Investigation of the Lottery-like Effect and the Idiosyncratic Volatility Puzzle in the UK Stock Market.

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ABSTRACT

This work provides an empirical investigation on the return predictability and the informational efficiency of the UK stock market. Specifically, the work examines the predictive power of risk-related anomalies for the returns of UK stocks. Through three overlapped empirical studies, this work investigates the ability of the idiosyncratic volatility (IVOL) and other speculative features (i.e., lottery-like features) to predict the future stock returns in the UK market. Also, the explanations and many issues related to this predictability are investigated. The first study examines the ability of the lottery-like features to predict the future return across UK stocks. The analysis reveals convincing evidence on the existence of the lottery effect and the associated IVOL puzzle among the stocks in the UK market. Despite being risky (e.g., have high beta), on average, the stocks with speculative features, e.g., high IVOL and low price, underperform the stocks with non-speculative features, e.g., low IVOL and high price. The findings suggest a possible role for the arbitrage frictions and the left-tail risk in generating the puzzling performance reported for the lottery-like stocks. In addition to the IVOL puzzle, the second study examines the ability of the left-tail risk to predict the future returns in the UK market and the role of the underreaction behaviour (e.g., the anchoring bias) in explaining the return predictability in the UK market. The results outlined in the third chapter show that both the idiosyncratic volatility risk and the left-tail risk inversely predict the six-month ahead returns across the stocks. Moreover, the portfolio analysis and the Fama-MacBeth procedures indicate the key role of the underreaction behaviour in generating a large part of the reported persistent underperformance of the stocks with high IVOL and left-tail. In addition to the anchoring bias (proxied by the 52-week high ratio). The third empirical work investigates the incremental power of the firm's fundamental-based expected profitability to explain the negative future return associated with the high-IVOL stocks (i.e., IVOL puzzle). The results reveal that the 52-week high ratio (the anchoring bias) and the expected profitability are both independently important in determining the puzzling persistent underperformance of the stocks with high IVOL. The IVOL puzzle is largely generated by the investors' underreaction to the bad news revealed by the market and the firm’s fundamentals. However, the overreaction behavior of the lottery-seeking investors is important to explain the lower future returns for the high IVOL stocks. In sum, the IVOL puzzle is a behavioural phenomenon generated by the irrational underreaction and overreaction behaviour that is magnified by the limit to arbitrage and the investors' emotion.

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TABLE OF CONTENTS

LIST OF TABLES

CHAPTER ONE

Introduction to Asset Pricing in Finance

1.1. Asset Pricing: Theoretical Background and Empirical Evidence.

1.1.1. Theoretical Background and Early Empirical tests.

Understanding the movements in the prices of financial assets is a pivotal step that shapes many financial applications. Portfolio management, risk management, capital structure, utility pricing, and other aspects of finance all depend on the nature of the price movements. Consequently, an enormous part of the financial research has been spent to theorise and inspect the nature of such movement. Despite the intensive efforts that have been spent by financial researcher over the past decades, market behaviour is still an ongoing topic with heated debate over the nature of stock price movements and the forces that stand behind these movements.

In 1959, Markowitz introduced the first algebraic model of the investment in the financial market. In this model, the investors are risk-averse who care only about the first two moments of the returns' distributions, namely, the mean and variance. According to this framework, the investor allocates his/her fund among the available assets to build "mean-variance-efficient" portfolios, in the sense that the portfolios 1) maximise the expected returns for a given level of variance and 2) minimise the variance for a given level of expected returns.

Markowitz's work paved the way for the development of the equilibrium theory of asset pricing in the capital market. Building on Markowitz's mean-variance model, Sharpe (1964), Lintner (1965), and Mossin (1966), independently, developed the so-called capital asset pricing model (the CAPM). They add two important assumptions to simplify the mean-variance model into a linear mathematical formula that describes the expected return as a function of risk. They assume that the investors have identical beliefs regarding the joint distribution of asset returns and that they can, equally, borrow and lend funds at a risk-free rate. This framework identifies the portfolio that is mean-variance efficient. The investors hold the portfolio that diversifies all the unsystematic (idiosyncratic) variance. Thus, according to the CAPM, the mean-variance-efficient portfolio is the value-weighted market portfolio of the available risky assets. Consequently, the expected returns for the risk-averse investors under the CAPM is defined by the following testable linear formula,

$$R_{i,t} - rf_t = rf_t + \beta_i (R_{m,t} - rf_t) \qquad (1)$$

$$\beta_i = cov(R_i, R_m)/\sigma 2(R_m) \qquad (2)$$

Where $R_{i,t}$ is the return on the risky asset i at time t, rf_t is the risk-free rate, $R_{m,t}$ is the return on the market portfolio, and β_i, the market beta of asset i, is the covariance of asset i return with the market return divided by the variance of the market return. The market beta is a measure of the sensitivity of asset returns to variation in market return. According to equation (1), any risky asset should generate a return equal to the risk-free rate (i.e. security with a beta of zero) and risk compensation (risk premium) that equals its beta times the risk premium for the market portfolio, which is the expected market return, Rm, minus rf_t. Under this logic, the CAPM assumes that the investors can diversify all the unsystematic risk, the variation in asset's return that is uncorrelated with the variation in market return. Therefore, they should only be compensated for bearing the systematic risk. This compensation (risk premium) is proportional to the asset's beta, the amount of risk the asset i contributes to the market portfolio.

The theoretical foundations underlying the standard mean-variance theory imply that the market is informationally efficient. The efficient market hypothesis states that the asset prices reflect all available information (Fama 1965). As the current price reflects all available information, this price is the best representation of the expected price and the future movement is random. Therefore, the price movement follows the random-walk distribution. One important implication of this setting is the inability to build an investment strategy in a way that generates an abnormal return over the risk premium implied by the assumed asset pricing model. Testing the validity of the efficient market hypothesis depends on the nature of the underlying equilibrium asset pricing model (Fama 2014). Intuitively, the role of this model is to specify the characteristics of expected returns in a market equilibrium.

The development of CAPM and the testable statement shown in equation (1) offer a great opportunity to test the validity of the efficient market hypothesis. Therefore, if the single linear relationship, described by equation (1), is empirically proved to be valid, the market is informationally efficient and the future changes in the prices of risky assets are unpredictable

Both the efficient market hypothesis and the CAPM represent the background for many functional decisions in finance. Primarily, the model offers explicit measures of the cost of capital for the purpose of capital structure decisions and asset valuation.

Regardless of the appealing theoretical background behind the CAPM, the ongoing empirical tests of the model posit a challenge to its validity. For instance, the empirical evidence shows that the investors are neither risk-averse nor is the expected return unpredictable.

1.1.2. Anomalies and Informational Efficiency of the Stock Market.

Motivated by the important role played by the CAPM in many financial tasks, the empirical test of the model takes a large part of the research efforts in finance. These efforts have been designed to test the validity of the restrictive assumptions that underlie both the mean-variance theory and the CAPM. Explicitly, as shown in equation (1) the CAPM states that the asset expected return can simply be decomposed into two components. The first component is an intercept that equals the risk-free rate whereas the second component is risk premium which is defined as the asset's beta multiplied by the average risk premium of the market. Early tests of the CAPM had focused on testing this structure.

