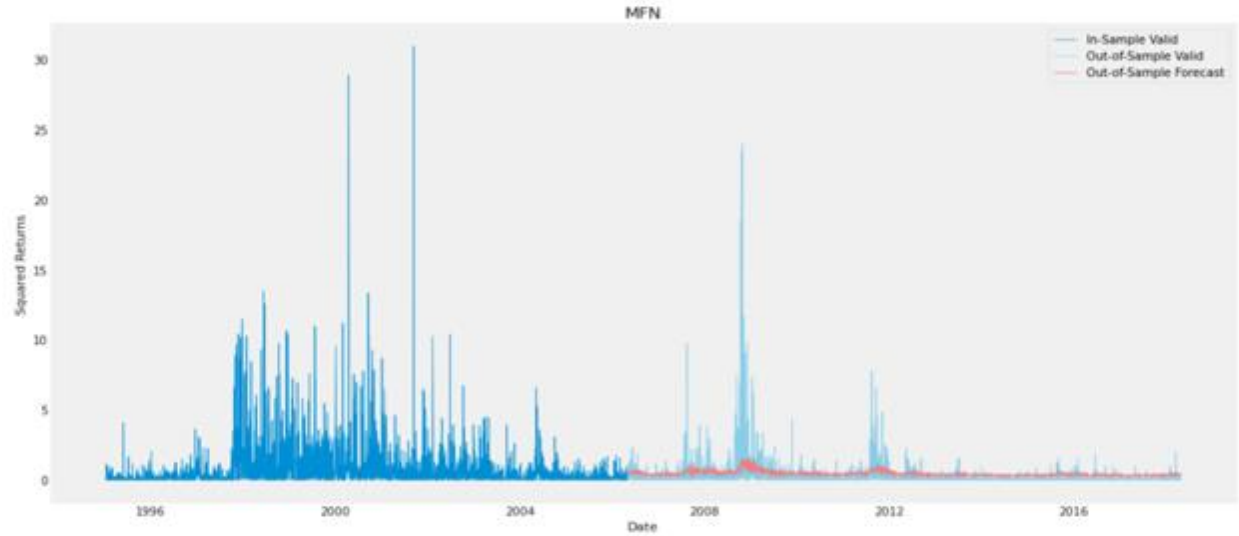
Figure C.9: Out-of-sample performance of ANN models for KOSPI index

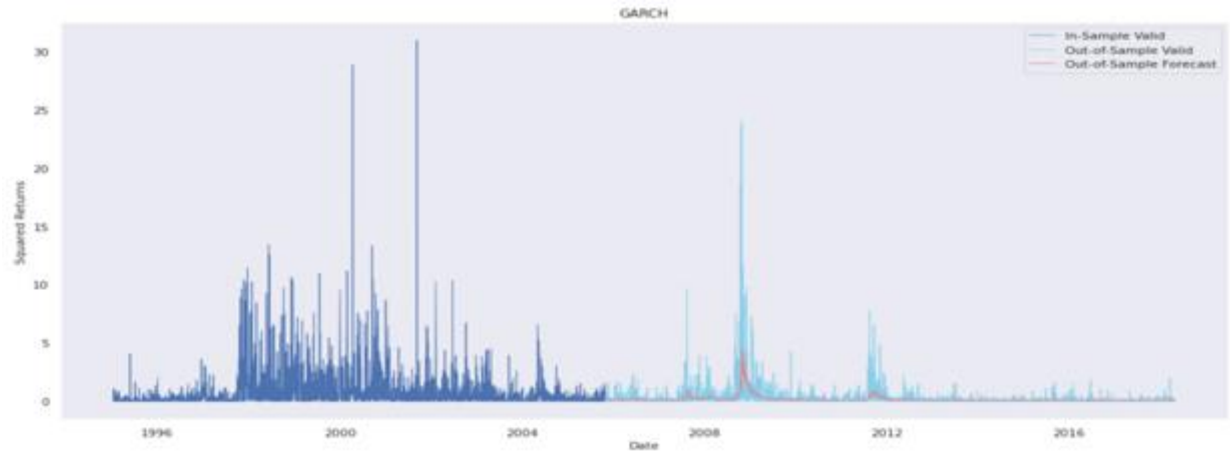



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
20
25
30
1996
2000
2004
2008
2012
2016


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
20
25
30
1996
2000
2004
2008
2012
2016

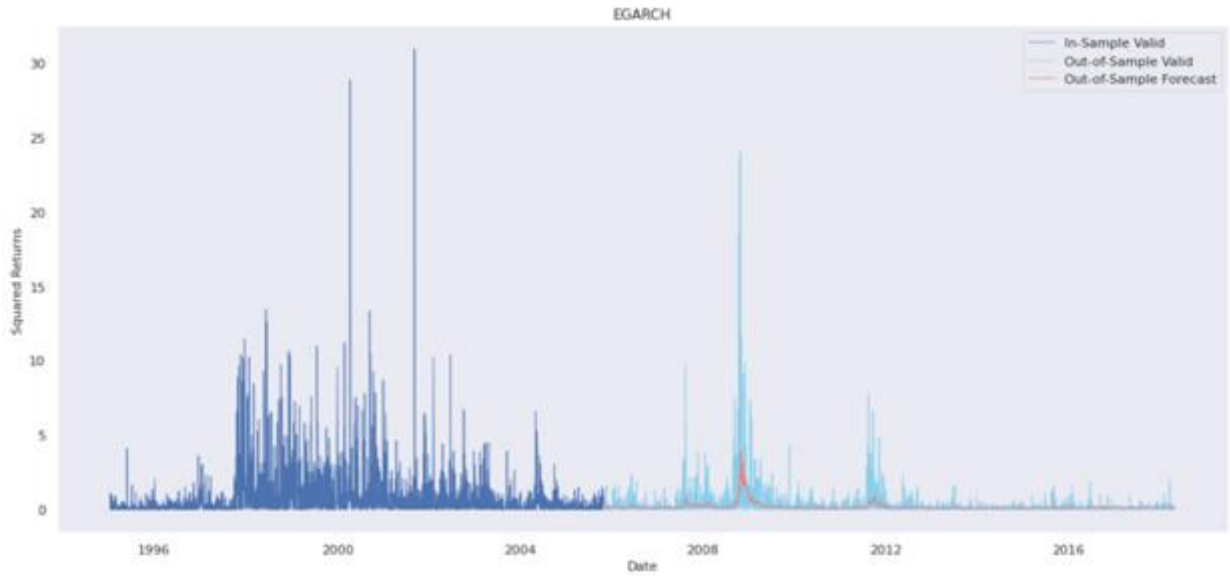
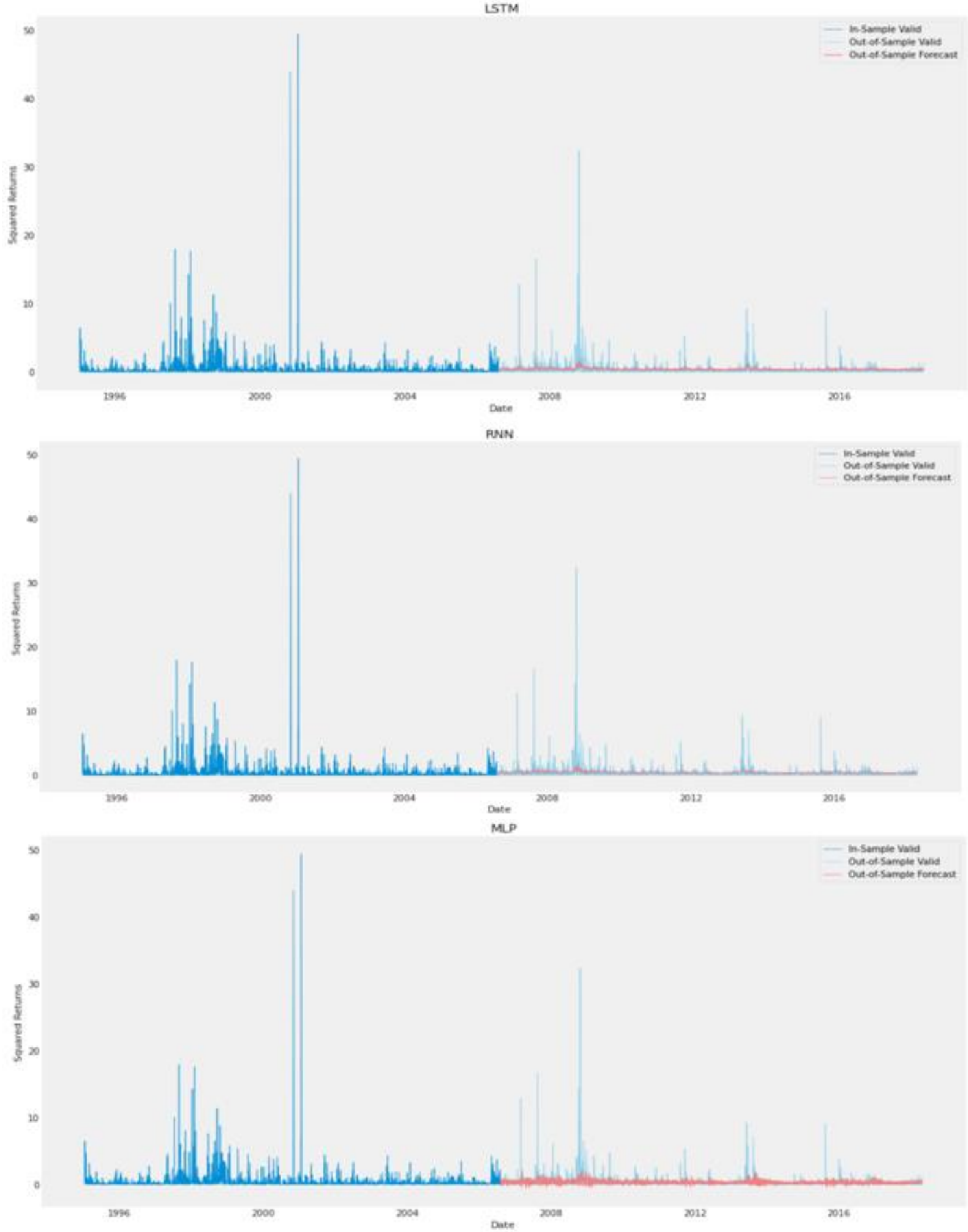
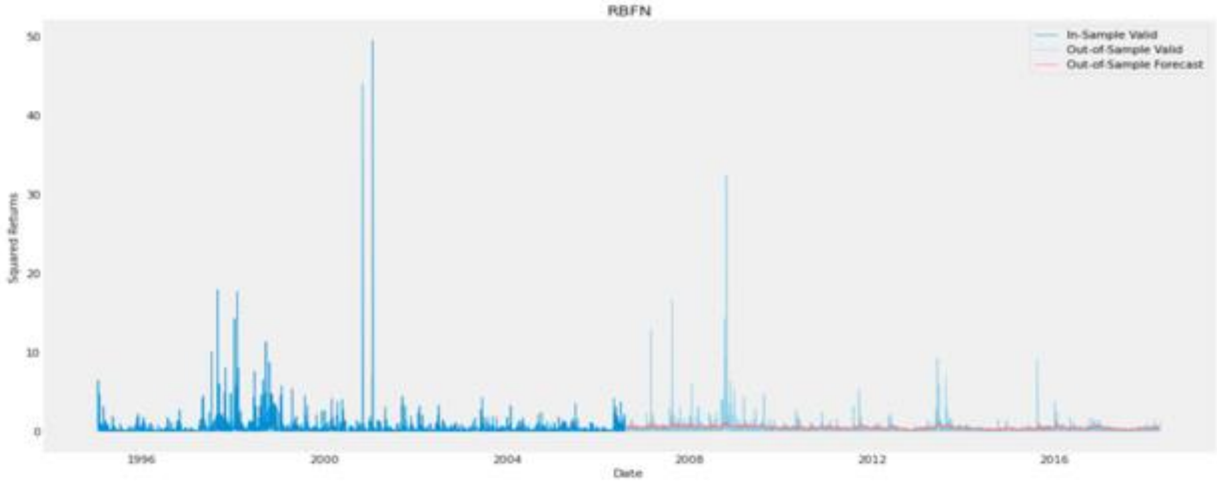
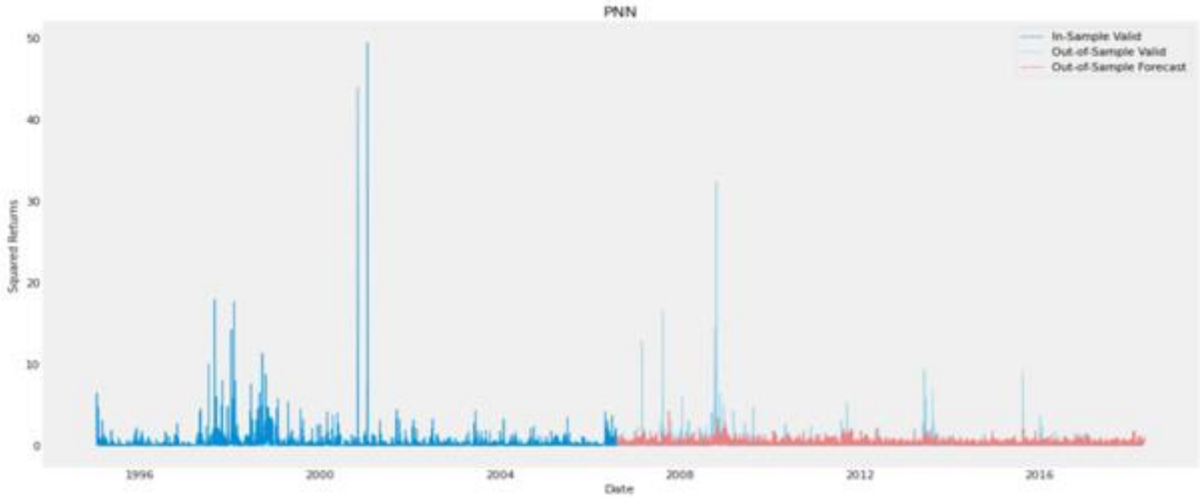
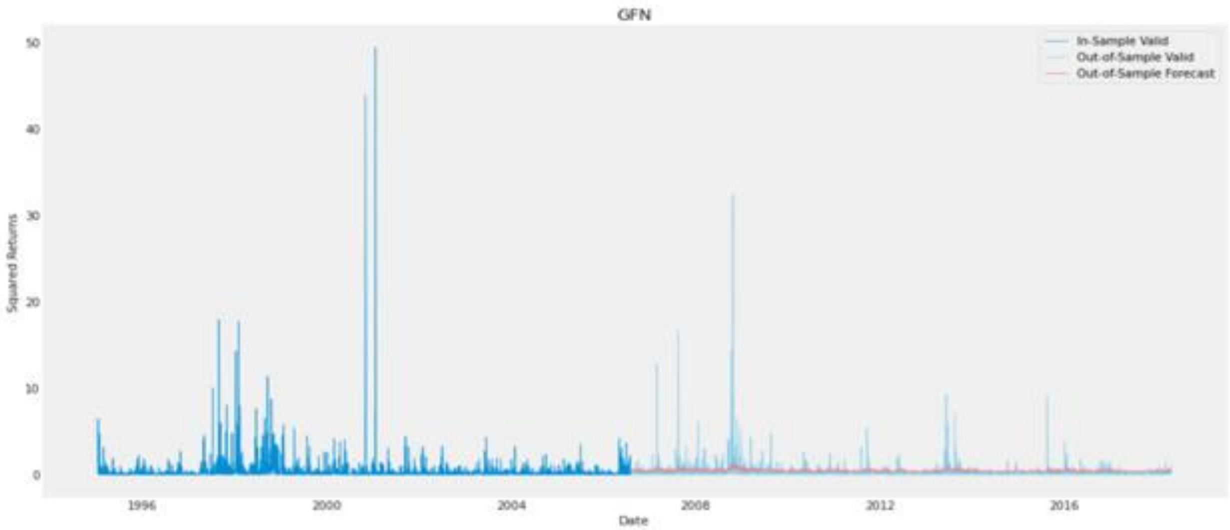

