Cross-Border Exchanges and Volatility Forecasting

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Abstract

We test for the performance of a series of volatility forecasting models (GARCH 1,1; EGARCH 1,1; CGARCH) in the context of several indices from the two oldest cross-border exchanges (Euronext; OMX). Our findings overall indicate that the EGARCH (1,1) model outperforms the other two, both before and after the outbreak of the global financial crisis. Controlling for the presence of feedback traders, the accuracy of the EGARCH (1,1) model is not affected, something further confirmed for both the pre and post crisis periods. Overall, ARCH effects can be found in the Euronext and OMX indices, with our results further indicating the presence of significant positive feedback trading in several of our tests.

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1. Introduction

The globalization process that has been underway since the 1990s has enhanced co-operation among stock markets internationally, culminating in the formation of cross-border exchange groups (Nielsson, 2009). Stocks listed on a group's member-markets are traded via a uniform trading system based on a single common trading platform for all member-markets, whose advanced technological infrastructure allows for increased turnover-capacity and reduced latency in order-execution. This, in turn, facilitates the participation of investors both from within the group and internationally, thus suggesting that cross-border groups comprise sophisticated market environments, characterized by high liquidity and investors' heterogeneity, promoting international financial integration. It is interesting to note, however, that despite the proliferation of such groups, very little work (Dorodnykh and Youssef, 2012; Slimane, 2012) has been undertaken in their context on issues related to risk-measurement, in particular volatility forecasting.

Our study contributes in that direction by addressing the following three issues. First, we test whether volatility forecasts in cross-border markets are accurate by employing an array of established forecasting models accounting for several stylized volatility features (such as asymmetry and long-memory) in the context of cross-border group indices. Second, having identified the best performing forecasting model, we then examine whether its accuracy is affected when controlling for investors' heterogeneity, by taking into account the presence of feedback traders, whose link to stock market volatility has been denoted in several studies (Koutmos, 2014). Third, we investigate whether the accuracy of the best performing model varies prior to as opposed to after the outbreak of the recent global financial crisis, in view of evidence (Poon and Granger, 2003; Bao et al., 2006; Kambouroudis and McMillan, 2015) denoting an effect of crises' outbreaks over the forecasting precision of volatility models and given that their nature as vehicles of global financial integration (Ferrando and Vesala, 2005) renders cross-border groups more exposed to global shocks.

Our findings overall indicate that a series of forecasting models of the GARCH-family (GARCH 1,1; EGARCH 1,1; CGARCH) perform well with all our sample indices, with the EGARCH (1,1) model outperforming the other two, both before and after the outbreak of the global financial crisis. Controlling for the presence of feedback traders, the accuracy of the EGARCH (1,1) model is not affected, both pre and post crisis. Overall, ARCH effects can be found in the Euronext and OMX indices, with our results further indicating the presence of significant positive feedback trading in several of our tests, especially pre crisis. Our work produces a series of distinct contributions to research related both to cross-border exchanges specifically and volatility in general. First, it demonstrates - to the best of our knowledge, for the first time - that volatility in cross-border exchanges exhibits similarities in terms of its dynamics (clustering; asymmetry; long memory) and forecasting ability to the volatility documented in national stock exchanges. Second, it denotes that the outbreak of a financial crisis does not affect the choice of the best performing model in terms of volatility forecasting in cross-border exchanges, thus confirming that the models that provide the most accurate forecasts during periods of financial stability also appear to provide the best forecasts during financial crises (Brownlees et al. 2012; Kambouroudis and McMillan, 2015). Third, we show that accounting for feedback trading does not introduce an effect over volatility forecasting, in terms of either the best performing model or its performance before/after a crisis' outbreak. Fourth, we report evidence for the first time that, much like in national stock exchanges, feedback traders command a significant presence in cross-border exchanges, thus indicating that the sophisticated structures of integrated markets do not necessarily discourage investors from employing non-fundamental trading patterns.

Our results contain useful risk-management implications for investors, primarily those with a global investment outlook, as they suggest that extant risk-metrics' models established over the decades following research on the premises of national markets produce satisfactory forecasts in the context of cross-border markets. Furthermore, the presence of significant feedback trading in most of our tests indicates the potential for return-patterns in cross-border exchanges' indices over time that could perhaps be profitably exploited via *ad hoc* trading strategies, a possibility theoretically advocated by several early studies (De Long et al., 1990; Farmer, 2002; Farmer and Joshi, 2002). From a regulatory perspective, the presence of feedback traders in the Euronext/OMX indices is of key interest, given this trader-type's frequent association with destabilizing phenomena in capital markets. To mitigate the latter, a possible measure that cross-border markets' regulators could consider would be to offer an enhanced range of sophisticated products (e.g. index futures) linked to these markets' indices, in view of evidence (Antoniou et al., 2005) demonstrating that the introduction of such products attracts rational investors and reduces feedback trading at the spot market level.

The next section presents an overview of the literature on volatility, its modelling and its association with feedback trading, before discussing the evolution of cross-border exchanges. Section 3 outlines the data and methodology employed and presents some descriptive statistics. Section 4 presents and discusses the results and section 5 concludes.

2. Literature Review

2.1 Managing risk: The evolution of volatility modelling

The ongoing process of global financial integration has fostered a phenomenal growth in the range of products and markets available to international investors, thus increasing the challenges of managing risk in a constantly evolving investment landscape. Over the decades, considerable research has been devoted to the development of empirical models capable of capturing and accurately forecasting volatility, with the relevant debate being ongoing to date. At first, time series analysis was employed to model and forecast volatility. Simple historical models were developed, with the tendency for stock market volatility towards exhibiting "clustering" being first noted by Mandelbrot (1963) and Fama (1965). Examples of such models include Random Walk (RW), Moving Averages (MA), Exponential Weighted Moving Averages (EWMA), the RiskMetrics procedure by JP Morgan RiskMetrics (1996), Smooth Transition Exponential Smoothing by Taylor (2004), Autoregressive Moving Averages (ARMA) and Autoregressive Fractionally Integrated Moving Averages (ARFIMA).