Unfortunately, the early tests rejected the CAPM predictions regarding the financial market behaviour. The evidence from the U.S. stock market shows that the beta is positively related to average return, but the relationship is too "flat". Cross-sectionally, the estimated intercept is higher than the average risk-free rate which is proxied by the return on a 1-month Treasury Bill, also, the coefficient on estimated beta is less than the average excess return on the market portfolio (Fama, 2014). These findings are reported in studies of Douglas (1968), Black, Jensen, and Scholes (1972), Blume and Friend (1973), and Fama and MacBeth (1973). Besides, time-series tests in Friend and Blume (1970) and Black et al. (1972) confirmed the "flat" relationship between beta and the average return. Also, the time-series regressions of excess asset returns on the excess market return produce a negative intercept for the assets with high beta and positive intercepts for the assets with low beta.

More recently, a growing body of research has documented the ability of variables other than beta to explain a large part of the variation in the expected return in the financial markets. Since the late 1970s, many of these return predictors have been uncovered by the ongoing research efforts.

Scaled accounting ratios have been found to have marginal explanatory power of the expected return over that by beta. Basu (1977) finds that stocks with higher earnings-price ratios (E/P) tend to generate higher future returns than stocks with lower E/P ratios. Accordingly, he concludes that the market model (i.e. CAPM) and the efficient market hypothesis are invalid. Also, Statman (1980) and Rosenberg et al. (1985) document the value effect: when the stocks are sorted on book-to-market equity ratios (B/M), on average, the stocks with higher B/M tend to generate higher future return than would be warranted by their CAPM betas.

Another important violation of the efficient market hypothesis was documented by Banz (1981) who finds stock market capitalisation negatively predicts future returns across the stocks in the U.S. market. Particularly, he finds that stocks with a lower market capitalisation tend to outperform stocks with a higher market capitalisation in terms of future return. This nonstandard pricing behaviour is widely known as the size effect.

These results suggest that beta, as the only returns driver under the CAPM framework, is insufficient to fully explain the variation in the asset returns. Furthermore, it seems that the investors are inappropriately responding to the value-relevant information, therefore the above evidence imposes a challenge to the efficient market hypothesis. Also, achieving abnormal profits by exploiting the information in the currently available information (e.g. B/M) indicates that the arbitraging trades such as short selling are hindered by the trading cost in the market.

The documented failure of the single-factor framework, assumed under the CAPM, indirectly supposes an extended model with a multi-factor structure may underlie the return generating process in the financial market. Extending the CAPM, multi-factor pricing models such as the intertemporal capital asset pricing model (ICAPM) of Merton (1973) and the arbitrage pricing theory (APT) of Ross (1976) could offer a rationale for the evidence of return predictability by variables other than beta.

Merton (1973) extends the static equilibria condition of CAPM to a dynamic investment environment where the investors face stochastic investment opportunities set over time. The investors' goal is to maximise the utility of their lifetime consumption, so expectations about final wealth beyond the end of single-period analysis are affected by information other than the market-factor (i.e. Beta). Merton’s analysis shows that, in addition to the market factor (i.e. beta), the investors also care about any factors that affect the future investment opportunity set (i.e. state variables). According to this dynamic setting, holding of the market portfolio is not enough to diversify all risk regarding the final consumption utility, therefore the investors also build a hedge fund(s) to offset the effect of unfavourable shift(s) in the investment opportunity set. Thus, the expected return is a linear function of the market return and return on assets that mimic the innovation in state variables.

Ross (1976) simply derives a multi-factor pricing model, the so-called arbitrage pricing theory (APT). APT is a more generalizable theory than CAPM, the investor is risk-averse with monotone preferences and no need to be a quadratic utility maximiser. In addition to relaxing the hypothetical form of utility, APT doesn't require the data to obey normal distribution. As a result of relaxing these two restrictive assumptions, the APT generalises the pricing function to embrace more than one risk factor, so it is more comprehensive in describing the risk-return relationship in the capital market.

Although the ICAPM and the APT generalise the unrealistic single factor structure to a more generalised multi-factor framework, they are silent regarding the number and the identity of these factors. Practically, the empirical evidence on the return predictors could help identify such factors. For example, the size effect and the value effect are possibly related to priced risk factors. Indeed, Fama and French (1993) add two factors to the market factor: the size factor and the value factor. They argue that stocks with the same level of market capitalisation and B/M covary together and their payoffs are compensation for a common state variable. The higher average abnormal returns on small stocks and high B/M stocks may represent unidentified state variables. Therefore, the abnormal returns on small stocks and high B/M stocks may reflect undiversifiable risks in returns that are not captured by the market return, and thereby priced separately from market betas.

Contradicting the market efficiency, numerous empirical works show that patterns in the future returns are predictable by the past returns. In an influential work, DeBondt and Thaler (1985) demonstrate the ability of the cumulative returns over the past 3 years to inversely predict the future returns up to the next 36 months. They argue that this predictable reversal pattern in the stock prices is a manifestation of the investor's improper response to the available information. Another important predictable pattern is the continuation in stock returns over the midterm horizon. Jagadeesh and Titman (1993) document a midterm momentum in return, cumulative return over the past 12 months positively predicts the returns over 3- to 12-month holding periods. They claim that this predictable continuation pattern is an indication of the investors' delayed reaction (underreaction) to the value-relevant information. Accordingly, they state the need for a more sophisticated model of asset pricing.

In the sense of Fama and French (1993) approach, Carhart (1997) introduced a four-factor model by adding a factor that mimics the momentum trend to the Fama and French (1993) model.

Combined with the failure of the rational mean-variance paradigm, the evidence on predictable reversal and continuation pattern in asset returns encourage the shift to the behavioural pricing model. Under the behavioural model, the investor's decision, hence their response to information, is cognitively biased, and consequently, they systematically produce erroneous expectations regarding the stocks' prospect (Barberis and Thaler 2003). Also, to explain the persistent anomalous pricing phenomena, this model assumes restricted limited arbitrage activity. This approach derives its logic from the evidence cited by psychology studies regarding the investors' cognitive biases (see, Tversky and Kahneman 1974). For instance, limited attention and other underreaction-related behaviour can plausibly explain the momentum anomaly documented by Jagadeesh and Titman (1993). While investor's overconfidence may drive the reversal in the stock returns like one observed in DeBondt and Thaler (1985).

The behavioural explanations have attracted the attention of researchers in finance and many attempts have been made to produce a unified behavioural finance theory. A notable example of these attempts is the behavioural models by Daniel et al. (1998), Barberis et al. (1998), and Hong and Stein (1999). Developing these models, the next natural step is to test the ability of these models to explain the documented challenges to the rational model. Responding to this requirement, a growing amount of studies have confirmed the ability of the channels suggested by the behavioural pricing theory (Hong et al. 2000, George and Hwang 2004, Grinblatt and Han 2005, and among others).

Nevertheless, the evidence in favour of behavioural theory is convincing, they are scattered, it is difficult to list the documented behavioural pricing anomalies under one of these models. More importantly, none of these behavioural models so far introduced specify a parsimonious testable function like the CAPM, e.g., there is no consensus on the kind of behaviour that controls the financial markets and there are no well-identified proxies for the behavioural channels described under the suggested models. Therefore, more efforts are needed to understand the behavioural biases in the actions of traders in the financial market. Additional examinations may help to theorise a more realistic model of investors' behaviour.

1.1.3. Risk-seeking Behaviour and High-volatility Anomaly.

Unsurprisingly, adding these factors enhance the explanatory power of the CAPM. However, even with the three factors in Fama and French (1993) pricing model, the information inefficiency remains an evident challenge to the rational theory of behaviour in the financial market. Like the CAPM, the multi-factor model of Fama and French (1993) fails to explain the many anomalous pricing behaviours within the stock markets. Since the introduction of this model, empirical studies have documented many predictable patterns that challenge the risk structure assumed by this model for the stock market.