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
5
10
15
20
25
30
1996
2000
2004
2008
2012
2016

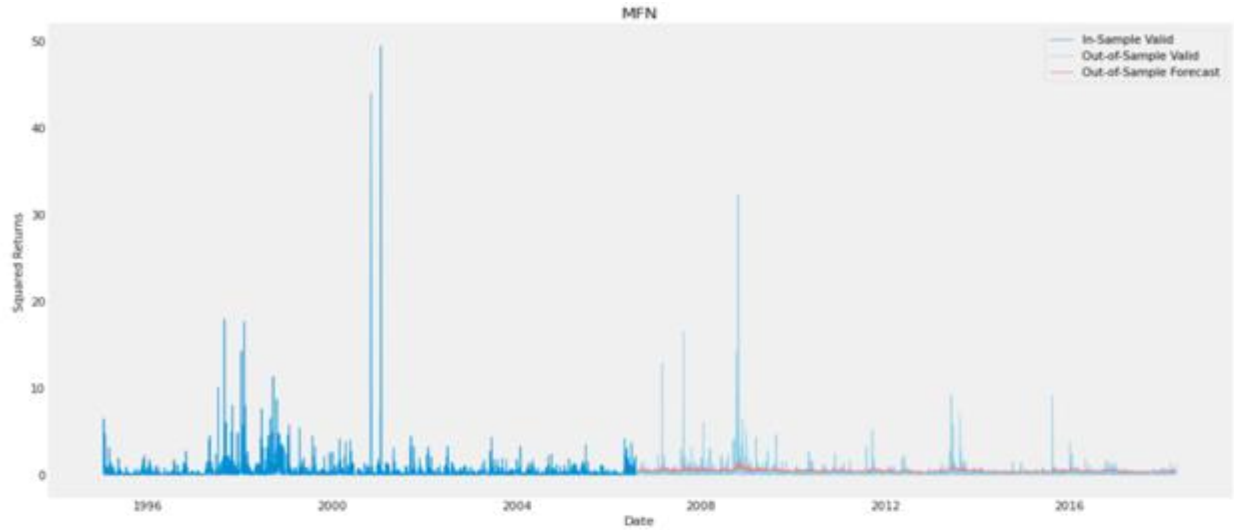
Figure C.10: Out-of-sample performance of ANN models for PSE index

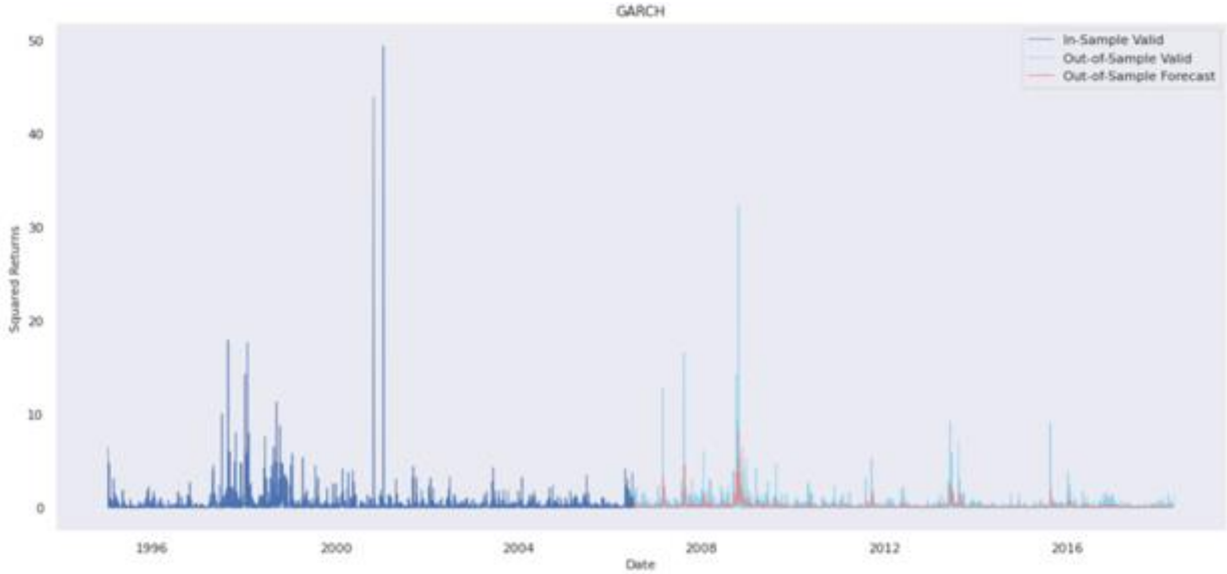



RBFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016


PNN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016


GFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
Date
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016