Although the initial time series models were capable of capturing volatility clustering, it was only after the introduction of the more sophisticated family of Autoregressive Conditional Heteroscedasticity (ARCH) models by Engle (1982) and Generalized ARCH (GARCH) models by Bollerslev (1986) and Taylor (1986) that the second and higher moments were formally modelled. As Poon and Granger (2003) observed, ARCH/GARCH models do not make use of sample standard deviations as the earlier time series volatility models, but rather model the conditional variance of returns using the maximum likelihood method.[1] Evidence from earlier empirical studies (Jorion, 1995, 1996; Frances and Dijk, 1996; Figlewski, 1997; Andersen et al., 1999; McMillan et al., 2000) examining the forecasting ability of the available models (including those belonging to the GARCH-family and the more simple models) has overall been mixed. Nonetheless, in more recent studies (McMillan and Speight, 2004; Hansen and Lunde, 2005; McMillan and Kambouroudis, 2009) the GARCH-type models appear to possess superior forecasting ability.

[1] Examples of GARCH model-specifications that allow for non-symmetrical dependencies are the Exponential GARCH by Nelson (1991) and the Threshold GARCH (also known as GJR GARCH) by Glosten, Jagannathan and Runkle (1993). Volatility persistence is another feature captured by this class of models; examples of long memory models include the Integrated GARCH by Engle and Bollerslev (1986), the Fractionally Integrated GARCH by Baillie et al. (1996), the Fractionally Integrated Exponential GARCH by Bollerslev and Mikkelsen (1996) and the Component GARCH by Engle and Lee (1999).

An additional approach towards volatility forecasting that has recently grown in popularity is that based on implied volatility. This approach utilizes the options market as a source of information about volatility (Engle, 2003) and has led to the introduction of an array of "fear indices" internationally. The first such index launched was the CBOE VIX in the US, which, according to Simons (2003), indicates how much market participants are willing to pay in terms of implied volatility to hedge stock portfolios with the S&P 500 index put options or to go long by buying S&P 500 index call options. Fleming et al. (1995) found that the VIX performs better in forecasting future volatility in the US than other historical measures, with Carr and Wu (2006), Yu et al., (2010) and Yang and Liu (2012) reaching similar conclusions.

Since the aftermath of the 1987 stock market crash (when the Dow Jones Industrial Average dropped by more than 22% in one day), volatility modelling and forecasting have been at the forefront of the finance literature. The importance of accurately modelling and forecasting volatility during periods of financial instability and crises motivated a large amount of research over the years. Koutmos and Booth (1995) showed that volatility in one market is correlated with price fluctuations in different markets, a phenomenon that came to be known as the 'spill over' effect. An example of this (which came to be known as the 'Tequila effect') occurred during the mid 1990s, when the 1994 financial crisis in Mexico instigated a sharp rise in volatility in African stock exchanges (which were both geographically distant from Latin America and overall of low degree of integration in the global financial system; see Appiah-Kusi and Pescetto, 1998). Increases in volatility are often used to define a financial crisis. The challenge of modelling and forecasting volatility becomes bigger during a financial crisis, with evidence suggesting that volatility forecast accuracy is also impacted upon (Bao et al., 2006; Kambouroudis and McMillan, 2015). A solution to this was given by Brownlees et al. (2012), who demonstrated that volatility model re-estimation might be necessary depending on the data frequency employed. On the other hand in model comparison exercises the models that provide the most accurate forecasts during periods of financial stability also appear to provide the best forecasts during financial crises (Brownlees et al. 2012; Kambouroudis and McMillan, 2015).

2.2 Volatility and feedback trading

A factor that has been found to be strongly related to stock market volatility, yet has not been considered in the context of volatility forecasting, is investors' heterogeneity; this is particularly important, considering the fact that global financial integration (expressed, for example, via the liberalization of capital flows or the formation of cross-border stock exchanges) renders each market more accessible to international investors of varying trading strategies. An interesting issue in this respect, as a series of studies (Brennan and Cao, 1997; Kim and Wei, 2002a, b; Sias, 2004; Lin and Swanson, 2008) has reported, is that investors internationally appear to have a notable tendency towards pursuing a variety of strategies based on extrapolating from historical returns, i.e. they are susceptible to feedback trading. The term "feedback trading" itself is an umbrella one, encompassing a series of established price-based strategies, including momentum trading, contrarian trading, technical analysis, portfolio insurance, stop-loss orders and margin trading (see Koutmos, 2014 for an excellent review). Feedback trading can be positive or negative in sign. Positive feedback traders tend to buy (sell) when prices rise (fall), i.e. they are momentum traders; conversely, negative feedback traders buy (sell) when prices fall (rise), thus aiming at "bucking the trend" (i.e. are contrarian traders).

Empirically, much research (De Long et al., 1990; Farmer, 2002; Farmer and Joshi, 2002) has indicated that investors' heterogeneity, reflected through the interaction of fundamentals-driven investors with noise traders subscribing to feedback trading, can lead to temporary return-patterns deviating from fundamental values. Drawing on the empirical framework proposed by Sentana and Wadhwani (1992), a series of studies has confirmed the presence of feedback traders in equity (Koutmos, 1997; Koutmos and Saidi, 2001; Watanabe, 2002; Schuppli and Bohl, 2010) and futures (Antoniou et al., 2005; Chau et al., 2008) markets. Overall, these studies have indicated the presence of widespread positive feedback trading in most cases, with their evidence suggesting that this is associated with a rise in volatility. Positive feedback traders were also found to induce negative autocorrelation in returns, which increased in magnitude with volatility, indicating that their presence in the market fosters return-predictability by giving rise to return-patterns.