Recently, empirical studies of the investor's behaviour uncover evidence that contradicts not only the informational efficiency hypothesis but also the risk-averse behaviour. The findings indicate that some types of investors prefer stocks with high risk-related characteristics more than stocks with low risk.

In a seminal paper, Ang et al. (2006) document a puzzling negative relationship between the idiosyncratic risk and the future returns across the stocks. Surprisingly, they show that stocks with high idiosyncratic volatility (measured relative to the Fama and French (1993) model) underperform the stocks with low idiosyncratic volatility. Also, a similar puzzling inverse relationship is found between the risky lottery-like stocks (e.g., Bali et al. 2011) and stocks with high left-tail risk (e.g., Atilgan et al. 2020).

For the mean-variance advocate, such a negative relationship is in contradiction to all expectations. Pricing of the idiosyncratic (unsystematic) returns volatility by the investors leads to the rejection of the restrictive fully diversification hypothesis and the associated investors' ability to eliminate the unsystematic risk. Therefore, this part of the total volatility is relevant to the firm value. The more puzzling part of the empirical findings in Ang et al. (2006) is the negative sign of the relationship between the future returns and the idiosyncratic volatility. This inverse relationship contradicts not only the standard mean-variance model but also the later amendment to this theory. For instance, Merton (1987) proposes an equilibrium pricing model that provides a rationale for the pricing of the idiosyncratic risk by the investors in the financial market. In his theory, Merton assumes that the investors face an environment with incomplete information where they possess information only about a subset of the available securities. Subsequently, they hold sub-optimally diversified portfolios hence the idiosyncratic risk is positively related to returns.

The puzzling results in Ang et al. (2006) are related to other pricing anomalies reported later by the empirical studies in the stock market. Notably, Bali et al. (2011) find that the past maximum daily returns inversely predict the subsequent month's returns across the stocks. They argue that the investors are attracted to stocks with option-like features. This lottery-preference behaviour leads the investors to overvalue stocks with extreme return observations. Kumar and Han (2014) support the link between the puzzling negative risk-return relationship and speculative retail trading.

The speculative behaviour of the investors is one of several explanations that have been suggested by prior studies for the puzzling inverse risk-return relationship. Microstructure biases represented by short-term reversal and bid-ask bounce are found to be responsible for this puzzling poor performance of stocks with high idiosyncratic volatility (Huang et al. 2010, and Han and Lesmond 2011). While Stambaugh (2015) suggests that the reported puzzling underperformance of the stocks with high idiosyncratic volatility is a manifestation of the persistent overpricing of difficult-to-arbitrage stocks. An et al. (2019) find a link between the disposition effect and the negative returns of the stocks with high lottery-like features (e.g. high idiosyncratic volatility). Chen and Petkova (2012), Barinov (2018), and Barinov and Chabakauri (2019) provide a risk-based explanation in the sense of the ICAPM.

Whatever is the reason behind the puzzling behaviour of the speculative stocks, this anomaly poses a formidable challenge to the standard mean-variance model (i.e. CAPM) and the information efficiency hypothesis. Driven by its important implications to asset pricing, the debate over the origins and the nature of the puzzling behaviour of the stocks with high idiosyncratic volatility and the other lottery-like features has occupied a large part of the literature.

1.2. Organisation of this Work and its Main Findings.

The puzzling inverse risk-return relation and the associated pricing anomalies (e.g. the IVOL puzzle and the lottery-like effect) pose a challenge to the variant applications of the standard asset pricing theory and suggest many important implications to a different important topic in finance. For instance, considering the market frictions, the investors could generate an investment strategy with abnormal risk-adjusted returns. Generally, analysing the nature of this anomaly will help to enrich our understanding of the investor's behaviour in the financial markets.

Evidence on the return predictability and the market inefficiency has been reported in much of the UK literature. For example, price continuation (Sprou et al. 2007), underreaction to persistent losses (Jiang et al. 2016), financial strength anomaly (Kumsta and Vivian, 2019), and accruals anomaly (Papanastasopoulos 2020). These imply that the UK stock market is informationally inefficient, and the investors may suffer from cognitive biases that would lead to mispricing of stocks in the UK market.

Despite this, the IVOL puzzle and the lottery-like effect have received little attention from the UK literature in contrast to the U.S. literature. Empirical works on the nature of such anomalous trading behaviour are rare. One exception is Cotter et al. (2015) who test the pricing of the idiosyncratic volatility in the London stock exchange (LSE) and find that, unconditionally, the idiosyncratic volatility is irrelevant to the stock's prices in the LSE. Interestingly, they employ a coarse sampling (monthly returns) to measure the volatility. However, the empirical works on measuring the volatility have demonstrated the importance of more frequent sampling (e.g. daily observations) to generate a more accurate estimate of volatility (French et al. 1987). Moreover, speculative investors are more concerned about the daily fluctuation than the monthly fluctuation. Therefore, the method used in Cotter et al. (2015) to measure the volatility might be the reason behind the disappearance of the unconditional relationship between the idiosyncratic volatility and the returns across the stocks in the LSE.

Motivated by the above discussion, this academic work aims to shed more light on the nature of the risk-return relationship in the UK stock market. This will be done by investigating the behaviour of the lottery-like effect and the idiosyncratic puzzle. In particular, this work consists of three working papers that investigate the behaviour of these anomalies and the possible channels behind such puzzling behaviour.

In the first working paper (Chapter Two), the performance and the main features of the lottery-like stocks are analysed. Moreover, the link between this pricing anomaly (lottery-like trading) and the other previously reported pricing anomalies. In addition to the idiosyncratic volatility, the second paper extends the analysis and examines the left-tail risk relationship with the future returns. Also, in this paper, the ability of one of the possible channels in irrational behaviour is tested, namely, the underreaction-related behaviour (e.g. limited attention). Lastly, in the third paper, the link between the investors' response to the expected profitability news and the idiosyncratic puzzle.

In the first work (Chapter Two), I start this academic investigation by testing whether the inverse return predictability by the lottery-like features is held in the LSE. Therefore, the works extend the prior literature by adding an out of sample evidence on the existence of the lottery-like effect and the idiosyncratic puzzle from the UK stock market. In terms of both the market capitalisation and the number of traded shares, the UK stock market is one of the biggest markets around the world which makes it a natural selection to validate the various pricing theories and the phenomenon. To this end, four proxies of lottery-like features are employed. In addition to idiosyncratic volatility, the past maximum daily returns, the price, and the conditional jumps in returns are employed to represent the lottery-like trading. Also, an index of lottery-like trading is built by averaging the four different proxies. The sample includes all the common stocks that traded in the LSE during the period from January 1991 to December 2017.

The so-called univariate-sort technique is employed to uncover the pattern in the future performance (i.e. next month return) that is associated with the lottery-like trading. To examine the association with other return predictors, the predictive ability of the lottery-like features is investigated by performing a bivariate-sort analysis and the multivariate Fama and MacBeth cross-sectional regression. Also, the robustness of the lottery-like effect is tested against different sampling and important issues.

The empirical analysis reports many important findings. In line with the U.S. literature, the results reveal the existence of the anomalous lottery-like effect. The idiosyncratic volatility and the other lottery-like features inversely predict the next-month return across the stocks in the UK market. The multivariate analysis shows that the reported underperformance of these risky stocks is a manifestation of mispricing by the investors. The misvaluation of the left-tail risk and the sentimental-driven trading is closely related to this nonstandard trading behaviour.