MFN
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016
Date


GARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016
Date

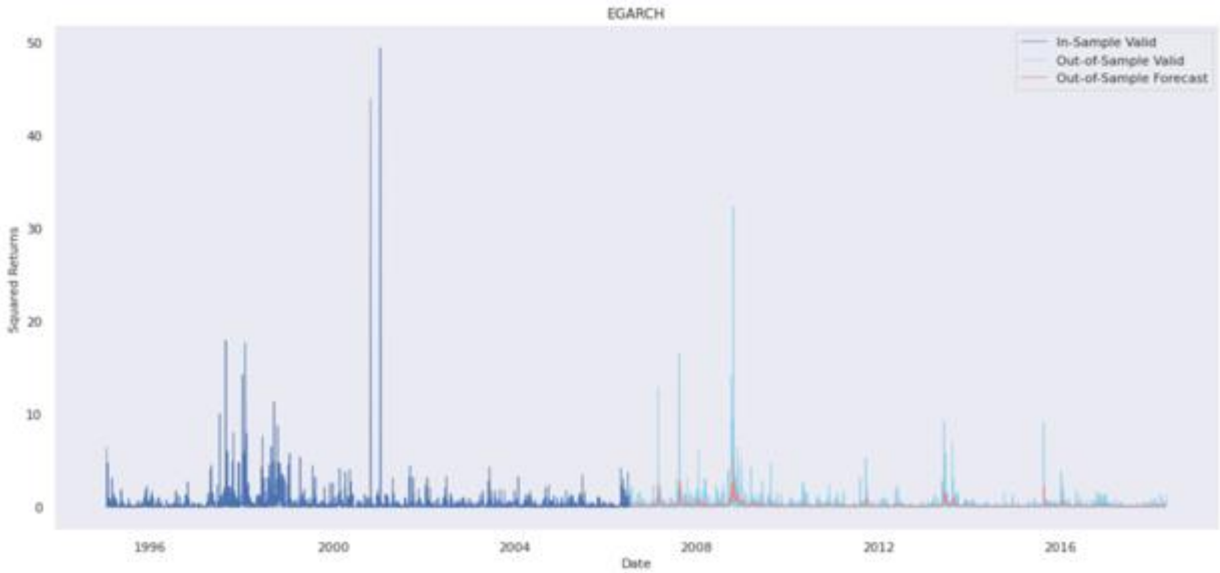
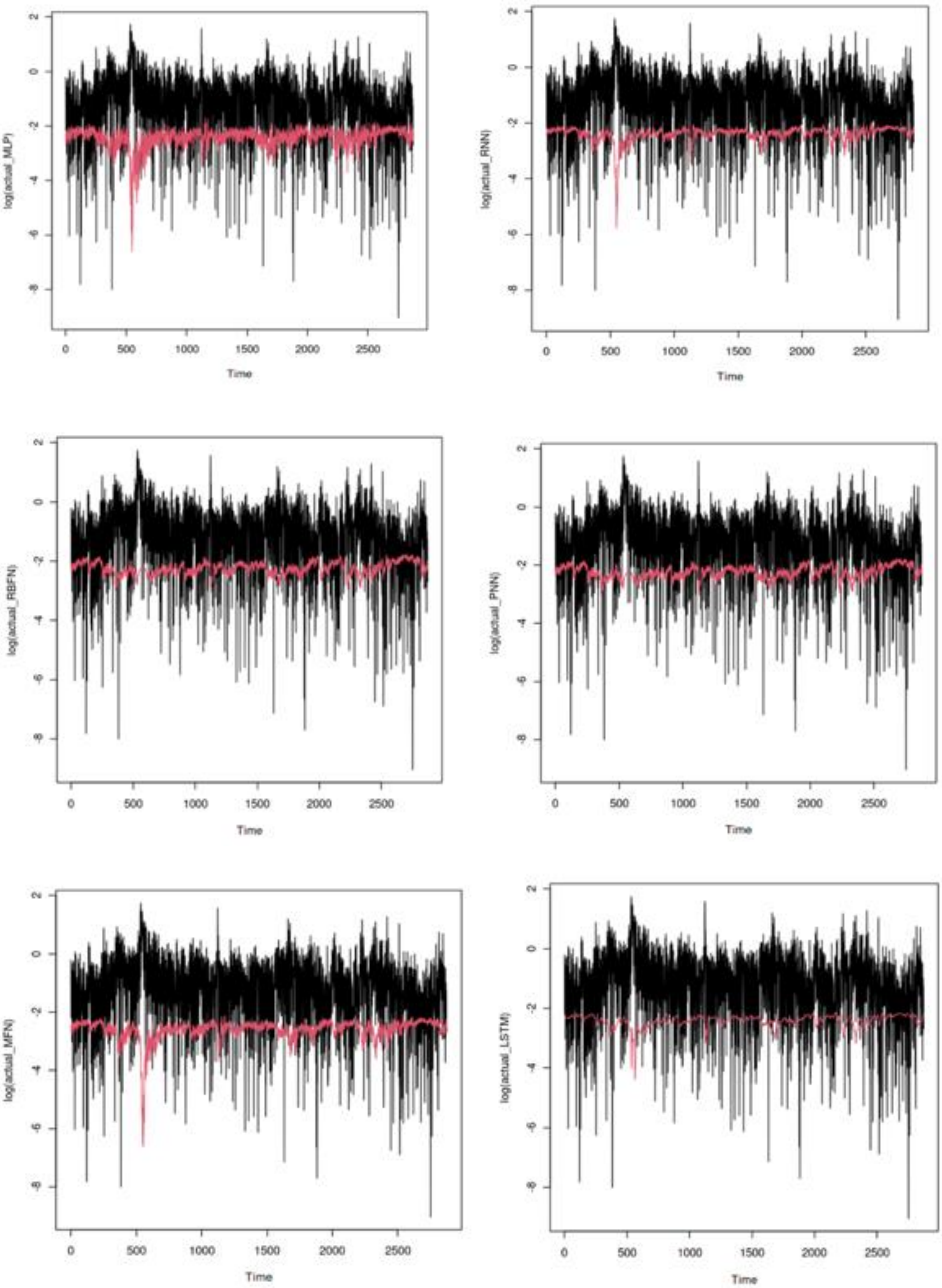
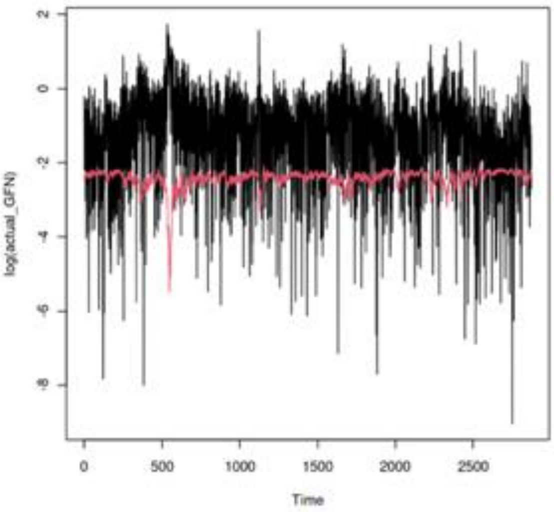
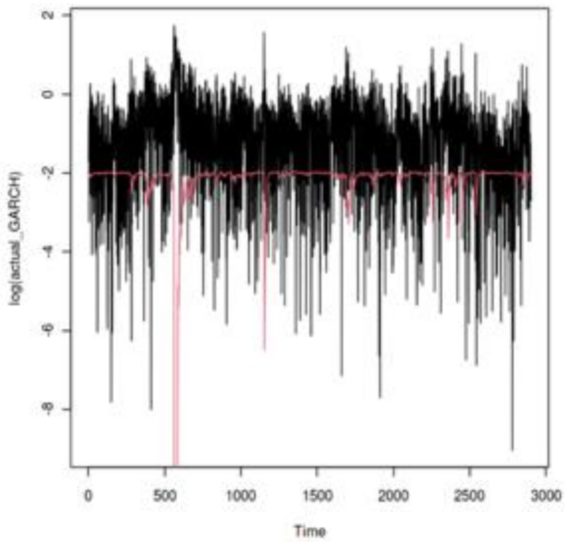

EGARCH
In-Sample Valid
Out-of-Sample Valid
Out-of-Sample Forecast
Squared Returns
0
10
20
30
40
50
1996
2000
2004
2008
2012
2016
Date

Figure C.11: VaR plots of the selected models for NIKKEI index




log(actual_GFN)
Time


log(actual_GARCH)
Time

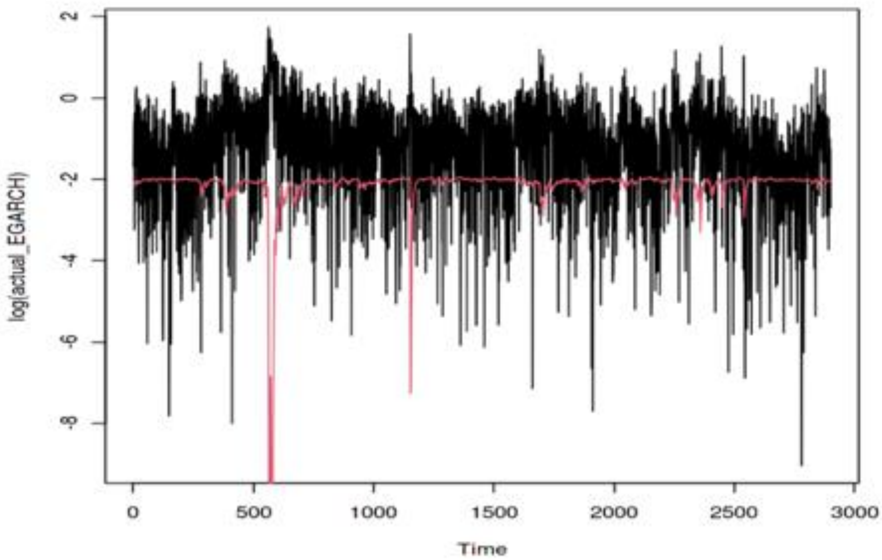
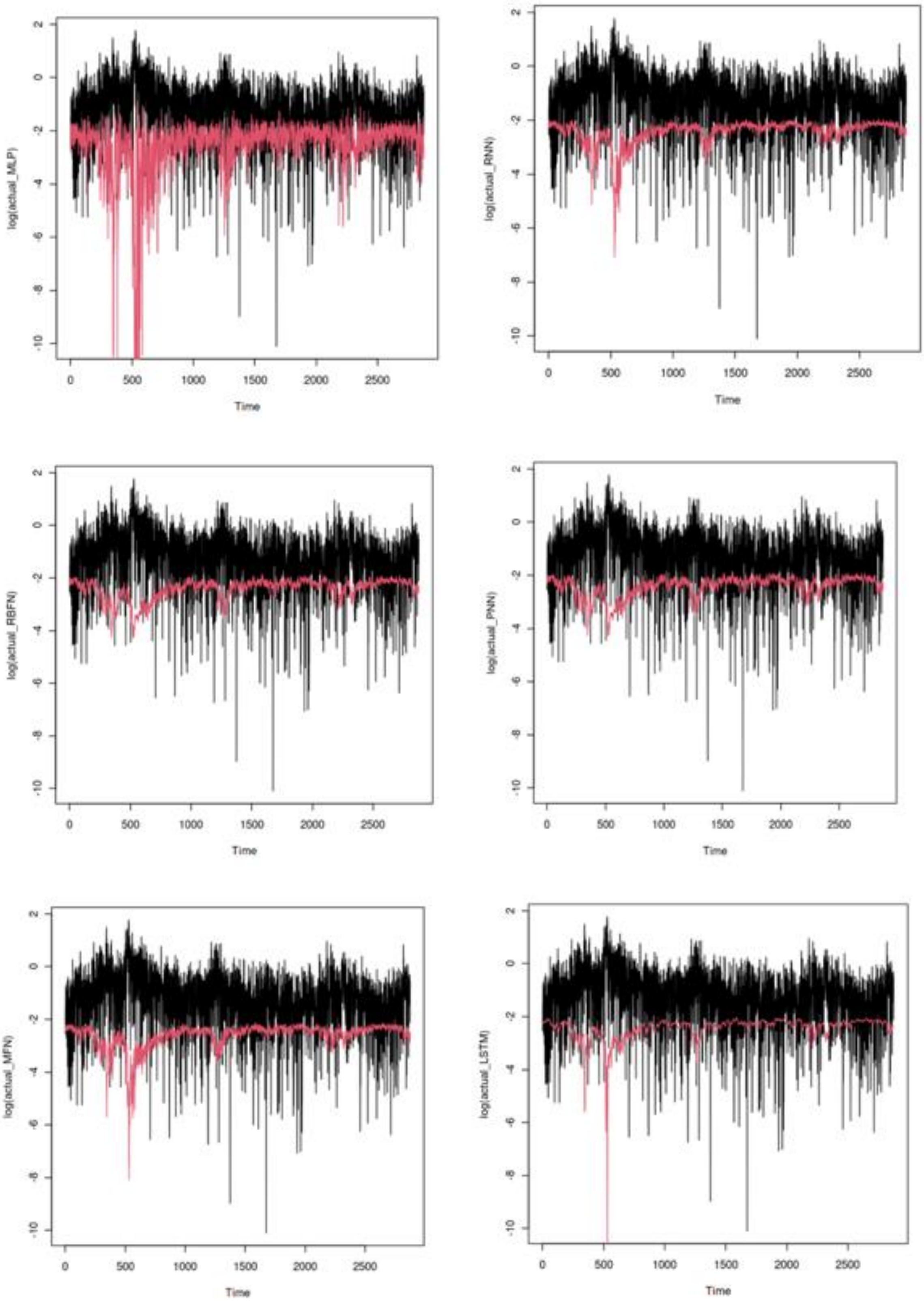
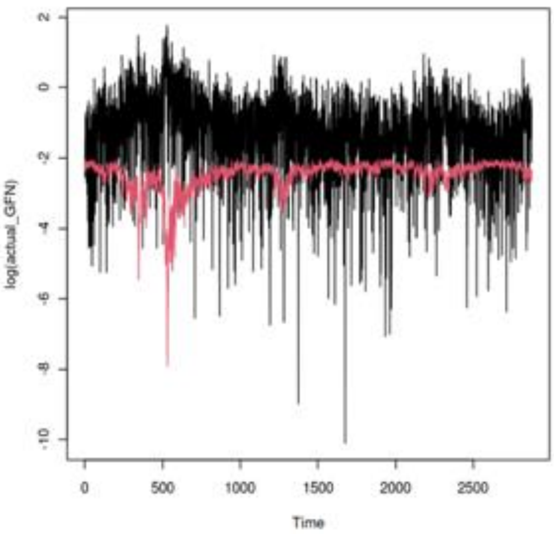
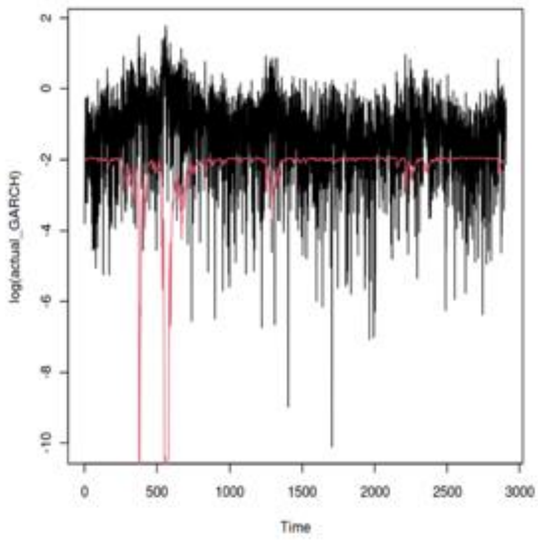