2.3 Cross-border stock exchanges

Cross-border markets are products of the wider process of global financial integration which has already been under way since the early 1990s. This process has been characterized by a gradual abolition of barriers in international capital flows, resulting in a rise in foreign direct and portfolio investments; a rise in cross-listings has also been noted, with companies seeking listings in different stock exchanges worldwide to tap into capital beyond that available in their home markets. This has led to the intensification of competition among stock markets in terms of attracting new listings and new investors, culminating to radical changes in their business model. A first step in that direction was demutualization (Aggarwal and Dahiya, 2006), namely the transformation of stock exchanges from mutual-ownership entities to private companies, motivated by profit-maximization incentives. Amid an increasingly competitive global financial environment, the newly privatized stock markets gradually engaged in considerable investments in financial innovation (e.g. by developing new lines of financial products) and financial technology (to enable themselves to handle larger trading volumes) in order to sustain their viability and profitability.

However, the costs of both financial innovation and financial technology grew progressively larger, thus rendering investing in them less than perfectly feasible for individual stock markets.

The response of exchanges across the world to this was to seek synergies through alliances with other exchanges, both within their home-country and internationally. Since 2000, the financial industry has witnessed markets from across the world joining forces and forming cross-border exchange groups, be they of regional (the Euronext and OMX in Europe) or global (NYSE-Euronext; NASDAQ-OMX) orientation (Nielsson, 2009). Key to the operations of such groups is that they offer their member-markets the opportunity to have their stocks listed and traded on a common trading platform, the advanced technological infrastructure of which allows for the implementation of a sophisticated trading system uniformly applied to all member-markets. This, in turn, enhances integration among a group's member-markets, by allowing investors from one of them the opportunity to trade the stocks of another member-market more easily (Ferrando and Vesala, 2005). Research to date on exchange groups has been rather limited, with reported findings indicating that the formation of these groups tends to boost liquidity in their constituent markets (Arnold, 1999; Pagano and Padilla, 2005; Nielsson, 2009), while from a behavioural perspective, evidence (Andrikopoulos et al., 2014; Economou et al., 2015) suggests that merging into an exchange group leads overall to an increase in investors' herding in its member-markets.

Despite the wealth of evidence on volatility forecasting from national market indices, there exists very little work on this issue in the context of cross-border exchanges, even though the latter have grown in size and significance in recent decades. Our paper aims at contributing to this by assessing the performance of volatility forecasting in the main indices of the world's first two cross-border exchange groups, namely the Euronext and the OMX, for the January 2003 – December 2015 period. The next section shall introduce the sample of indices utilized, alongside some descriptive statistics, before presenting the empirical design upon which we examine the research questions outlined in the beginning of this paper.

3. Data-methodology

3.1 Data

Our data contains daily observations of closing prices from the main indices of the first-ever cross-border exchange groups forged, namely the Euronext and the OMX. The indices are the Euronext 100 and Next 150 from the Euronext group and the OMX Nordic All Shares, OMX Nordic 40 and OMX Baltic 10 from the OMX group. The Euronext-group was the first-ever cross-border group to be launched, following the merger of the Amsterdam, Brussels and Paris stock exchanges in September 2000; by 2002, the Lisbon market had also joined the group, with these four markets comprising Euronext's equity segment to date. The Euronext 100 index includes the 100 most liquid shares listed on Euronext's four constituent markets; the Next 150 index includes the 150 stocks immediately below the Euronext 100 constituents in terms of market capitalization (i.e. it represents Euronext's midcap segment). The OMX-group consists of eight equity markets (Armenia; Denmark; Estonia; Finland; Iceland; Latvia; Lithuania; Sweden) and was launched in September 2003. The OMX Nordic All Shares index includes all stocks listed on the OMX-Nordic platform (comprised of the Danish, Finnish, Icelandic and Swedish markets), while the OMX Nordic 40 includes the 40 largest stocks listed on that platform; the OMX Baltic 10 index includes the ten largest stocks listed on the OMX-Baltic platform (comprised of the Estonian, Latvian and Lithuanian markets).

Our sample window covers the 1/1/2003 – 31/12/2015 period and the data on the indices' time series were obtained from the Thomson Reuters DataStream database[2]. In view of the global financial crisis that began taking shape in 2007, we distinguish between two sub-periods during our sample window, namely a *pre-crisis* (1/1/2003 – 31/8/2007) and a *post-crisis* (1/9/2007 – 31/12/2015) period. The selection of September 2007 as the cut-off point here is motivated via the fact that it was during that month that the trend in most Western stock exchanges switched

[2] The data for the time window of our study amounts to 3,330 daily observations for each of our sample indices.

to descending, as the first turbulences of the global financial system began to be felt during that time. We use daily compounded returns for each index, calculated using the first logarithmic differences of their closing prices, as shown below:

$$R_{i,t} = \log(\frac{p_{i,t}}{p_{i,t-1}}) \quad (1)$$

where $R_{i,t}$ is the return for index i on day t; $p_{i,t}$ is the closing value of index i on day t; and $p_{i,t-1}$ is the closing value of index i on day $t\text{-}1$.

Table 1 presents a series of descriptive statistics on the five indices' time series used in this study. As the evidence from the table suggests, the mean and median values of the returns are broadly consistent and close to zero. In ranking the indices, we first observe that all five indices generate positive mean values, with the Next 150 index producing the highest average return and the OMX Baltic 10 index the smallest. The OMX Nordic 40 index is the riskiest index in terms of the standard deviation of its raw returns; the Next 150, on the other hand, reports the lowest standard deviation of the five indices. The time series of all five indices exhibit significantly negative skewness and are all leptokurtic; this suggests departures from normality, something further confirmed via the significant Jarque-Bera test-statistic values.

3.2 Methodology

3.2.1 Volatility forecasting

Our empirical design hinges upon a two-stage process, since, as mentioned previously we aim at examining volatility dynamics in Euronext/OMX indices in terms of both forecasting and feedback trading. In the first stage we perform a volatility forecasting exercise for our sample indices, before and after the global financial crisis, to identify which model specification gives us the best volatility forecasts based on the measures of forecasting accuracy. The model with the best overall performance is then selected and used in the second stage as a conditional variance specification in the estimation of a feedback trading model. Having estimated the latter, we use it to forecast volatility and then employ measures of volatility accuracy to compare the findings of the first stage with the forecasting result from the feedback model.