The second empirical investigation (Chapter Three) extends the analysis in two ways. Firstly, the midterm performance of the trading strategy based on the idiosyncratic volatility is examined. In addition to the idiosyncratic volatility, another closely related pricing anomaly is also tested, namely, the left-tail momentum (see, Atilgan et al. 2020). Secondly, the paper contributes to the prior literature by testing the behavioural explanation. Particularly, the paper tests whether the underreaction-related behaviour can explain the persistent underperformance associated with idiosyncratic volatility and the left-tail risk. The argument here is that the investor underreacts to stocks with past losses thereby create a continuation pattern in the returns, especially for the stocks with high uncertainty (e.g. high IVOL).

The left-tail risk is proxied by the nonparametric expected shortfall (ES) and the idiosyncratic volatility is the standard deviation of residuals from the Carhart four-factor model. like other financial behaviour concepts, the underreaction behaviour has no explicit measure and can be originated and related to many other behavioural phenomena. Prior studies have identified many variables and cognitive biases that could drive such behaviour. Following the prior studies, to measure the underreaction behaviour, four proxies are employed, the 52-week high ratio, the information discreteness in sense of Da et al. (2014), the abnormal volume, and the delay response measure of Hou and Moskowitz (2005). Measuring these individual proxies, the principal component analysis is performed to extract the first common component of these proxies as an index of underreaction behaviour (i.e. the Attention). Also, the analysis control for many alternative explanations, most importantly for liquidity and information uncertainty.

Like the analysis in the first empirical chapter (Chapter Two)), the predictive power of the IVOL and ES5% (i.e. left-tail risk) for the stock returns over the next 6 months is analysed through different econometric approaches and subsamples. Confirming the next-month predictability, the single-sort analysis shows the ability of IVOL and the ES to predict the future returns over the next 6 months across the UK stocks. This predictability is partially driven by the suggested underreaction mechanisms. The empirical results of the sorting methods and the cross-sectional regression show that this explanatory power of the underreaction behaviour is robust to a list of alternative channels.

Thus far the analysis uncovers important mechanisms that could explain a non-trivial part of the anomalies investigated under this work. In the second empirical chapter (Chapter Three), the underreaction behaviour is represented by many market-based proxies. However, prior works demonstrate the importance of the investors' response to the fundamental-based information in explaining the variation in the stock prices. Theoretically, some behavioural models successfully generate the widely observed continuation and reversal patterns in stock returns by suggesting heterogeneous investor groups who process different kinds of information (past market performance and fundamental news). Also, prior empirical findings indicate that both market-based news and fundamental-based news are independently informative regarding the returns in the financial markets.

The third empirical chapter (Chapter Four) sheds some light on the rule of investors' response to the expected accounting earnings in deriving the IVOL puzzle. Specifically, the chapter tests whether the expected profit has incremental explanatory power, over the market-based information, to explain the persistent IVOL effect. The joint ability of the market-based information and the fundamental-based information to explain the IVOL puzzle is tested in both cross-sectional and time-series settings. The conjecture here is that the investors show biased responses (i.e. response with delay) to the readily available signals of future profitability, especially to the persistent earnings. Therefore, expected profitability positively predicts future returns on the stock market.

To measure the expected profit, the work employs procedures similar to the one used in Fama & French (2006) and Hou & van Dijk (2019). Particularly, each month, we will employ a cross-sectional regression to fit the firm's profitability to a set of candidate predictors. To generate a reliable out-of-sample prediction of the next year's profitability, the procedure requires the fitted variables to be available at the time of forecasting. We claim that the fitted value is a reliable proxy of future profitability. Depending on the results reported in the first and second empirical chapters, the 52-week high ratio is selected to represent the market news. This variable is employed to represent the underreaction behaviour (i.e. Anchoring bias), and it is found to explain a large part of the IVOL puzzle.

In addition to the cross-section test, this chapter contributes to the literature by testing an augmented version of the asset pricing model (i.e. the CPAM plus the size factor). In specific, employing the well-known Fama & French (1993) portfolio sorting technique, two factors are built to mimic the payoffs of the expected profitability and 52-week high ratio. We conjecture that these two additional factors are informative about the persistent IVOL effect.

As will be shown in the results section, indeed, the expected profitability (EROA) and the 52-week high ratio (PH52) are useful in predicting the future realised returns over the next 12 months, across the stocks in the UK market. Consistent with the main conjecture in this study, the expected profitability and the IVOL are negatively associated. This strong negative association helps the EROA to absorb a substantial part of the IVOL effect. Interestingly, the triple sort analysis reveals that the EROA and the PH52 are incrementally informative regarding the IVOL effect. The IVOL effect is completely absent in the group of stocks with high EROA and PH52. Within the high EROA and high PH52 groups, the value-weighted

IVOL hedge strategy is undistinguished from zero.

Moreover, in a multivariate setting, the results from the Fama-MacBeth cross-sectional regression confirm the ability of the EROA and the PH52 to predict the future returns and subsume the IVOL effect across the stocks in the UK market. Accounting for a set of competent returns predictors, the EROA and the PH52 preserve their ability to predict the future returns and the IVOL-return relationship.

In the time-series analysis, two factors are built to mimic the time-variation in payoffs of the EROA and PH52 trading strategy. The evidence re-emphasises the ability of EROA and PH52 to predict the IVOL effect. In particular, the pricing model that incorporates the EROA and the PH52 related factors, in addition to the market-factor and size-factor, outperforms the Carhart (1997) pricing model.

In sum, this work is an investigation of the return predictability in the UK stock market, therefore the information efficiency of this market. The findings uncover useful implications for the trading strategies and other important tasks related to asset pricing in general.

CHAPTER TWO

Lottery Preference in the UK Stock Market

Abstract

The performance of the lottery-like stocks has been found to contradict the standard paradigm of risk-return trade-off. Consistent with the international findings, this study reports a poor future performance for the lottery-like stocks in the UK stock market. The findings indicate that this underperformance persists after controlling for other returns predictors such as size, momentum, and systematic downsize risk. However, the results reveal that the left-tail measure subsumes the reported lottery-like effect in the UK market. Also, the findings in this study indicate that the poor performance of the lottery-like stocks could be partially explained by the anchoring bias and the limited arbitrage proxies. Moreover, the reported lottery preference is concentrated in the crisis period. In sum, it seems that the lottery-like effect exists in the UK market and it is closely linked to the pricing of the left-tail of the return distribution, which is magnified by the limited arbitrage and the investors' sentimental trading. Therefore, the evidence in this study cast doubt on the efficiency of the UK stock market, hence the application of the standard finance tools to the various asset pricing tasks in this market.

Keywords: Market Efficiency; Risk-averse; Return Predictability; Lottery Preference; Idiosyncratic Volatility.

2.1. Introduction.

The standard theory of finance and the later development to this theory assume a rational risk-averse investor who optimally allocates his/her capital to diversify the idiosyncratic risk. That is, Both the CAPM and the later multi-factor theories (e.g., ICAPM of Merton 1973, and the APT of Ross 1976) agree on the importance of the risk-averse behaviour for the well-functioning market.

Surveying the investors' holding behaviour in the financial market, many empirical studies find evidence that contradicts the optimal allocation behaviour assumed by the standard asset pricing model. To illustrate, the empirical survey of the U.S. stock market revealed the investors tendency to hold a concentrated (under-diversified) portfolio of no more than two stocks (Blume and Friend 1975, Kelly 1995, and Polkovnichenko 2005). Furthermore, analysing data of individual accounts available from brokerage houses, Barber and Odean

(2000) and Goetzmann and Kumar (2008) confirm this inefficient allocation behaviour. For example, Goetzman and Kumar (2008) demonstrate that more than 70% of the individual investors in the U.S. stock market hold only 5 stocks or fewer. Also, they point out that holding an under-diversified position is linked to the skewness and volatility preference behaviour. Such behaviour is widely linked to the speculative behaviour by the investors.