log(actual_EGARCH)
Time

Figure C.12: VaR plots of the selected models for HANG SENG index




log(actual_GFN)
2
0
-2
-4
-6
-8
-10
0
500
1000
1500
2000
2500
Time


log(actual_GARCH)
2
0
-2
-4
-6
-8
-10
0
500
1000
1500
2000
2500
3000
Time

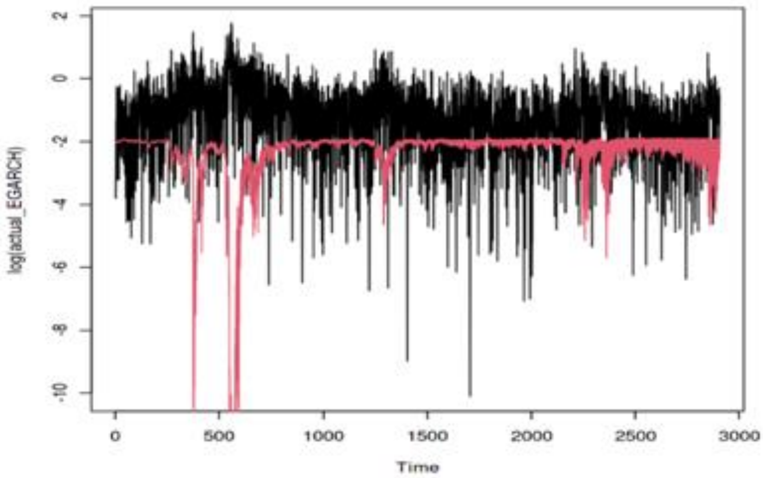
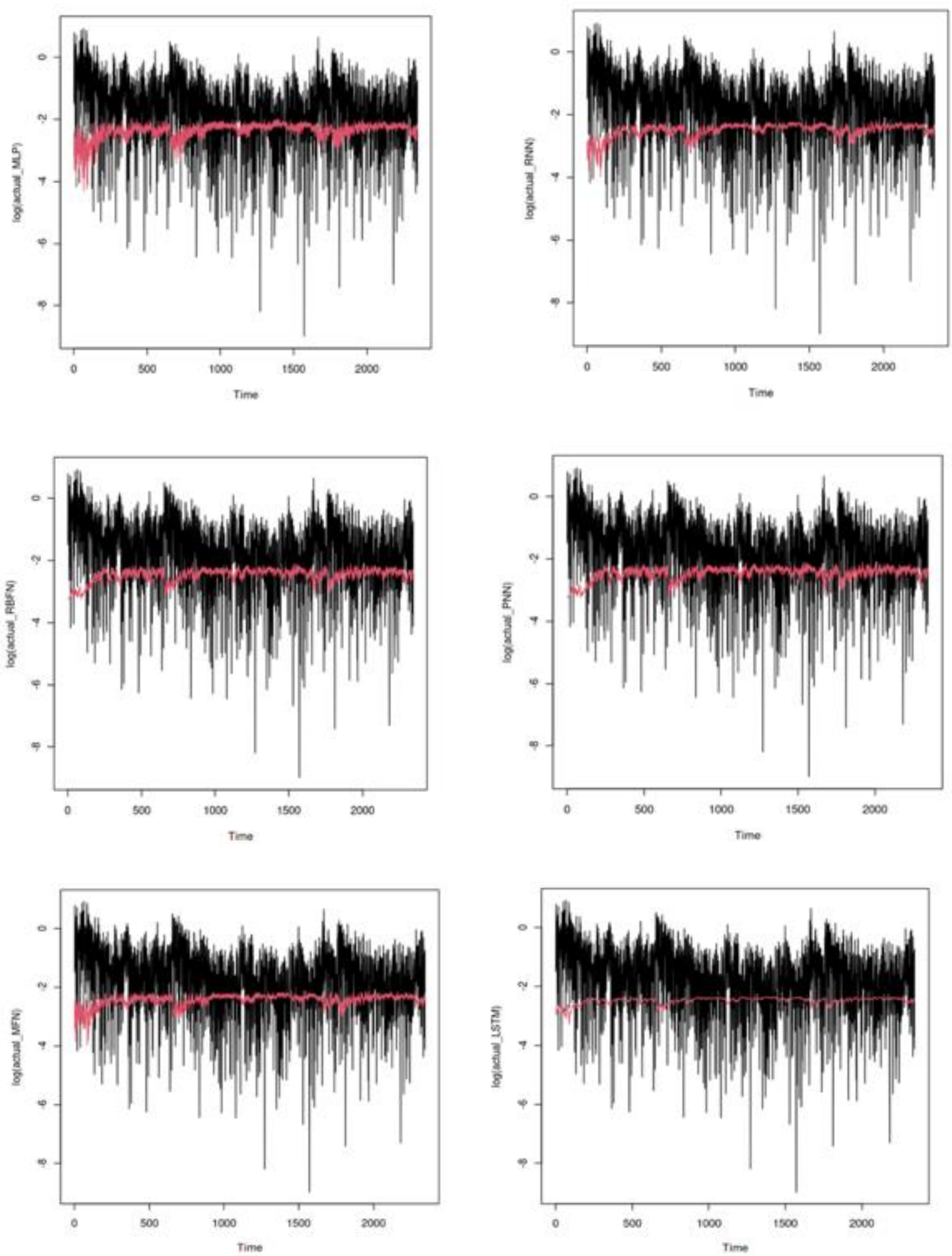
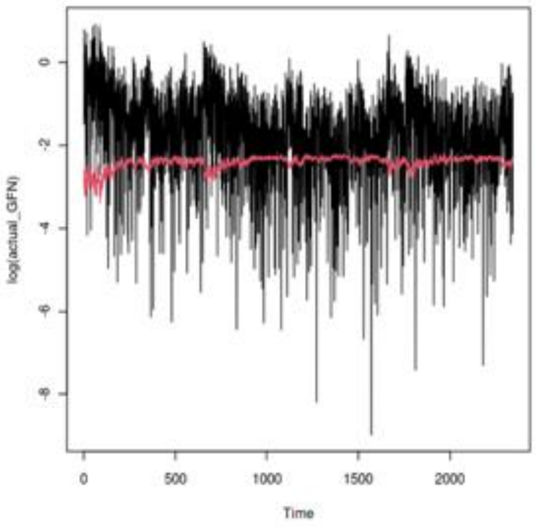
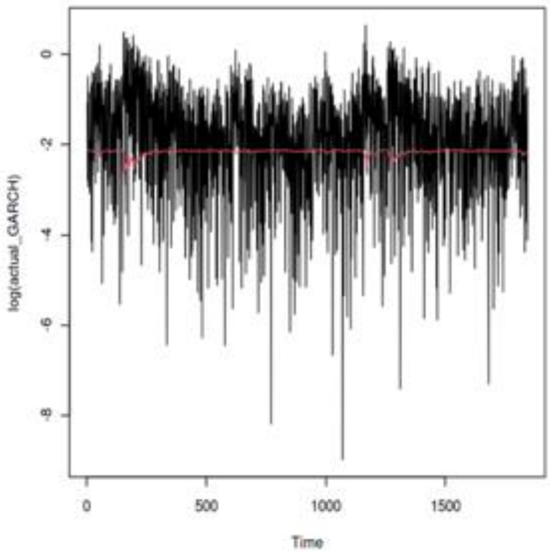

log(actual_EGARCH)
2
0
-2
-4
-6
-8
-10
0
500
1000
1500
2000
2500
3000
Time

Figure C.13: VaR plots of the selected models for STI index




log(actual_GFN)
Time


log(actual_GARCH)
Time

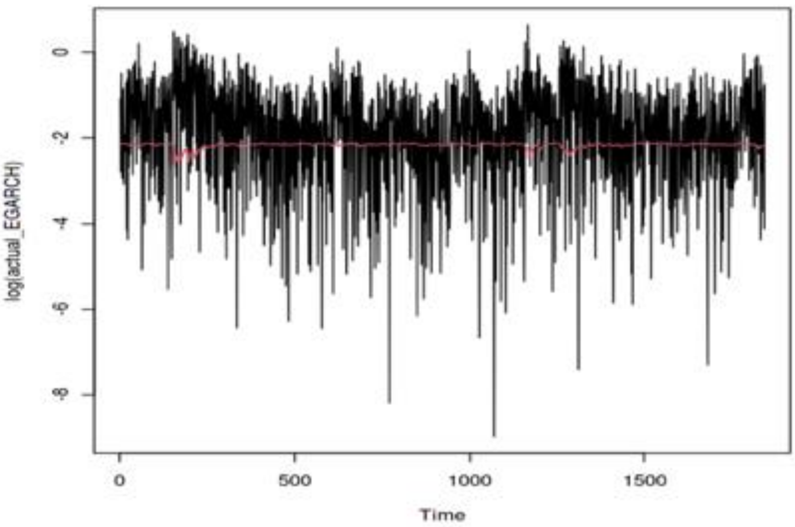
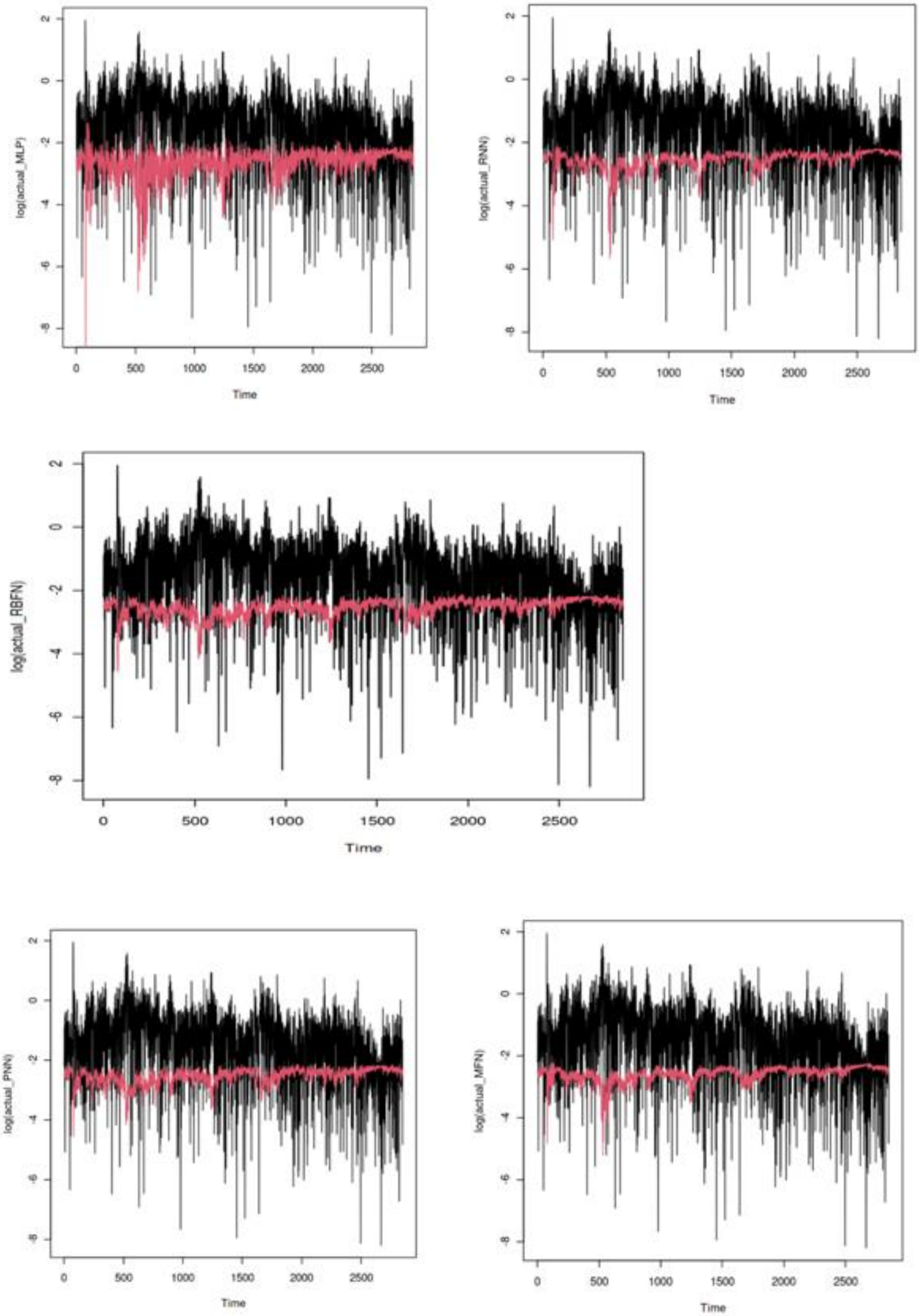