Early evidence (Mandelbrot, 1963; Fama, 1965) demonstrated that the empirical distribution of stock returns exhibits significant departures from normality. More specifically, the time series of stock returns appears in most cases to be leptokurtic (its kurtosis is larger than the kurtosis of the normal distribution), exhibit significant skewness (be it positive or negative), while its variance (a proxy for volatility) may not be constant over time and may well exhibit clustering (periods of high volatility followed by relatively tranquil periods). Motivated by the above evidence, we first employ a methodology that hinges upon the well-established volatility forecasting literature dating back to the early works of Engle (1982) and Bollerslev (1986). This line of literature proposed a series of models collectively known as Autoregressive Conditional Heteroscedastic (ARCH) and Generalized Autoregressive Conditional Heteroscedastic (GARCH) models, which aimed at addressing several stylized features of stock return volatility that violate the normality assumption. Such features include volatility clustering, asymmetry and long-memory and we shall now present the models proposed to address them in the first stage of our empirical design.

To begin with, assume that the returns-generating process is given by:

$$R_t = m_t + \varepsilon_t \tag{2}$$

where m_t is the conditional mean process, whose error term can be decomposed as:

$$\varepsilon_t = \sigma_t z_t \tag{3}$$

In equation (3), z_t is an idiosyncratic zero-mean and constant variance noise term, and σ_t is the volatility process to be estimated and forecast, with forecast values denoted σ^2_{t+1}.

To model volatility through a GARCH-framework (Engle, 1982; Bollerslev, 1986) requires joint estimation of the conditional mean model and the variance process. The GARCH model captures the well-known volatility clustering effect, where, according to Mandelbrot (1963) "large changes tend to be followed by large changes of either sign, and small changes tend to be followed by small changes" (Mandelbrot, p. 418), which becomes visible once returns are plotted through time. Assuming ε_t to be normally distributed with zero mean and time-varying conditional variance, σ_t^2, the GARCH(1,1) model is given by:

$$\sigma_{t+1}^2 = \omega + \alpha \varepsilon_t^2 + \beta \sigma_t^2 \tag{4}$$

where all the parameters must satisfy the non-negativity constraints $\omega > 0$ and $\alpha, \beta \geq 0$ while the sum of $\alpha + \beta$ quantifies the persistence of shocks to volatility.

Volatility has also been found to exhibit asymmetric behaviour (it tends to be higher following a large price fall compared to a price rise of the same magnitude). A technique that incorporates asymmetries in the modelling of volatility is the Exponential GARCH (or EGARCH) model introduced by Nelson (1991), which is given by:

$$\log(\sigma_{t+1}^2) = \omega + \psi \left| \frac{\varepsilon_t}{\sigma_t} \right| + \vartheta \frac{\varepsilon_t}{\sigma_t} + \beta \log(\sigma_t^2) \tag{5}$$

ϑ captures the asymmetric impact of news, with negative shocks having a greater impact than positive shocks of equal magnitude if $\vartheta < 0$, while the volatility clustering effect is captured by a significant ψ. The use of logarithmic form allows the parameters to be negative without the conditional variance becoming negative.

Volatility can also exhibit long-memory, with "shocks" in stock returns being capable of persisting for a considerable amount of time; in order to take into account the long-memory effect, the component GARCH (CGARCH) model of Engle and Lee (1999) is used which allows mean reversion to a time-varying trend, q_t. The component model specification is:

$$\sigma_{t+1}^2 = q_{t+1} + \alpha(\varepsilon_t^2 - q_t) + \beta(\sigma_t^2 - q_t) \tag{6}$$

where $q_{t+1} = \omega + \rho q_t + \varphi(\varepsilon_t^2 - \sigma_t^2)$ represents the long-run (or trend) volatility provided $\rho > (\alpha + \beta)$. The forecasting error $(\varepsilon_t^2 - \sigma_t^2)$ serves as the driving force for the time-dependent movement of the trend, and the difference between the conditional variance and its trend $(\sigma_t^2 - q_t^2)$ is the transitory component of the conditional variance.[3]

As previously discussed, the whole sample is divided into two sub periods, the pre (1/1/2003 till 31/8/2007) and post (1/9/2007 till 31/12/2015) European crisis period. Due to data availability,[4] the pre- and post-crisis periods do not contain the same number of observations. The determination of an in-sample period is a necessary step in order to conduct the volatility forecasting exercise, and this is also based on the principle of unequal sub samples. More specifically, for the pre-crisis sub period the in-sample period expands between 1/1/2003 and 31/8/2006, leaving an out-of-sample period of one year (1/9/2006 till 31/8/2007)[5] and for the post-crisis period the in-sample period is between 1/9/2007 and 31/12/2012, leaving an out-of-sample period from 1/1/2013 till 31/8/2015.[6] In order to assess forecast accuracy we consider three generally accepted statistical methods, the mean absolute error (MAE), the root mean squared error (RMSE) and the Mincer-Zarnowitz (1969) regression:

[3] Stationarity is achieved provided $(\alpha+\beta)(1-\rho)+\rho<1$, which in turn requires $\rho<1$ and $(\alpha+\beta)<1$. The transitory component then converges to zero with powers of $\alpha+\beta$, whilst the long-run component converges on q_t with powers of ρ.

[4] We obtained the earliest possible data for all our indices. Data prior to 1/1/2003 were not available for several of our indices; for consistency the start date of our sample is 1/1/2003.

[5] For the pre-crisis period the in-sample (out-of-sample) period contains 1218 (261) daily observations.