The revealed under-diversification behaviour would indicate that the investors (especially the individual investors) tend to speculate and that the idiosyncratic risk may be relevant to the value. Theoretically, Merton (1987) provides a rationale for such a non-optimal behaviour. He introduces a pricing model with an informationally incomplete market. Within such an environment the investors possess information only about a subset of the available securities. Subsequently, they hold sub-optimally diversified portfolios, hence the idiosyncratic risk is positively related to returns.

Strikingly, recent evidence from the stock market reveals a puzzling negative cross-sectional relationship between the future returns and the stock's idiosyncratic volatility and other speculative features. In a seminal paper, Ang et al. (2006) document a puzzling negative relationship between the idiosyncratic risk and the future returns across the stocks. Surprisingly, they show that stocks with high idiosyncratic volatility (measured relative to the Fama and French (1993) model) underperform the stocks with low idiosyncratic volatility.

Failure of the rational setting proposed in Merton (1987) to explain the puzzling results in Ang et al. (2006) leaves room for another plausible story, namely, the speculative behaviour. Notably, Bali et al. (2011) find that the past maximum daily returns inversely predict the subsequent months returns across the stocks. They attribute this anomalous behaviour to the investors' tendency to prefer stocks with lottery-like features (e.g., Large positive daily returns). In turn, this lottery-preference behaviour leads the investors to overvalue the stocks with extreme return observations. Interestingly, they find that this lottery-like preference significantly absorbs the idiosyncratic volatility puzzle documented by Ang et al. (2006). Also, Kumar (2009) and Birru and Wang (2016) postulate that the low-priced stocks are overweight by the investors as they overstate the future upside potential of such stocks. Han and Kumar (2013) define low-priced stocks as a lottery-like asset, and they support the link between the puzzling negative risk-return relationship and speculative retail trading. This interpretation is consistent with the behavioural theoretical works of Mitton and Vorkink (2007) and Barberis and Huang (2008).

The speculative behaviour of the investors is one of several explanations that have been suggested by prior studies for the puzzling inverse risk-return relationship. Microstructure biases such as short-term reversal and bid-ask bounce are found to be responsible for this puzzling poor performance of stocks with high idiosyncratic volatility (Huang et al. 2010, and Han and Lesmond 2011). While Stambaugh (2015) suggests that the reported puzzling underperformance of the stocks with high idiosyncratic volatility is a manifestation of the persistent overpricing of difficult to arbitrage stocks. An et al. (2019) find a link between the disposition effect and the negative returns of the stocks with high lottery-like features (e.g., high idiosyncratic volatility). Chen and Petkova (2012), Barinov (2018), and Barinov and Chabakauri (2019) provide a risk-based explanation in the sense of the ICAPM.

Whatever is the reason behind the puzzling behaviour of the speculative stocks, this anomaly poses a formidable challenge to the standard mean-variance model (i.e., CAPM) and the information efficiency hypothesis.

Kumar et al. (2016) demonstrate that gambling-motivated investors' demand for the lottery-like stocks is correlated and compromises a significant part of the overall trade in the stock market. Therefore, understanding the nature of the lottery-like stocks' behaviour is extremely important and has many implications related to the asset pricing task. For instance, ignoring the inverse risk-return relation in the lottery-like stocks leads the risk-averse investors to misallocate their funds.

Extending the above discussion, this work seeks to contribute and extend the existing literature in two ways. First, the existence of the puzzling behaviour of the lottery-like stocks is examined in UK stocks. Second, this work examines the characteristics and the forces that drive the anomalous behaviour of such stocks. Prior evidence focusses on US stocks while keeping the UK stocks under-researched. The UK stock market is one of the largest in the world, which makes this market a natural base for out-of-sample evidence. What supports this aim is the distinctive features in the structure and the organisational rules of the UK market. Generally, the stocks in the UK are smaller and less liquid than the stocks in the US market (Petrovic et al. 2016). Besides, there are influential differences in the accounting standards and the taxation law (Papanastasopoulos 2020).

The rest of the work is organised as follows. In Section 2, the related literature is reviewed. Section 3 represents the data and the methodological approaches applied to test the relationship assumed under this work. Section 4 outlined the empirical results. In Section 5, the association between the lottery-like effect and other widely-known predictors is analysed. Section 6 adds the robustness check. Section 7 concludes.

2.2. Literature review.

In this section, we will review the previous theoretical and empirical studies on the existence of the puzzling inverse relation between risk and expected return in the financial markets, the idiosyncratic volatility puzzle, and the lottery-like effect. Many stocks' characteristics have been documented by the previous studies to proxy the speculative features. The previous empirical research revealed many anomalous pricing behaviours that are likely to be a manifestation of speculative trading. Theoretically and empirically, Mitton & Vorkink (2007), Kumar (2009), and Han & Kumar (2013) argue that stocks with low price and high idiosyncratic volatility are preferred by the investors as they consider these stocks as speculative assets that offer a greater potential for extreme upside gains. Also, Bali et al. (2011) employ the maximum daily returns over the recent past months as a lottery-like attribute.

2.2.1. Pricing of the Idiosyncratic Risk and Other Lottery-like Attributes.

As mentioned before, the uncovered evidence on the invalidity of the optimal diversification hypothesis and the associated pricing models (e.g., The CAPM) encourage many researchers to investigate the pricing of the idiosyncratic component of risk in addition to the systematic part. The alternative theory of the mean-variance paradigm implies that the investor is constrained and the investment environment intuitively compensates the investor for holding a suboptimal position and thus for bearing the idiosyncratic variation in returns. This view is supported in the works of Levy (1978), Merton (1987), and Malkiel & Xu (2002) among others.

The cross-sectional pricing of the idiosyncratic risk had received little attention until a monumental turning point occurred with the results documented in Ang et al., (2006). Surprisingly, they find contradictory and puzzling results to the intuition of the risk-return trade-off. In specific, they find an inverse relationship between the idiosyncratic volatility and the future returns across the U.S. stocks. Simply, they measure the idiosyncratic risk as the standard deviation of the daily residual returns corresponding to the pricing model suggested by Fama and French (1993). Sorting the stocks according to the idiosyncratic volatility, the cross-sectional spread in the returns between the lowest decile portfolio and the highest decile portfolio is economically and statistically significant, more than 1% per month. Moreover, the documented idiosyncratic volatility puzzle is independent of the widely reported return predictors.[1]

This baffling cross-sectional discount on the idiosyncratic volatility induces many researchers to investigate the anomaly and to check the robustness of the results under different methodologies. Interestingly, Fu (2009) criticises the methodology of Ang et al. (2006) and argues that the idiosyncratic volatility is time-varying therefore its past level is a weak proxy of the expected value. Consequently, the negative relationship found between the future returns and the lagged value of the idiosyncratic volatility should not be used to infer the relation between idiosyncratic risk and the expected returns. Employing the conditional idiosyncratic volatility forecasted by EGARCH (Exponential generalized autoregressive conditional heteroscedasticity) within F-F three-factor model, the result supports the theoretical positive relationship between the idiosyncratic risk and the expected returns in Merton (1987). Other researchers follow Fu's conditioning methodology and confirm the positive relationship, for example, Spiegel & Wang (2007), Huang et al. (2010), Brockman et al. (2012), Eiling (2013), and Peterson & Smedema (2011). But this support has not protected the conditional approach of Fu (2009) and others from criticism. Studies of Bali et al (2010), Fink et al. (2012), and Guo et al. (2014) point out the inferential problem that results from using the in-sample forecasted volatility like in Fu (2009) and his followers. In-sample forecasted volatility includes forward-looking information and spuriously creates a positive relationship between the expected returns and the expected idiosyncratic volatility. Controlling for the look-ahead bias, the out-of-sample forecasted volatility is used as a proxy for the expected idiosyncratic volatility and the results reveal a weak and negligible relationship between the expected returns and the expected idiosyncratic volatility. Furthermore, Ang et al. (2009) argue that idiosyncratic volatility is persistent, hence the lagged value is highly correlated with the future value. They show that considering the expected component of future volatility doesn't affect the puzzling negative relationship between the expected returns and the past idiosyncratic volatility. Also, Peterson and Smedema (2010) report the pricing of both components, the past idiosyncratic volatility, and the expected idiosyncratic volatility.