log(actual_EGARCH)
Time

Figure C.14: VaR plots of the selected models for SET index



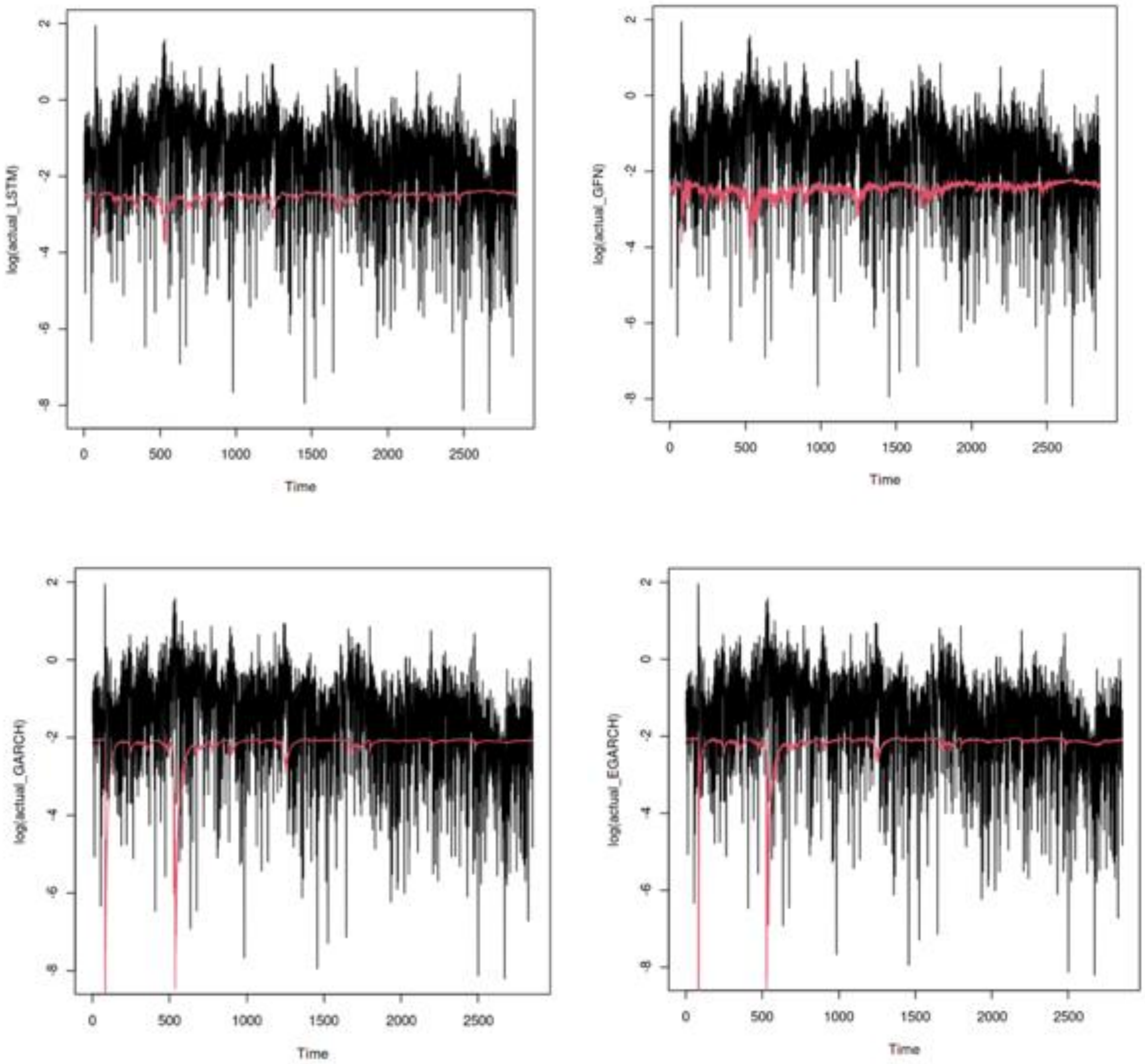
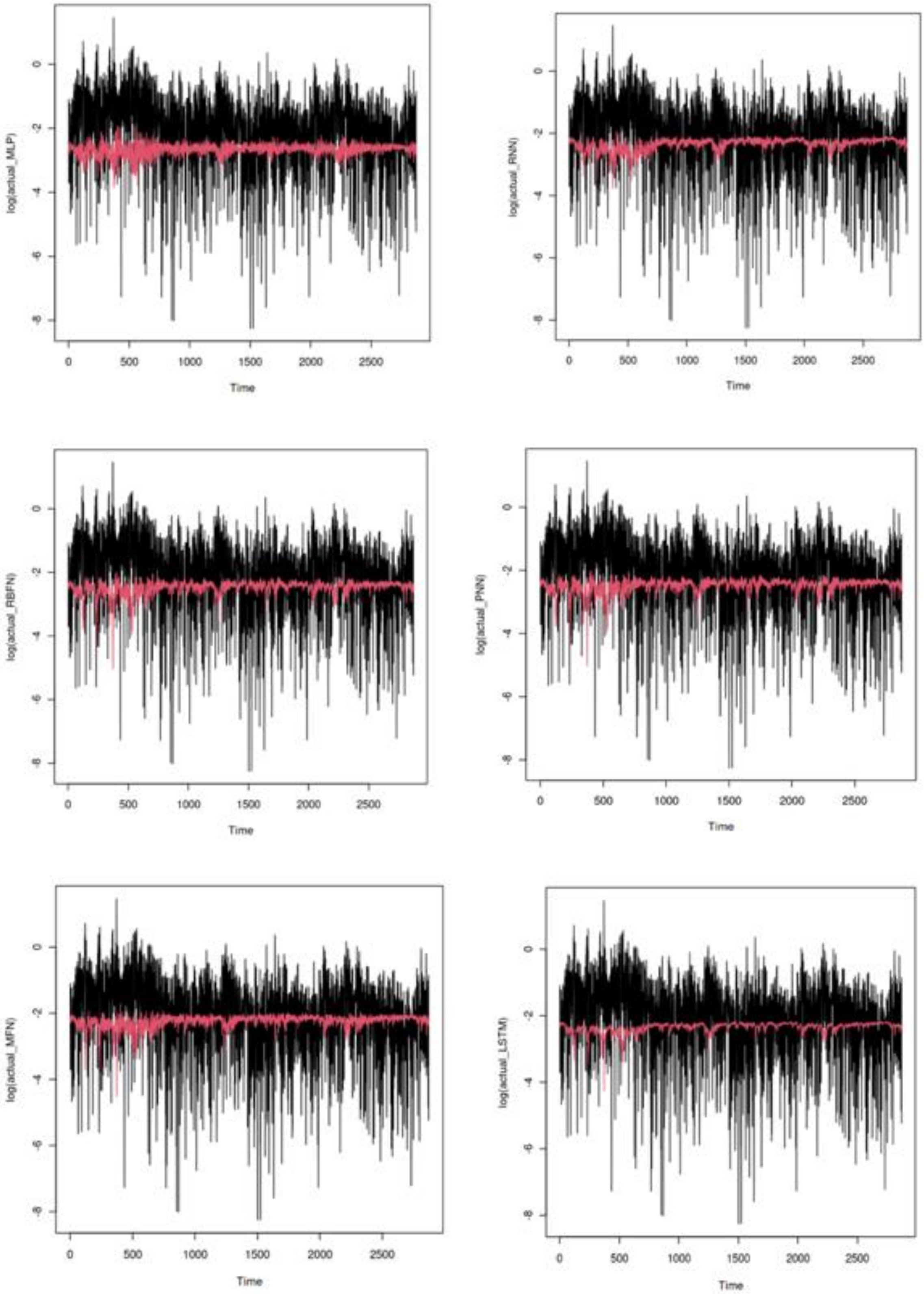
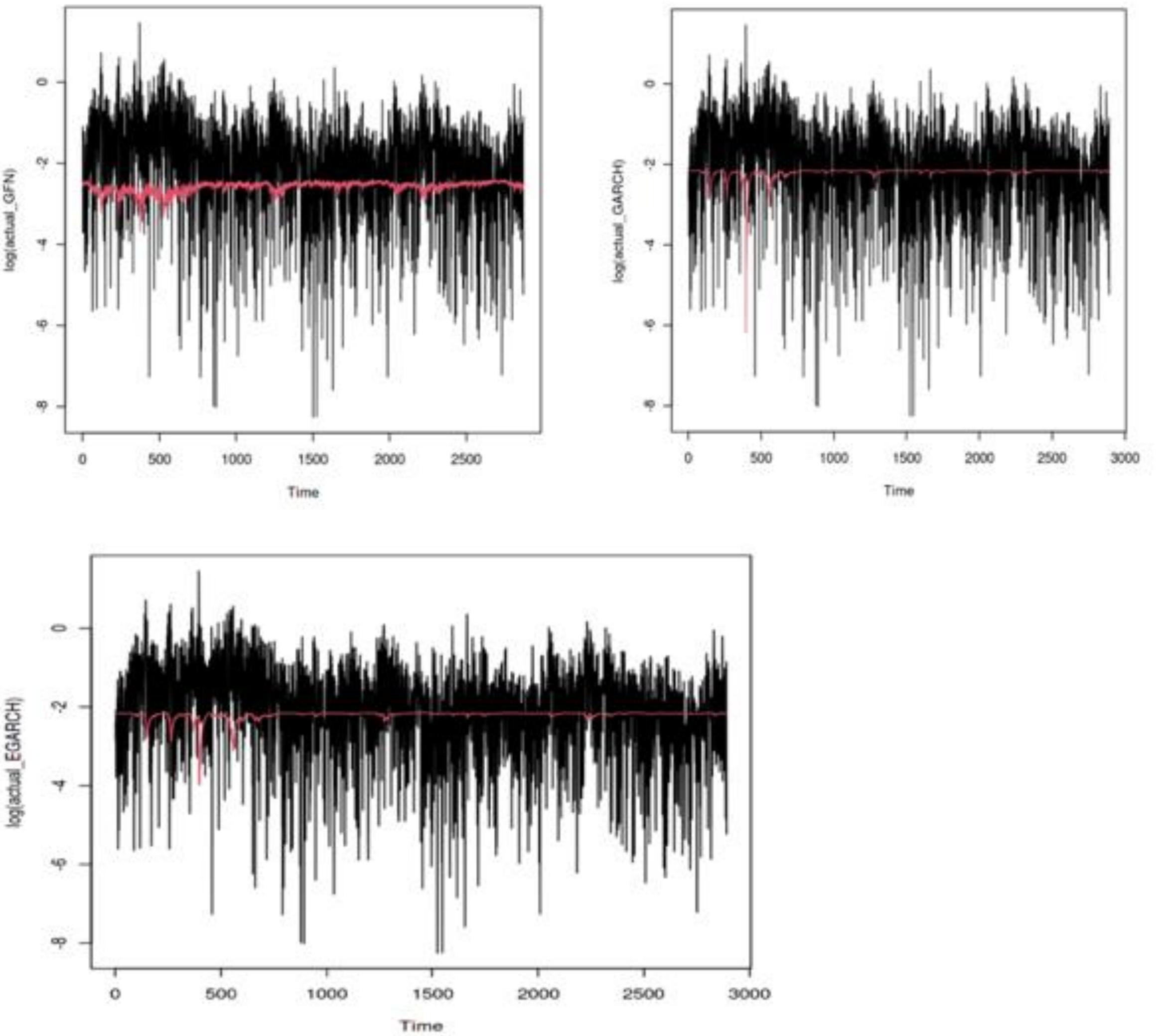

log(actual_LSTM)
Time
log(actual_GFN)
Time
log(actual_GARCH)
Time
log(actual_EGARCH)
Time