[6] For the post-crisis period the in-sample (out-of-sample) period contains 2174 (869) daily observations.

$$MAE = \frac{1}{J}\sum_{t=1}^{J}|\sigma_t^{*2} - \sigma_t^2| \quad (7)$$

$$RMSE = \frac{1}{J}\sum_{t=1}^{J}(\sigma_t^{*2} - \sigma_t^2)^2 \quad (8)$$

$$\sigma_t^{*2} = \alpha + \beta\sigma_t^2 + \varepsilon_t \quad (9)$$

As an alternative to the popular forecast evaluation methods of MAE and RMSE measures of differential between the true volatility and the forecasts, we also use the Mincer-Zarnowitz (1969) regression which projects true volatility on a constant and the various model forecasts. By obtaining the coefficient of determination of the regression we can quantify the degree of similarity between the series of true volatility and the forecasts.[7] The higher the coefficient of determination the closer the forecast series is to true volatility. As a measure of true volatility for all the above forecast evaluation techniques we define true volatility based on the Pagan and Schwert (1990) procedure where true volatility is proxied by the squared error from the conditional mean model for returns estimated over the whole sample.[8]

3.2.2 Feedback trading

To test for feedback trading and its effect over volatility forecasting, we employ the widely popular empirical design proposed by Sentana and Wadhwani (1992), which detects feedback trading through the interaction of return-autocorrelation with volatility. Sentana and Wadhwani (1992) assumed the existence of two trader-types in the marketplace. The first type, rational, utility-maximizing, speculators bear the following demand function:

$$\mathrm{Q_t} = \frac{\mathrm{E_{t-1}(R_t)} - \alpha}{\kappa\sigma_t^2} \quad (10)$$

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[7] Examples of studies where the MZ regression is used as a volatility comparison measure are Andersen and Bollerslev (1998) and Ericsson (2017), amongst others.

[8] Squared returns as a true volatility proxy are known to be a noisy measure of true volatility and often very low R^2 values are reported; see Andersen and Bollerslev (1998).

Bearing in mind that our study is based on market indices, Q in the above equation represents the fraction of shares of the index' constituents-basket held by rational speculators, $E_{t-1}(R_t)$ is the expectation of the return of the index in period *t* as of period *t-1*, α is the risk-free rate, κ is the coefficient of risk aversion and σ_t^2 is the conditional variance of the index at period *t*.

The second type of investors are feedback traders with the following demand function:

$$Y_t = \gamma \; R_{t-1} \tag{11}$$

As equation (11) suggests, feedback traders' demand is based on the returns of the immediately previous period (in our case, day, given the daily frequency of our data). If the feedback coefficient (γ) is positive (negative), then this will be an indication of them engaging in positive (negative) feedback trading.

In equilibrium, rational speculators and feedback traders must hold all shares ($Q_t + Y_t = 1$), hence by setting the sum of equations (10) and (11) equal to one we have:

$$\mathbb{E}_{t-1}(R_t) = \alpha - \gamma R_{t-1} \kappa \sigma_t^2 + \kappa \sigma_t^2 \tag{12}$$

We convert equation (12) in regression form by setting $R_t = E_{t-1}(R_t) + u_t$ and replacing the conditional expected return with the actual one and a stochastic error term:

$$R_t = \alpha - \gamma R_{t-1} \kappa \sigma_t^2 + \kappa \sigma_t^2 + u_t \tag{13}$$

Equation (13) depicts an interactive relationship between volatility, returns and feedback trading. We first observe that the magnitude of the first-order return-autocorrelation is a function of risk, since, given $\gamma R_{t-1} \kappa \sigma_t^2$, the larger the value of σ_t^2, the larger autocorrelation grows. The sign of this autocorrelation, however, depends on the sign of feedback trading, reflected through γ; if γ is positive (negative), then the first-order autocorrelation of returns will be negative (positive). An unclear issue in equation (13), however, is whether the observed first-order autocorrelation is the result of feedback trading or market frictions, such as non-synchronous trading. To disentangle between the two possibilities, Sentana and Wadhwani (1992) re-arranged equation (13) and proposed its following specification:

$$R_t = \alpha + \kappa\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} + u_t \qquad (14)$$

ϕ_0 is the constant part of the first-order return-autocorrelation, capturing the part of the latter due to market frictions, while ϕ_1 denotes the existence of feedback trading. With $\phi_1 = -\kappa\gamma$, a positive (negative) value for ϕ_1 implies the presence of negative (positive) feedback traders.

The estimation of equation (14) requires the identification of its conditional variance (σ_t^2) specification. As mentioned previously, the latter shall be the specification that provides us with the best volatility forecasts in the first stage (i.e. either the GARCH (1,1), EGARCH (1,1) or CGARCH). Once this has been identified, we shall estimate the Sentana and Wadhwani (1992) model, assess the dynamics of volatility and feedback trading and then use it again to forecast volatility, in order to compare its forecasting performance with the findings of the first stage (i.e. from the GARCH-specification without the feedback trading model as its conditional mean) before and after the outbreak of the global financial crisis.

4. Results-discussion

Tables 2 and 3 present the pre and post crisis results for the forecasting exercise, where we compare the forecasting performance of the five cross border indices using the three GARCH-type models, namely the GARCH (1,1), EGARCH (1,1) and CGARCH (capturing respectively the clustering, asymmetry and long memory effects as previously described). The EGARCH (1,1) produces for all cases the smallest MAE's and RMSE's pre crisis for the five indices (there is one exception for the OMX Baltic 10 index where the GARCH model and EGARCH models give the same RMSE which is jointly the smallest value), suggesting that the specification accounting for asymmetry is the overall best-performing model during that period. Similar results are reported for the post-crisis period, where the EGARCH (1,1) specification continues to generate the smallest MAE and RMSE values (with one exception for the OMX Baltic 10 index where the smallest RMSE is obtained by the GARCH model). Overall the exponential GARCH model outperforms all other models[9], in line with the results reported in similar comparison exercises in the academic literature (Hansen and Lunde, 2005; Bao et al., 2006; Brownlees et al., 2012; Kambouroudis and McMillan, 2015).[10]

To assess the robustness of our findings, we use the MZ regression where we regress true volatility (as defined by Pagan and Schwert, 1990) on a constant and the volatility forecast generated using each of the GARCH-type models. Results are reported in Tables 4 and 5. The EGARCH (1,1) provides us with the highest coefficients of determination for all indices and for both our subsamples, thereby confirming our previous findings on the overall dominance of the EGARCH (1,1) model in our volatility forecasting exercise. It is worth noting that, as previously discussed, the financial crisis appears to have impacted on the accuracy of the volatility forecasts as we can see from the coefficients of determination of the MZ regressions also appearing to be higher before the financial crisis than after the crisis. Overall, our results confirm earlier research (Brownlees et al. 2012; Kambouroudis and McMillan, 2015) denoting that models that provide the most accurate forecasts during periods of financial stability also appear to provide the best forecasts during financial crises.