[1] cannot be explained by commonly used returns predictors such as market factor, market capitalization, book-market ratio, momentum, liquidity, bid-ask spread, co-skewness, analyst dispersion, and market states.

The controversial evidence on the pricing of idiosyncratic volatility in the U.S. stock market prompts many researchers to explore the phenomenon in other markets. Ang et al. (2009) investigate the pricing of the idiosyncratic volatility in an international sample of 23 countries during the period from 1980 to 2003. They confirm the puzzling idiosyncratic volatility pricing in the world market. Moreover, they test some potential explanations such as trading fractions, information dissemination, and higher moments, but none of them found to be a good explanation for the idiosyncratic risk anomaly. They conclude that the common movement in the idiosyncratic volatility around the world indicates the existence of an undiversifiable common force behind the phenomenon. In addition to this large-scale evidence, there are many supportive evidence found in individual samples outside of the U.S market. Studies of Gharghori & Veeraraghavan (2011), Zhong & Gray (2016), and Zhong (2018) analyse the Australian market through different periods and all of them report a negative relation between the idiosyncratic volatility and the expected returns. Also, Luis et al. (2012) provide evidence on the existence of the idiosyncratic volatility-puzzle in the Spanish market over the period from 1987 to 2007. Besides, Cotter et al. (2015) provide results for the UK market, Nartea et al. (2013), and Wan (2018) for the Chinese market.

In contrast to the widely reported negative relationship, many studies provide evidence on the existence of a positive relationship between the idiosyncratic volatility and the subsequent returns. Examples of these studies, Nartea et al. (2011), Aboulamer & Kryzanowski (2016), and Liu & Iorio (2016).

Considering the above review, the puzzling idiosyncratic volatility anomaly is found in different stock markets around the world. However, this evidence is inconclusive.

Another important manifestation of the speculative trading in the stock market is pricing of extreme positive returns. Bali et al., (2011) document the investors’ tendency to prefer the stocks that experienced extreme positive daily returns over the recent past period (e.g., past month). They document a negative cross-sectional spread between the portfolio of stocks that build based on the extreme daily returns over the past month (MAX-effect). Practically, ranking stocks according to their highest past daily returns, the stocks with the extreme positive daily returns underperform other stocks in the market. They argue that the stocks with extreme returns over the past month are perceived by the retail investors as lottery-like assets therefore these stocks are heavily weighted by the speculators who push their prices away from the fundamental values. Consequently, these stocks generate negative returns in the future. Controlling for the well-known returns predictors, such as size, book-market, momentum, short-term reversal, liquidity, and skewness, this pricing anomaly remains statistically and economically significant. Bali et al. (2017), Fong & Toh (2014), Barinov (2018), Kumar, et al., (2018), and Lin and Liu (2018) are examples of studies that confirm the existence of the Max-effect in the U.S. market. Byun & Kim (2016) show that the documented Max-effect and the gambling features of the underlying stocks are also considered by the options traders.

The uncovered Max–effect in the U.S. sample motivates others to investigate the anomaly out of the U.S sample. Cheon and Lee (2018) study a comprehensive sample of 47,000 stocks from 42 markets and show empirical evidence on the universality of the Max-effect. Annaert et al. (2013) study the European countries and provide evidence on the existence of the max-effect in a sample of 13 European countries, a portfolio of stocks with extreme returns in the prior month underperformed the one with the lowest returns in the prior month. Zhong & Gray (2016) study the Australian market through a period of 1990-2013 and provide evidence on the existence of the effect in this market. Also, the Max-effect is documented for the South Korean market (Nartea et al., 2014), Hong Kong stock market (Chan & Chui, 2016), Chinese market (Nartea et al., 2017, and Wan, 2018), Taiwanese market (Hung & Yang, 2018), and Brazilian market (Berggrun et al., 2017). In contrast, Aboulamer & Kryzanowski (2016) report a positive Max-effect for the Canadian market through the period of 1975-2012, however, for the small stocks sample and stocks with low institutional ownership the results are consistent with the documented negative Max-effect. They argue that the short-term reversal anomaly is responsible for the negative Max-effect, while for the Canadian market the short-term reversal anomaly is weaker, therefore the negative Max-effect that is documented by the U.S. literature does not exist in this market.

Moreover, Kumar (2009) demonstrates that individual investors in the U.S. stock market are more likely to consider the low-priced stocks as lottery-like assets. It seems that the investors overestimate the upside potential for these stocks as they believe there is no more room to fall-down. This view is supported by many empirical studies on the pricing of the low-priced stocks and the investors' speculative behaviour. For example, Han and Kumar (2013), Doran et al. (2012), Birru and Wang (2016), and Chan & Chui, (2016).

2.2.2. Alternative Explanations of the IVOL puzzle and MAX-effect.

Inconsistency of Merton (1987) prediction with the widely-reported negative relationship between the idiosyncratic volatility and future return, opens the door for alternative explanations. A plausible explanation of this anomalous pricing behaviour is the gambling behaviour (i.e., the lottery-like trading). A growing number of studies have claimed the investors' tendency, especially the individuals, to prefer stocks with speculative features (i.e.,lottery-like stocks), such as high idiosyncratic volatility (hereinafter IVOL) and past daily maximum returns (hereinafter MAX). Mitton and Vorkink (2007) develop a model that provides a rationale for the puzzling negative risk-adjusted returns for the lottery-like stocks. Under this rationale, the model assumes a group of investors with lottery preferences. These speculative traders tend to sacrifice the diversification and the risk-return optimisation position to achieve a positively skewed investment position. Therefore, some of the investors are gambling-motivated who are attracted by the speculative characteristics of the stocks. Consequently, these gambling-driven traders are risk-seekers and the lottery-like features (high IVOL and MAX) are positively priced in the market.

Much prior empirical evidence has attributed the IVOL puzzle and the Max effect to the investors' gambling behaviour. The tendency of the investors to hold an under-diversified position in chase of lottery-like payoffs has received enormous attention recently. For example, Boyer et al. (2010) and Malagon et al. (2015) study the U.S market and demonstrate that the skewness effect helps explain the idiosyncratic puzzle. Also, Bali et al (2011), Annaert et al. (2013), Walkshäusl (2014), Zhong & Gray (2016), and Egginton & Hur (2018) studied the maximum return effect (MAX-effect) as a proxy for lottery behaviour and gambling-motivated trading in the U.S sample, and they all show the ability of the maximum return effect (MAX-effect) to explain the idiosyncratic puzzle and that the puzzle is nothing more than a manifestation of gambling behaviour by the retail investors. In addition to the U.S. results, the ability of the lottery effect to explain idiosyncratic puzzle is reported for another market, for example, Hung and Yang (2018) examine the Taiwanese stock market, Dorn & Huberman (2010) confirm the effect in the German stock market and Kang et al. (2014) for the Korean stock market.