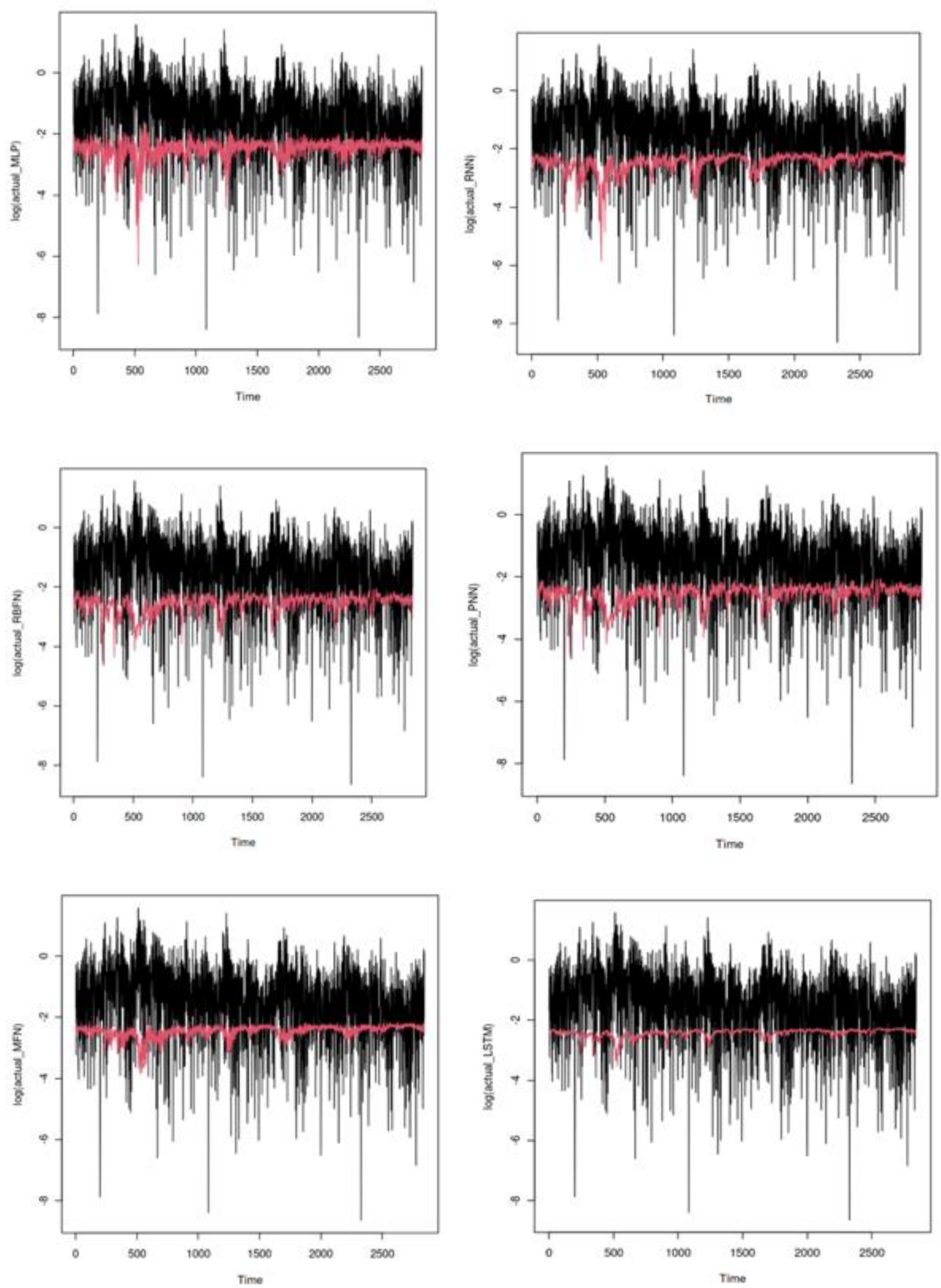
Figure C.15: VaR plots of the selected models for KLCI index

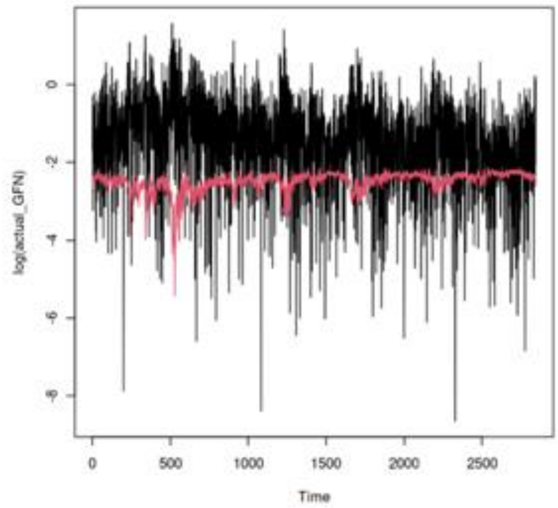


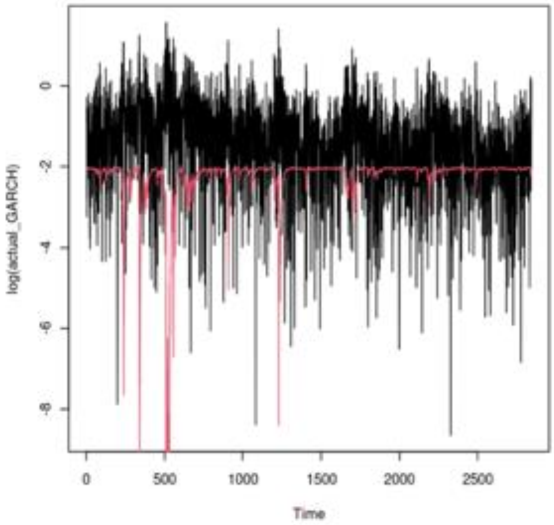


log(actual_GFN)
Time
log(actual_GARCH)
Time
log(actual_EGARCH)
Time
0
-2
-4
-6
-8
0
500
1000
1500
2000
2500
3000

Figure C.16: VaR plots of the selected models for JCI index




log(actual_GFN)
Time


log(actual_GARCH)
Time

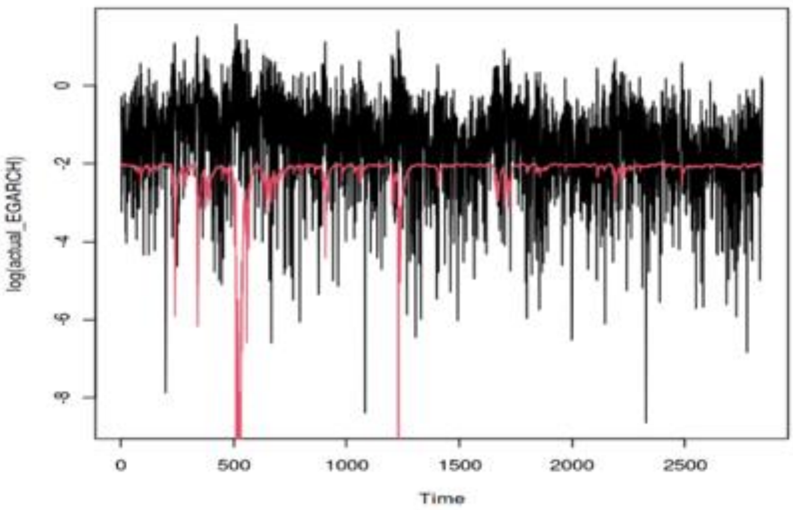
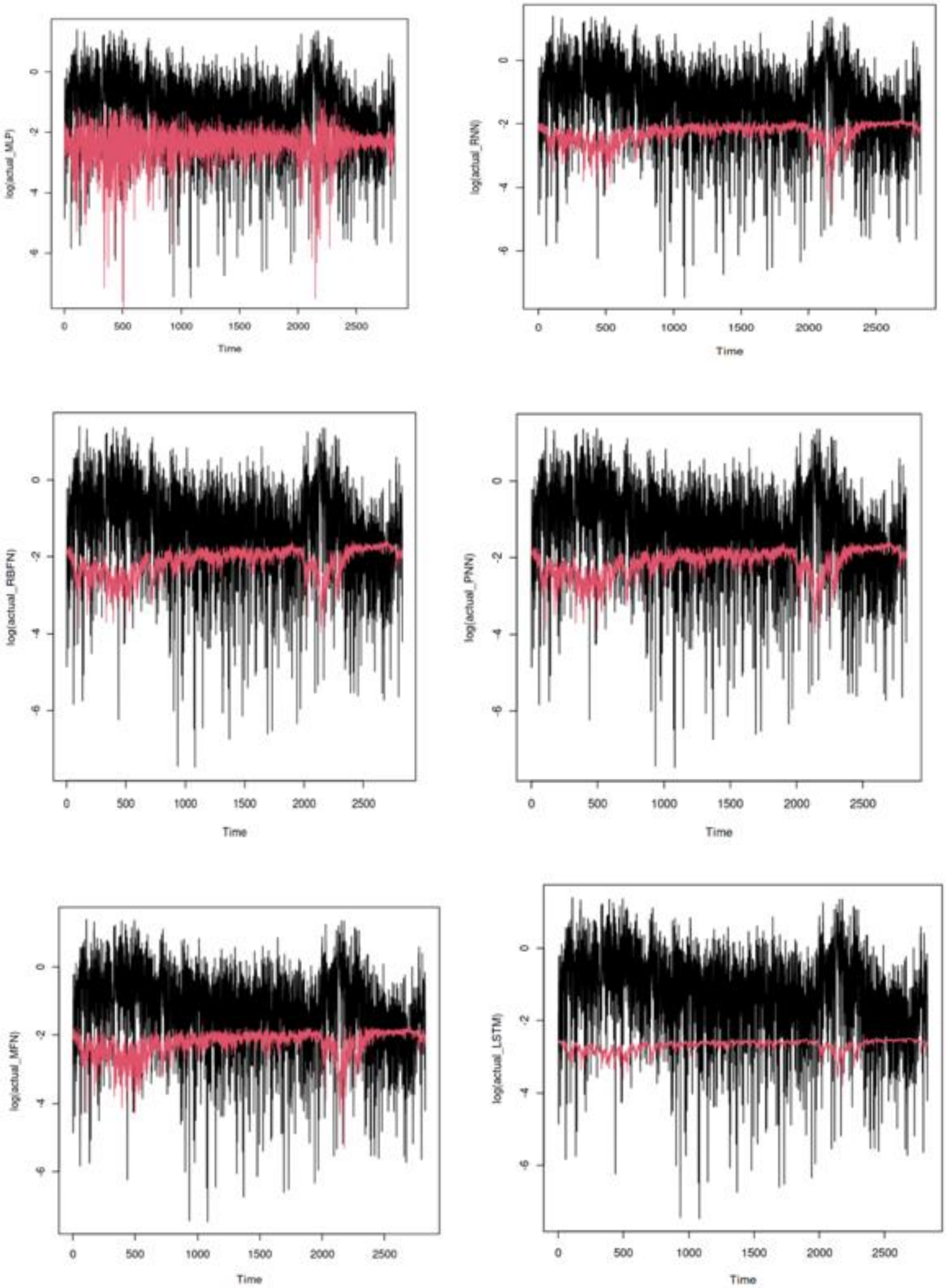
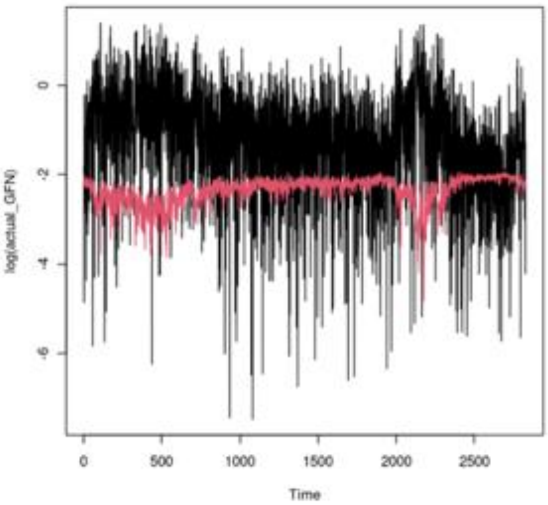
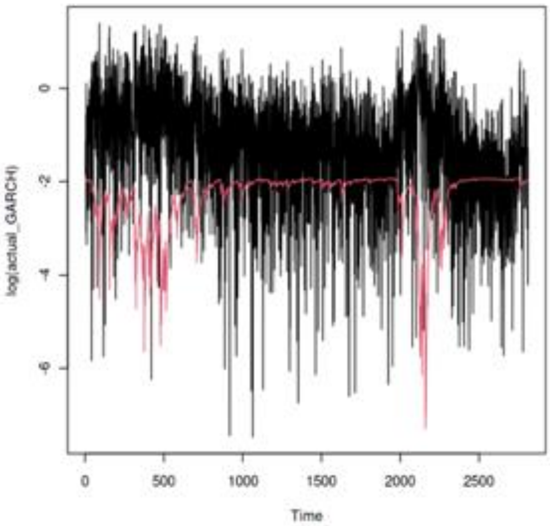