We now turn to assess whether the forecasting accuracy of the EGARCH (1,1) holds when accounting for the effect of feedback trading. Table 6 presents the maximum likelihood estimates from equation (14) with the EGARCH (1,1) model as its conditional variance

[9] To test for the robustness of our results, smaller sub-samples restrictive to the European Crisis were also considered (2009-2013; 2010-2014) in which again the asymmetric EGARCH model performed the best.

[10] We also forecast volatility on the premises of the TGARCH model (Glosten et al., 1993) as a second representative asymmetric model. Again here, EGARCH outperformed TGARCH in terms of forecast accuracy; results are not reported here for brevity reasons and are available from the authors upon request.

specification before and after the global financial crisis' outbreak. As the results in the table indicate, all five indices' volatility is typified by asymmetry (ϑ is significantly negative in almost all cases[11]) and persistence (ψ is always found to be significantly positive), thus confirming that cross-border exchanges' indices bear similar volatility-features to those known from national market ones. The coefficient ϕ_0 presents us with significantly positive values for the Euronext 100 (post crisis), the Next 150 (pre and post crisis), the OMX Nordic 40 (pre crisis) and the OMX Baltic 10 (pre and post crisis) indices. This is a clear indication of cross-border exchanges' indices entailing significantly positive first-order autocorrelation, which suggests the presence of predictability in their return-dynamics. This is rather interesting, considering the fact that one would not expect such sophisticated market structures to accommodate these inefficiencies, yet also serves to illustrate the similarities between cross-border markets' return-dynamics to those of other major markets across the world whose main indices have also been found to entail such patterns[12]. Evidence of feedback trading is detected for all indices, with the exception of the Euronext 100. Indeed, as the ϕ_1-estimates suggest, there exists significant positive feedback trading in the Next 150 (pre and post crisis), the OMX Nordic All Shares (pre crisis), the OMX Nordic 40 (pre crisis) and the OMX Baltic 10 (pre and post crisis) indices. The fact that the significance of positive feedback trading is concentrated mainly prior to the crisis' outbreak can be attributed to the fact that financial crises constitute major turning points, associated with the revelation of groundbreaking fundamentals. It is plausible that positive feedback traders were significant in presence pre crisis as a result of many investors following the prevalent consensus during that period; following the crisis' outbreak, it is likely that their trend-chasing became less useful, as the newly revealed fundamentals and the overall uncertainty of international markets prompted them to break away

[11] The only exceptions here are the OMX Baltic 10 index results pre and post crisis, where ϑ is insignificant.
[12] See, for example, the evidence on this in the review paper on feedback trading by Koutmos (2014).

from the pre crisis consensus (and the trends they were trading on) and rely more on fundamentals. Overall, our results suggest that cross-border exchanges exhibit significant predictability and positive feedback trading in their return-dynamics; this is a very interesting finding, considering that it is reported here for the first time in the literature and we now turn to gauge whether accounting for the above confers any effect over the forecasting accuracy of our best-performing model (the EGARCH model).

In Tables 7 and 8 we present the results from the forecasting exercise based on the EGARCH-specification (we also include, for comparison purposes, the rest of the GARCH models) with the Sentana and Wadhwani (1992) model as its conditional mean. Results indicate that, based on the MAE and RMSE figures, the EGARCH model is again the winning one with a very small number of exceptions (pre-crisis the GARCH model twice gives the smallest RMSE and post-crisis the CGARCH for the Euronext 100 index gives the smallest MAE and RMSE) Results from the MZ regression (Tables 9 and 10) also give us the same overall conclusion, namely that the GARCH model capturing the asymmetry effect is the best one, suggesting that the accuracy of the EGARCH (1,1) model is not affected, both pre and post crisis, controlling for the presence of feedback traders.

Overall, our study has denoted that cross-border exchanges bear considerable similarities in their volatility dynamics compared to national markets. As our estimates indicate, cross-borders markets' indices are characterized by volatility clustering, asymmetry and persistence, while most of them are also found to accommodate significant positive feedback trading. Established forecasting models can accurately predict their volatility, the latter being the case even after controlling for the presence of feedback traders, with these results appearing robust both before and after the outbreak of the ongoing global financial crisis.

5. Conclusion

The present study investigates volatility forecasting in the context of the main indices of the Euronext and the OMX, the world's two oldest cross-border exchange groups. Using a series of GARCH-family models (GARCH 1,1; EGARCH 1,1; CGARCH), we find the EGARCH (1,1) to be the best-performing one. The choice of volatility forecasting models is based on their popularity within the academic literature and their ability to capture specific volatility characteristics found in datasets. More specifically, our selection of models aimed at capturing the clustering, asymmetry and long memory effects by respectively employing the first generation of GARCH models, the GARCH 1,1 model, followed by the second generation of GARCH models, the EGARCH model, and finally the third generation of GARCH models, the CGARCH model. The EGARCH (1,1) also retains its forecasting accuracy when accounting for the presence of feedback traders in return-dynamics and the outbreak of the global financial crisis. Overall, volatility in cross-border indices presents us with ARCH-effects akin to those (clustering; asymmetry; long memory) detected in national market indices by earlier studies. Combining this with the fact that we report results confirming for the first time the presence of feedback trading in cross-border markets (most of the indices are found to accommodate significant positive feedback trading in several of the tests performed, especially pre crisis), our study contributes substantially to the literature, considering the fact that volatility in cross-border exchanges has received little research attention in terms of both its dynamics and forecasting, despite the proliferation of cross-border alliances among stock markets internationally.