Moreover, the prior studies have pointed out that the individual retail-traders are more likely than the institutional investors to seek the gambling-based strategy. This gambling behaviour is found to create or to be amplified by the limited arbitrage environment. In particular, the literature has described this gambling behaviour as noise trading that limits the ability of the informed arbitrageurs from going against any pricing discrepancies. The limited arbitrage suggests that the lottery-like stocks are likely to be overvalued under the proposition of Miller (1977), who argues that if the pessimistic investors are hindered by short-sale constraints, the market should biasedly reflect the view of the optimistic participants, which in turn leads to systematic overvaluation. Consequently, a predictable negative relationship between risk and returns appears in the market. Thus, a limit to arbitrage/short-sale constraints and mispricing by optimistic investors may account for the uncovered idiosyncratic volatility puzzle. Theoretically, Shleifer & Vishny (1997) and Pontiff (2006) support this view for the IVOL. Empirically, the overvaluation of the lottery-like stocks is supported by much evidence. For example, Boehme et al. (2009), Han & Kumar (2009), Stambough et al. (2015) and Aabo et al. (2017) Doukas et al. (2010) all show that the high idiosyncratic volatility stocks are more likely to be mispriced than low idiosyncratic volatility stocks. Also, others support the lottery preference and the associated mispricing hypothesis as an explanation for the MAX-effect, for examples, see, Conard et al. (2014), and Bali et al. (2017, Lin and Liu (2018), Hung and Yang (2018), and Kumar et al. (2018). In addition to this U.S. literature, evidence from the non-U.S. markets is also present. Zhong and Gray (2016) report evidence on the mispricing of high-MAX stocks from the Australian market, and Gu et al. (2018) investigate the Chinese market and demonstrate that the idiosyncratic puzzle is stronger in presence of the limited arbitrage. Walkshaul (2014) examines the European stock markets and reports a stronger MAX-effect for the stocks with high cash flow volatility.

The mentioned association between the lottery preference and the mispricing suggests that the lottery-like stocks are more likely to underperform following the period of optimistic-driven trading and for the group of overconfident investors. Interestingly, the inverse predictive power of the lottery-like features is found to be only significant or stronger following a period of high sentiment (see, for example, Fong and Toh 2014, Kang et al. 2014, and Stambaugh et al. 2015). Also, Cheon and Lee (2017) analyse a universal sample of 47,000 stocks from 42 countries and find that the MAX-effect is stronger for countries with a high individualism index of Hofstede (2001), which is one of the overconfidence-related characteristics exhibited by the gambling-motivated traders.

Another strand of the behavioural literature suggests the *prospect theory* of Kahneman and Tvesky (1979) as an alternative explanation for the observed nonstandard pricing of the lottery-like stocks. Under the prospect theory, the investor has a non-standard “S” shaped utility function, where the investor is risk-averse in the domain of gains while behaving as a risk-seeker in the domain of losses. Building on this structure, studies of Bhootra & Hur (2015) and Wang et al. (2017) suggest the proposed risk-seeking behaviour in the loss domain as an explanation for the IVOL puzzle.[2] They report evidence in support of their view, the idiosyncratic puzzle is a phenomenon that is attributed to a group of stocks with unrealised capital losses while it disappears within a group of stocks with unrealised capital gains. An et al., (2018) demonstrate similar reference-dependent behaviour for the MAX-effect. In a related endeavor, Barberis & Xiong (2012) develop a model with investors who derive their utility from realising gains and losses from their holdings. Under this model, the realisation utility leads the investors to prefer the volatile stocks as these stocks grant them more opportunities to realise gains in the future. Consequently, if this preference is translated into pressure by them on the highly volatile stocks, these stocks will be overpriced and subsequently generate a negative expected return. Han and Yang (2013) show empirical evidence that supports the main conjecture in Barberis and Xiong (2012).

In contrast to the all aforementioned behaviorally-based empirical evidence, some advocate a risk-based or fundamental explanation for the idiosyncratic puzzle. This group of literature attributes, theoretically and empirically, the puzzling negative return predictability by the lottery-like features to the real growth options that characterised these stocks. In specific, they show how these growth opportunities could provide a hedge against the change in aggregate market volatility. Cao et al. (2008), and Barinov (2011), Grullon et al. (2012), Chen & Petkova (2012), and Avramov et al. (2013) all provide empirical evidence in support of this rational risk-based explanation. Evidence by Da et al. (2011) demonstrates the failure of CAPM in explaining equity returns in the presence of real options as a result of nonlinearity between the equity expected returns and the returns of the underlying assets. Barinov (2018) demonstrates evidence in support of the growth options explanation of the MAX-effect.

2.2.3. Anomalies within the London stock exchange.

London stock exchange (LSE) is one of the most important equity markets in our world, either in market value or trading size. Similar to the other developed markets, empirical

[2] Empirically, both studies employ the measure developed by Grinblatt & Han (2005) to measure the level of unrealised gains and losses held by the investors in specific stocks, namely the capital gains overhang.

evidence about the failure of the mean-variance theory and the CAPM is frequently reported in the LSE. Numerous empirical studies have documented the existence of many widely-known anomalies in the U.K, for example, the size effect (Dimson & Marsh, 1999, and Levis, 1989), the value effect (Capaul et al., 1993, Miles & Timmermann, 1996, Gregory et al., 2001, and Dimson et al, 2003), the long-term reversal (Clare and Thomas, 1995, and Mazouz and Li, 2007), the short-term reversal (Antoniou et al., 2006), the Momentum effect (Lui et al., 1999, Rouwenhorst, 1998, and Hon & Tonks, 2003). Also, many empirical studies provide evidence on the ability of the CAPM alternatives to provide an incremental explanatory power for stock returns in the LSE. Gregory et al. (2013) tests the F-F three-Factor model and show that it has better performance than the CAPM in pricing the stocks at LSE. Clare & Thomas (1994) investigate the macroeconomic APT model, while Strong & Xu (1997) and Fletcher (2010) studies various forms of the multi-factor pricing model, and Florackis et al. (2011) test the ability of liquidity asset pricing factor to enhance the cross-sectional pricing in LSE. Evidence on the nonlinearity of the pricing function in the UK market was provided by Kostakis et al., (2012). They studied the ability of the higher co-moments (e.g., co-skewness) to explain the cross-sectional return premiums of the stocks in the UK market and report higher explanatory power for the model with a co-skewness factor.

Consistent with the empirical tests from other markets, recent UK literature reports empirical results on the existence of the idiosyncratic puzzle and the Max-effect in LSE. Angelidis & Tessaromatis (2008) investigate the pricing of idiosyncratic volatility in the UK during the period from 1979 to 2003. Aggregating the idiosyncratic volatility across the market and according to their market capitalisation (i.e., Small Vs Large), they test the ability of these different measures of idiosyncratic volatility to predict the market return, the value premium, and the size premium. For the market return and the value premium, they report a weak positive ability to predict the market return, while for the value premium, none of their aggregate measures of the idiosyncratic volatility showed predictive power. However, the idiosyncratic volatility of small stocks can predict the size premium. Recently, Cotter et al. (2015) provide another investigation on the pricing of the idiosyncratic volatility in the UK stock market. They employ a comprehensive sample of UK stocks during the period from 1990 to 2009. Their methodology differs from that of Angelidis & Tessaromatis (2008), as they test the predictive power across the individual stocks rather than aggregated portfolios. In the unconditional test, they find that the idiosyncratic volatility is not priced in the UK stock market. However, the idiosyncratic volatility is negatively related to returns of the UK stocks only during the down market (periods of negative market return).