log(actual_EGARCH)
Time

Figure C.17: VaR plots of the selected models for SSE index




log(actual_GFN)
0
-2
-4
-6
0
500
1000
1500
2000
2500
Time


log(actual_GARCH)
0
-2
-4
-6
0
500
1000
1500
2000
2500
Time

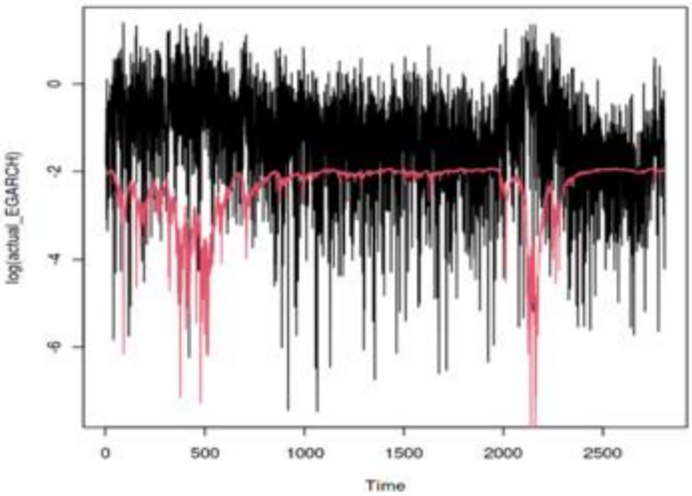
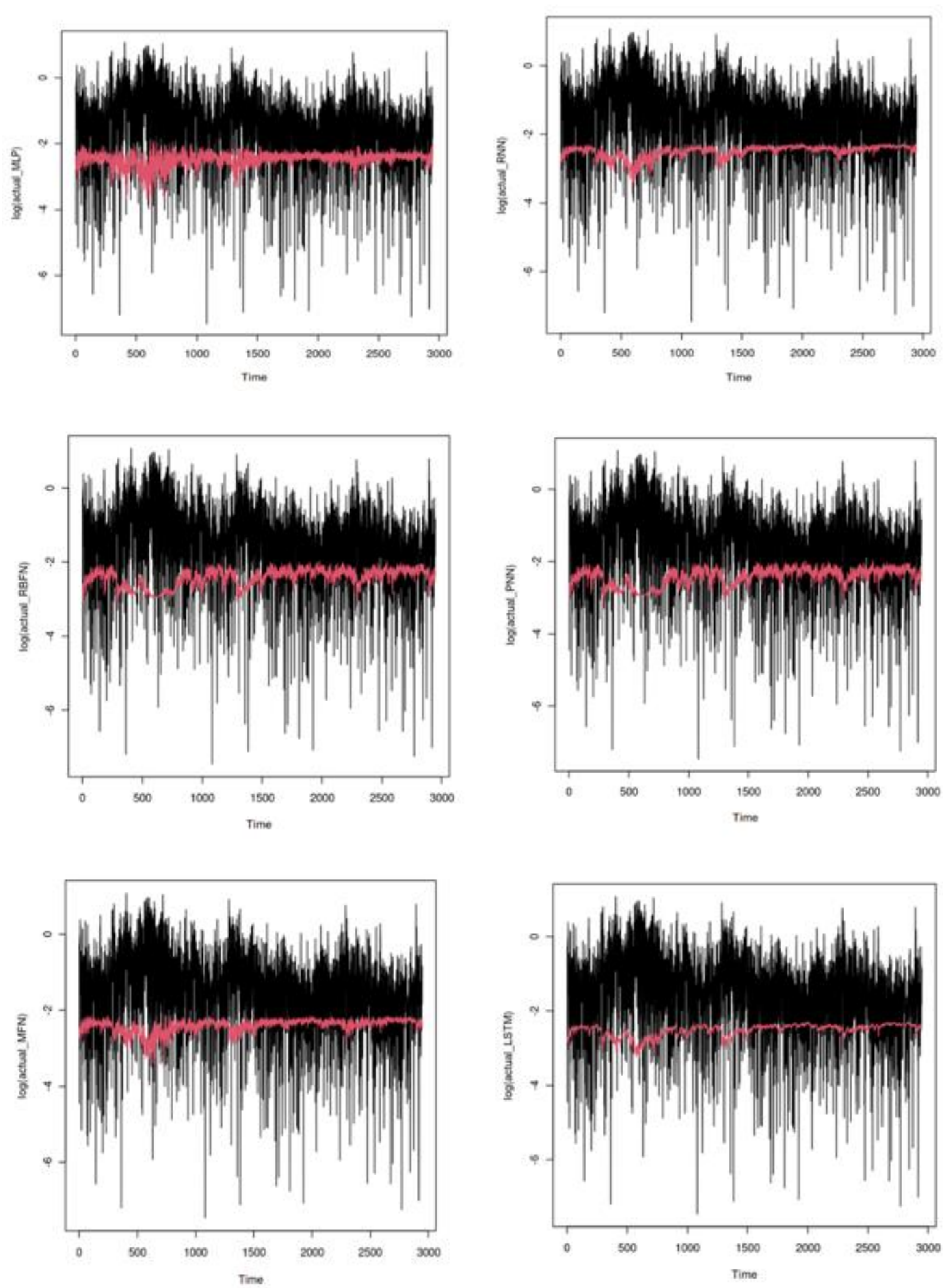
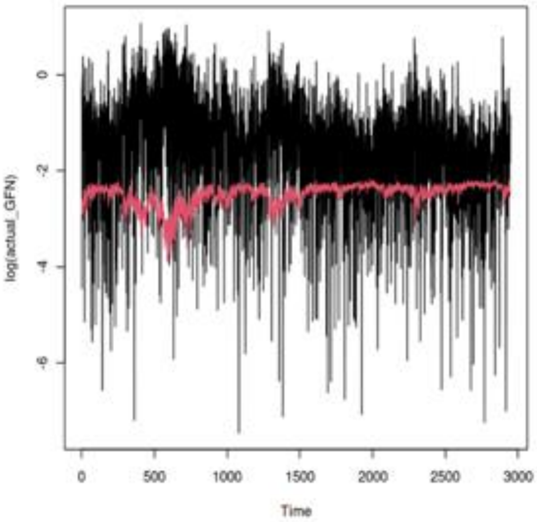
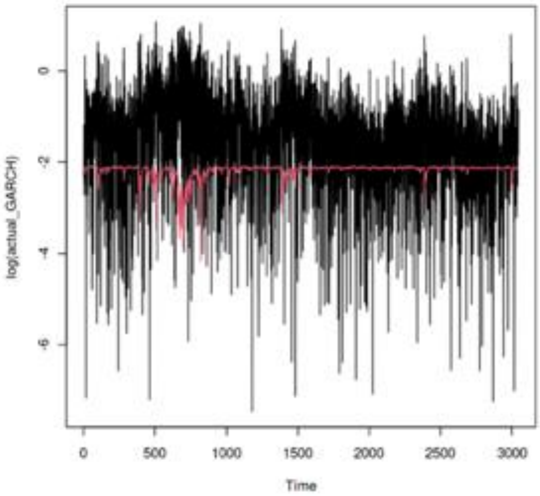