Our study contains important implications for both the investment community as well as regulators. As far as investors are concerned, the results reported in our work suggest that extant risk-metrics' models established over the decades following research on national markets' indices produce satisfactory forecasts in the context of cross-border markets. This is of interest, particularly to those investing in cross-border exchanges (i.e. investors with a global investment outlook), as it helps inform their risk-management. What is more, the presence of significant positive feedback trading in most of the indices examined denotes that cross-border exchanges' indices could generate return-patterns capable of being profitably exploited via *ad hoc* trading strategies. This is a very real possibility, considering earlier studies illustrating how rational speculators can take advantage of the feedback trading of their noise counterparts by either front-running it (De Long et al., 1990) or detecting deviations from fundamentals due to it (Farmer, 2002; Farmer and Joshi, 2002).

From a regulatory perspective, the presence of feedback traders in the Euronext/OMX indices is of key interest, in view of research (Kim and Wei, 2002a, 2002b) linking feedback traders with destabilizing phenomena in capital markets. To mitigate the latter, regulatory authorities of cross-border exchanges could consider expanding the range of sophisticated products linked to their exchanges' indices (i.e. offer a wider array of index-linked products), given earlier evidence (Antoniou et al., 2005) that such products tend to attract rational investors and lead to a reduction in feedback trading at the spot market level.

Table 1. Descriptive statistics for returns of all indices

Returns of Index/Statistic	Mean	Median	Maximum	Minimum	St. Dev	Skewness	Kurtosis	JB
Euronext 100	0.000144	0.000694	0.103216	-0.089511	0.012955	-0.02492	6.705419	2022.40
Next 150	0.000388	0.001217	0.085071	-0.080796	0.011160	-0.46174	4.7654	1059.40
OMX Baltic10	0.000054	0.000583	0.107585	-0.099735	0.011255	-0.50114	13.5889	4562.70
OMX Nordic40	0.000271	0.000782	0.093758	-0.087187	0.014361	-0.08213	4.5239	1167.50
OMX Nordic All Share	0.000320	0.000868	0.071915	-0.079600	0.011455	-0.20287	4.4667	1114.40

Note: Table 1 contains descriptive statistics on the mean, median, maximum value, minimum value, standard deviation, skewness, kurtosis and the Jarque-Bera test-statistic of the daily returns of the five sample indices. All returns are calculated as the first logarithmic differences of daily closing prices; sample window is 1/1/2003 – 31/12/2015.

Table 2. Results of forecast accuracy during the period 1/1/2003 - 31/8/2007

Model	GARCH		EGARCH		CGARCH	
Index/Metric	MAE	RMSE	MAE	RMSE	MAE	RMSE
Euronext 100	0.000069	0.000125	0.000066	0.000122	0.000069	0.000126
Next 150	0.000061	0.000159	0.000061	0.000156	0.000061	0.000158
OMX Baltic10	0.000118	0.000299	0.000109	0.000299	0.000117	0.000300
OMX Nordic40	0.000118	0.000202	0.000113	0.000197	0.000119	0.000202
OMX Nordic All Share	0.000092	0.000179	0.000089	0.000175	0.000093	0.000179

Note: Table 2 contains the forecasting results from our five sample indices for the pre crisis period (1/1/2003 – 31/8/2007); the figures reported here are those from the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Table 3. Results of forecast accuracy during the period 1/9/2007 - 31/12/2015

Model	GARCH		EGARCH		CGARCH	
Index/Metric	MAE	RMSE	MAE	RMSE	MAE	RMSE
Euronext 100	0.000099	0.000150	0.000090	0.000143	0.000100	0.000150
Next 150	0.000082	0.000114	0.000079	0.000110	0.000083	0.000114
OMX Baltic10	0.000073	0.000342	0.000097	0.000554	0.000069	0.000348
OMX Nordic40	0.000098	0.000148	0.000092	0.000143	0.000099	0.000147
OMX Nordic All Share	0.000085	0.000131	0.000079	0.000128	0.000086	0.000131

Note: Table 3 contains the forecasting results from our five sample indices for the post crisis period (1/9/2007 – 31/12/2015); the figures reported here are those from the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Table 4. Results for the forecasting performance of indices using Mincer Zarnowitz (MZ) regression during the period 1/1/2003 - 31/8/2007

Index Model / R^2	Euronext 100	Next 150	OMX Baltic 10	OMX Nordic 40	OMX Nordic ALL Share
GARCH (1,1)	0.153618	0.070102	0.088236	0.103889	0.105920
EGARCH	0.204804	0.096398	0.095734	0.150783	0.149663
CGARCH	0.146609	0.076732	0.083619	0.097696	0.106962

Note: Table 4 contains the coefficient of determination (R^2) from the MZ regression, generated by regressing true volatility (proxied as the squared returns as in Pagan and Schwert 1990) on a constant and volatility forecast (estimated using the GARCH, EGARCH and CGARCH models) for each index for the pre crisis period.

Table 5. Results for the forecasting performance of indices using Mincer Zarnowitz (MZ) regression during the period 1/9/2007 – 31/12/2015

Index Model / R^2	Euronext 100	Next 150	OMX Baltic 10	OMX Nordic 40	OMX Nordic ALL Share
GARCH (1,1)	0.040206	0.026142	0.000048	0.021230	0.024882
EGARCH	0.095199	0.079659	0.000091	0.055208	0.058641
CGARCH	0.046628	0.034156	0.000011	0.026185	0.033694

Note: Table 5 contains the coefficient of determination (R^2) from the MZ regression, generated by regressing true volatility (proxied as the squared returns as in Pagan and Schwert, 1990) on a constant and volatility forecast (estimated using the GARCH, EGARCH and CGARCH models) for each index for the post crisis period.

Table 6 Maximum likelihood estimates from the Sentana and Wadhwani (1992) model.