log(actual_EGARCH)
0
-2
-4
-6
0
500
1000
1500
2000
2500
Time

Figure C.18: VaR plots of the selected models for TAIEX index




log(actual_GFN)
Time
0
-2
-4
-6
0 500 1000 1500 2000 2500 3000


log(actual_GARCH)
Time
0
-2
-4
-6
0 500 1000 1500 2000 2500 3000

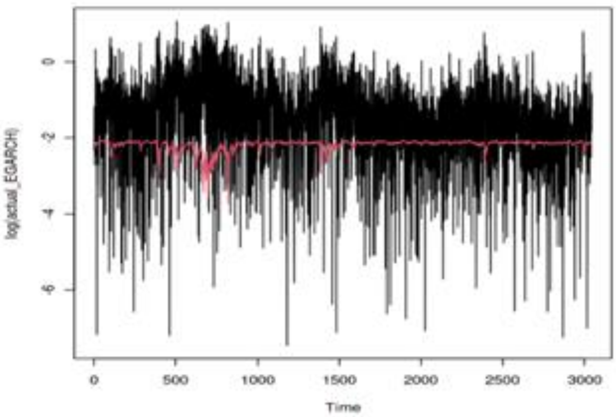
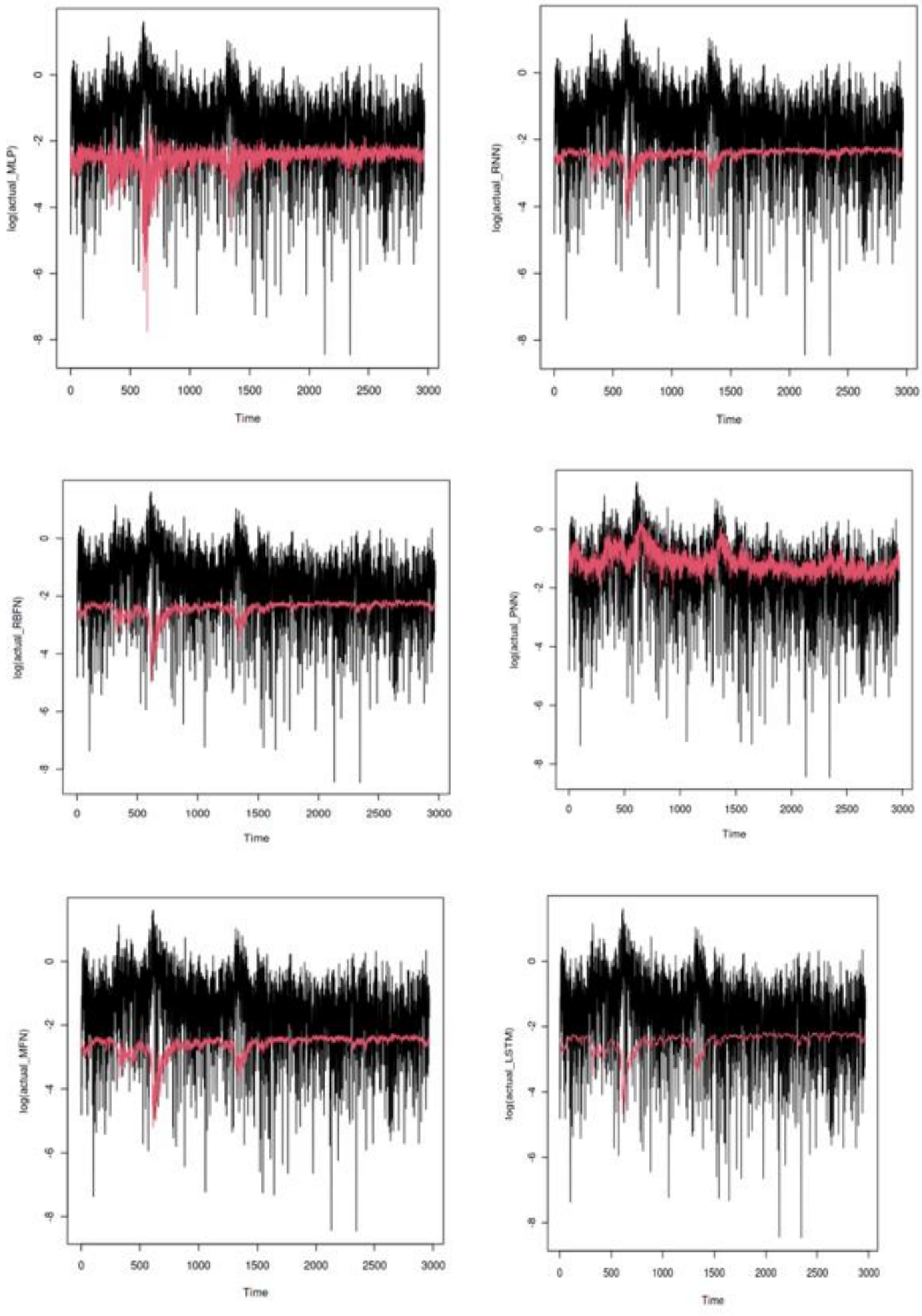
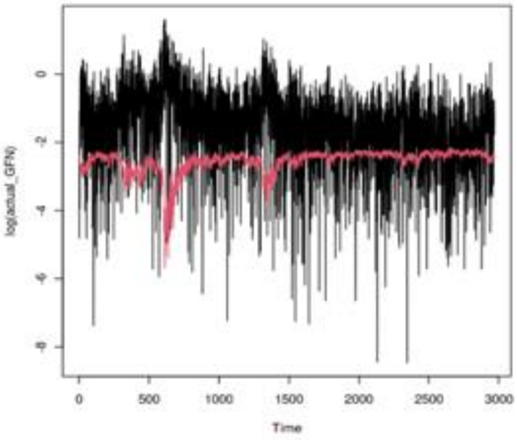
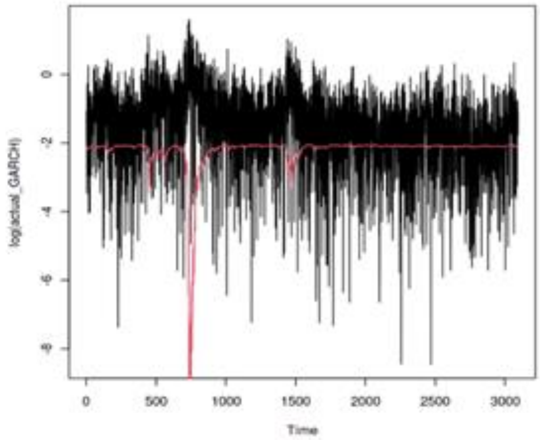

log(actual_EGARCH)
Time
0
-2
-4
-6
0 500 1000 1500 2000 2500 3000

Figure C.19: VaR plots of the selected models for KOSPI index




log(actual_GFN)
Time


log(actual_GARCH)
Time

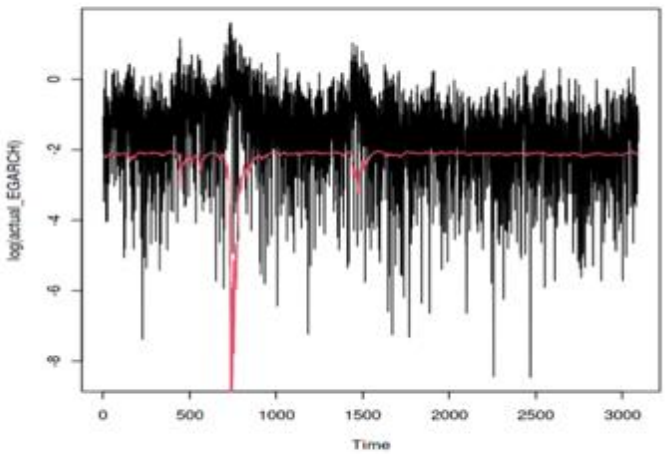
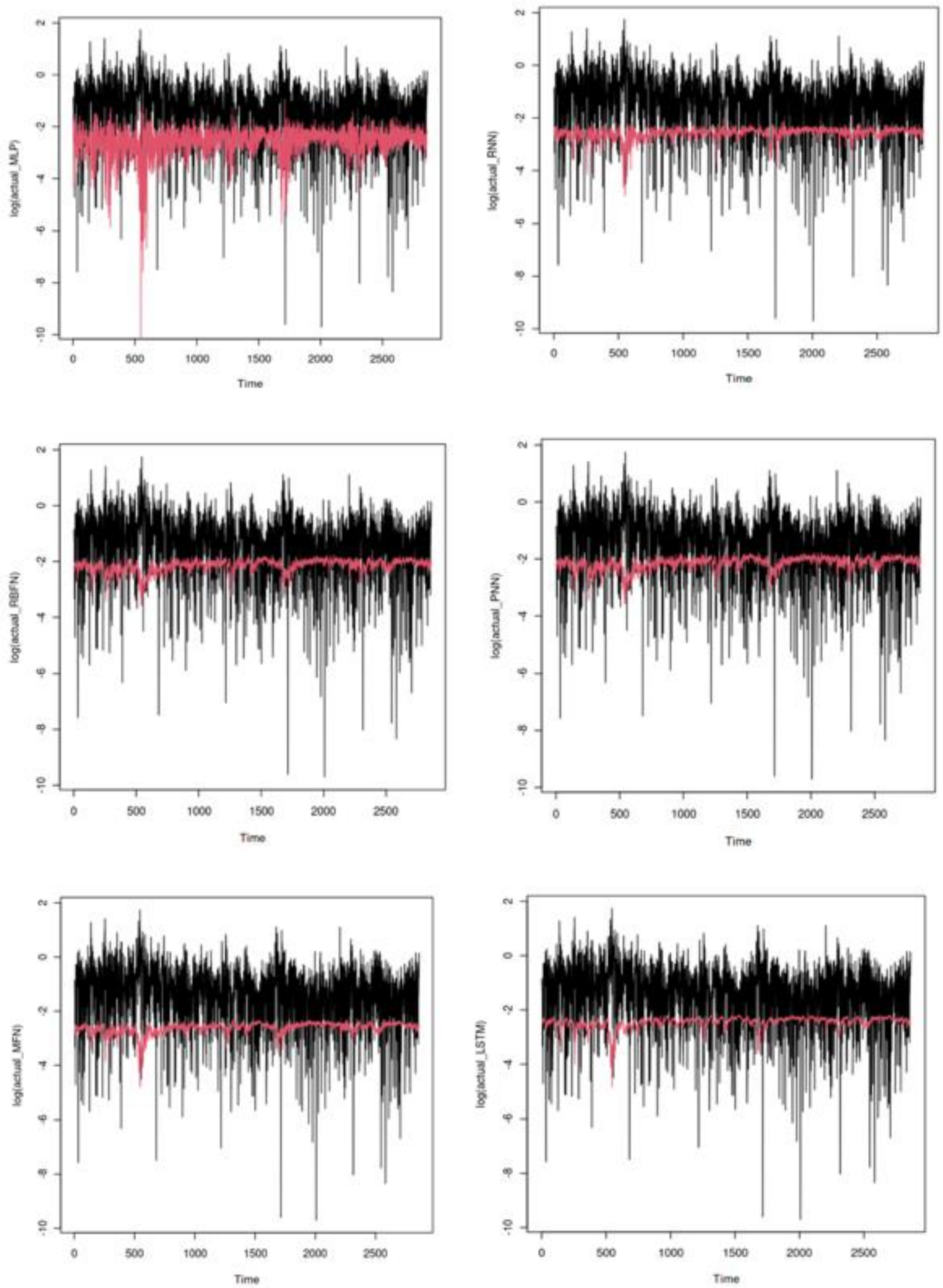
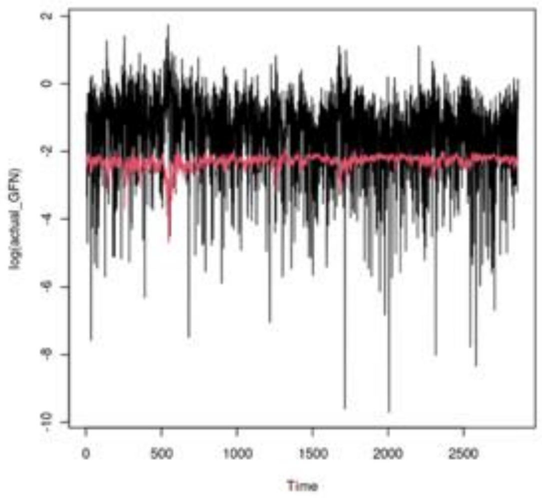
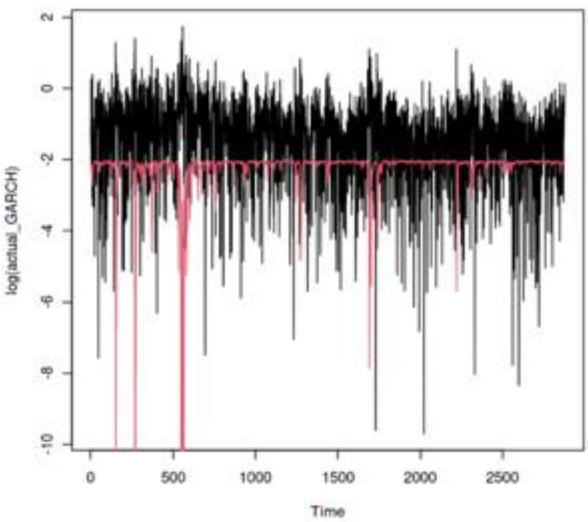
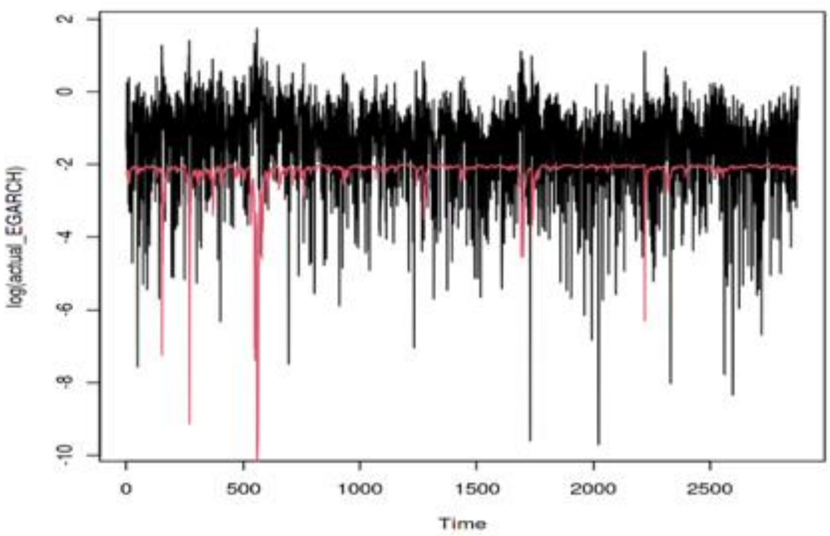

log(actual_EGARCH)
Time

Figure C.20: VaR plots of the selected models for PSE index




log(actual_GFN)
Time


log(actual_GARCH)
Time


log(actual_EGARCH)
Time