Conditional Mean Equation: $R_t = \alpha + \kappa\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2) R_{t-1} + u_t$

Conditional Variance Specification: $\log(\sigma_t^2) = \omega + \psi\left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \vartheta\frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta\log(\sigma_{t-1}^2)$

	EURONEXT100		NEXT150		OMX NORDIC ALL SHARES		OMX NORDIC 40		OMX BALTIC 10	
	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak	Pre-crisis outbreak	Post-crisis outbreak
α	-0.0024	-0.0465	0.1004	0.0262	0.0405	0.0160	-0.0022	-0.0196	0.0971	0.0459
	(0.9076)	(0.0000)	(0.0001)	(0.4799)	(0.1731)	(0.6504)	(0.9651)	(0.5211)	(0.0010)	(0.0000)
κ	0.0701	0.0277	-0.0550	-0.0059	0.0339	0.0107	0.0563	0.0207	-0.0470	0.0008
	(0.0000)	(0.0567)	(0.3248)	(0.7666)	(0.0000)	(0.6520)	(0.2988)	(0.2487)	(0.4552)	(0.2939)
ϕ_0	-0.0221	0.0166	0.2605	0.1442	0.1365	0.0326	0.0978	0.0050	0.3311	0.2579
	(0.5575)	(0.0039)	(0.0000)	(0.0000)	(0.3717)	(0.2942)	(0.0334)	(0.8216)	(0.0000)	(0.0000)
ϕ_1	-0.0094	-0.0084	-0.1172	-0.0184	-0.0928	-0.0048	-0.0660	-0.0057	-0.1143	-0.0079
	(0.7307)	(0.1010)	(0.0008)	(0.0001)	(0.0112)	(0.5553)	(0.0307)	(0.3156)	(0.0072)	(0.0000)
ω	-0.0102	0.0136	-0.0233	0.0093	-0.0077	0.0083	0.0029	0.0128	-0.0128	0.0515
	(0.0765)	(0.0000)	(0.0647)	(0.1738)	(0.3157)	(0.0278)	(0.5077)	(0.0029)	(0.5170)	(0.0007)
ψ	0.0943	0.1135	0.2303	0.1561	0.1231	0.1110	0.0917	0.1027	0.2461	0.3391
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0002)	(0.0000)	(0.0011)	(0.0000)	(0.0000)	(0.0000)
ϑ	-0.1313	-0.1639	-0.0989	-0.1389	-0.1164	-0.1028	-0.1017	-0.1031	0.0004	0.0626
	(0.0000)	(0.0000)	(0.0006)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.9915)	(0.2464)
β	0.9699	0.9662	0.9554	0.9597	0.9585	0.9811	0.9711	0.9813	0.9637	0.9705
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Parentheses include p-values.

Table 7. Results of forecast accuracy during the period 1/1/2003 - 31/8/2007

Model	GARCH		EGARCH		CGARCH	
Index/Metric	MAE	RMSE	MAE	RMSE	MAE	RMSE
Euronext 100	0.000398	0.000525	0.000345	0.000402	0.000380	0.000475
Next 150	0.001520	0.001923	0.001449	0.001591	0.001456	0.001802
OMX Baltic10	0.002213	0.003838	0.002203	0.004041	0.002224	0.004293
OMX Nordic40	0.000532	0.000712	0.000521	0.000747	0.000618	0.000842
OMX Nordic All Share	0.000864	0.001146	0.000836	0.001134	0.000872	0.001162

Note: Table x contains the forecasting results from our five sample indices for the pre crisis period (1/1/2003 – 31/8/2007); the figures reported here are those from the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Table 8. Results of forecast accuracy during the period 1/9/2007 - 31/12/2015

Model	GARCH		EGARCH		CGARCH	
Index/Metric	MAE	RMSE	MAE	RMSE	MAE	RMSE
Euronext 100	0.000312	0.000372	0.000322	0.000371	0.000227	0.000320
Next 150	0.000594	0.000777	0.000459	0.000775	0.000635	0.000817
OMX Baltic10	0.001081	0.001570	0.001063	0.001399	0.001205	0.001675
OMX Nordic40	0.000362	0.000481	0.000265	0.000469	0.000353	0.000469
OMX Nordic All Share	0.000133	0.000193	0.000133	0.000184	0.000168	0.000213

Note: Table x contains the forecasting results from our five sample indices for the pre crisis period (1/9/2007 – 31/12/2015); the figures reported here are those from the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE).

Table 9. Results for the forecasting performance of indices using Mincer Zarnowitz (MZ) regression during the period 1/1/2003 - 31/8/2007

Index Model / R^2	Euronext 100	Next 150	OMX Baltic 10	OMX Nordic 40	OMX Nordic ALL Share
GARCH (1,1)	0.093025	0.001456	0.000602	0.052923	0.022239
EGARCH	0.106711	0.016352	0.001532	0.062977	0.028658
CGARCH	0.093999	0.015236	0.004881	0.040937	0.025127

Note: Table x contains the coefficient of determination (R^2) from the MZ regression, generated by regressing true volatility (proxied as the squared returns as in Pagan and Schwert 1990) on a constant and volatility forecast (estimated using the GARCH, EGARCH and CGARCH models) for each index for the pre crisis period.

Table 10. Results for the forecasting performance of indices using Mincer Zarnowitz (MZ) regression during the period 1/9/2007 - 31/12/2015

Index Model / R^2	Euronext 100	Next 150	OMX Baltic 10	OMX Nordic 40	OMX Nordic ALL Share
GARCH (1,1)	0.005823	0.032694	0.000423	0.004690	0.000539
EGARCH	0.009995	0.036137	0.000617	0.013684	0.023473
CGARCH	0.000765	0.035563	0.000548	0.003659	0.003153

Note: Table x contains the coefficient of determination (R^2) from the MZ regression, generated by regressing true volatility (proxied as the squared returns as in Pagan and Schwert 1990) on a constant and volatility forecast (estimated using the GARCH, EGARCH and CGARCH models) for each index for the pre crisis period.

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