Ang et al. (2009) investigate the idiosyncratic puzzle in the sample consisting of 23 countries including the UK. Analysing a sample of 1077 equity shares from the UK market for the period from 1980 to 2003, they show that the idiosyncratic volatility is priced across the UK stocks. In addition to that, Cheon and Lee (2017) study the Max-effect across the world in a sample consisting of 42 countries. They reported a preliminary result on the existence of the Max-effect in the UK market (for the equal-weighted portfolio). In a related study, Gao et al. (2018) examine the distress risk anomaly in an international sample and report a high negative premium for UK stocks. They show that the distress risk puzzle is related to the level of individualism and overconfidence which both appear to be high in the UK. All this evidence supports the importance of conducting a deeper investigation of gambling behaviour within the UK market.

Reviewing the above studies reveals some important points that motivate this work. Angelidis & Tessaromatis (2008) examine the predictive power of the idiosyncratic volatility for the future returns in an aggregate setting, and they do not test the relationship at the firm level. Practically, data aggregation may smooth out a substantial amount of the cross-sectional variation in the financial variables. Most, if not all, the literature on the idiosyncratic puzzle and the lottery-like effect depends on the predictive power across the individual stocks rather than the time variation. Although Cotter et al. (2015) examine the idiosyncratic puzzle across the UK stocks, they employ a coarse sampling (monthly returns) to estimate the idiosyncratic volatility. In particular, they estimate the volatility by using monthly observations over the past two years. The literature on the estimation of volatility suggests that the low-frequency approach would provide a noisier estimate of current volatility, especially that the volatility is varying over time (see, French et al. 1987 and Goyal & Santa-Clara 2003). It could be that this coarse estimation is the reason behind the insignificant unconditional idiosyncratic/return relationship in Cotter et al. (2015). Moreover, none of the aforementioned international studies has provided a deep analysis of the lottery effect or the idiosyncratic puzzle in the UK market. For example, the reported results in the UK literature are nothing more than a general indication about the existence of lottery-related anomalies. Also, these studies rarely investigate the reasons behind the idiosyncratic puzzle in the UK market.

Considering the above discussion, the contribution of this work is two-fold. Firstly, the chapter investigates the lottery-like effect across the UK stocks by employing various proxies such as the idiosyncratic volatility and past maximum daily return. Interestingly, to measure the idiosyncratic volatility, an econometric methodology similar to that used in Ang et al. (2006) is employed. According to this methodology, the idiosyncratic volatility is measured as the standard deviation of the unsystematic daily returns (i.e. the residual from the fitting of the Fama and French three-factor model) over the past month or three months. The goal is to estimate a more accurate time-varying proxy of idiosyncratic volatility than that in Cotter et al. (2015). Secondly, this work contributes to the literature by more deeply analysing the characteristics and the explanation of the lottery-like anomaly. The association between the lottery-related effects (e.g. Idiosyncratic puzzle) and a set of selected market phenomena and potential explanations is analysed.

2.3. Data, Measures, and Methodology.

This section describes the sample that is selected to test the behaviour of the lottery-like anomalies in the UK stock market. Also, the main proxies of the lottery-related anomalies and other anomalies (as controlling variables) that proposed by the previous literature to be related to the gambling-motivated trading in the stock market. The set of control variables includes market friction proxies (i.e. Amihud (2002)'s impact ratio, the bid-ask spread, and the volume), value proxies (i.e. market value and market-to-book ratio), past performance proxies (i.e., momentum and the short-term reversal), the systematic risk measures (i.e. market beta and the Co-skewness), the total left-tail measure (i.e. the past minimum daily returns) and others.

2.3.1.Sample and Data.

To test the main relations in this study, a comprehensive sample of stocks from the LSE is used. The stocks' data is updated on monthly basis and the sample is selected to consist of both the currently traded stocks and the delisted stocks in a way to mitigate the well-documented survivorship bias that found to affect the cross-sectional asset pricing tests (e.g., see, Shumway, 1997). The total number of stocks in the sample is 5414. The data includes daily and monthly prices and other trading data of the selected stocks and spans the period from January 1991 to December 2017. The main variables (e.g. the idiosyncratic volatility and the other lottery-like features) are measured using the observations over the past three months (≈ 65 days). To mitigate the problem of non-synchronous trading, stocks with less than 36 trading days are excluded. Following these filters produce a time-varying monthly sample that ranges from 288 to 884 stocks. The data source is Thomson Reuters DataStream. Following asset pricing literature in the UK, the sample only includes the common equities (see, for example, Florackis et al., 2011). Data of the Fama-French Three-Factor model and the momentum factor are obtained from Gregory et al., (2013).

2.3.2. Variables and Measures.

This section describes the main variables of the study. Following the previous studies, the price, the past idiosyncratic volatility, the past maximum return as proxies for the lottery-like stocks. Also, this study employs a conditional jump measure to identify the lottery-like stocks. A set of control variables is used to check the dependency of the investigated speculative behaviour on the previous anomalies.

2.3.2.1. Lottery-like Proxies.

Following the previous empirical findings, this study employs four proxies of the lottery-like stocks. Namely: the idiosyncratic volatility (IVOL), the Maximum returns (MAX), the conditional jump in returns (Jump), and the price (Price). Except for the price, the rest of the lottery-like proxies are calculated using the returns over the past three months.

1. Idiosyncratic Volatility (IVOL).

As proposed in Ange et al. (2006), the idiosyncratic volatility is measured by the standard deviation of the residual from fitting the Fama and French (1993) three factors model. Technically, this measure is designed to represent the firm-specific fluctuations, derived from firm-specific news, rather than the systematic fluctuations. To illustrate, after disentangling the systematic variation that corresponds to the proposed risk structure the, the variation in the unsystematic returns is considered as a measure of the idiosyncratic fluctuations. By nature, speculative trading is more likely to exploit this part of total fluctuations. This study follows the same general approach and firstly fit the following Carhart (1997) Four-Factor model,

$$R_{i,d} = \alpha_i + \beta^*(R_{m,d}) + \beta_{smb}{*}SMB_d + \beta_{hml}{*}HML_d + \beta_{UMD}{*}UMD_d + \varepsilon_{i,d}\,, \qquad (1)$$

Where, $R_{i,d}$ is the stock risk premium, $R_{m,d}$ is the market risk premium, SMB is the size spread, HML is the value spread, and UMD is the momentum. After fitting this model using the past three months data of returns and pricing factors (approximately 65 days), the idiosyncratic volatility of stock *i* is defined as the standard deviation of the extracted daily residuals from the fitted model (ε_{ti}), the idiosyncratic returns:

$$IVOL_{it} = \sqrt{\frac{\sum_{1}^{N} \varepsilon^2}{N-1}} \qquad (2)$$

Where N is the number of days the stock traded. The data for the Fama and French three factors model is obtained from Gregory et al (2013). To mitigate the nonsynchronous trading issue, stocks traded for less than 35 days are excluded.

2. Maximum Returns (MAX):

In general, this variable is measured using daily returns over the past recent months (see, Bali et al., 2011). In this study, the maximum effect is the average of the 5 maximum daily returns over the past three months, and denoted by MAX,

$$MAX_{i,\,t} = \text{Average } (\max (R_{i,d})),\ d= 1\text{-}5, \ldots.., D_t, \qquad (2)$$

Where $R_{i,d}$ is the return on stock i on day d and D_t is the number of trading days in the past three months. As mentioned before, this variable proxies the upside potential of the stocks. The lottery-attracted investors are more likely to demand such stocks. Again, to rule out thinly traded shares, this study requires 35 trading days at least for the stock to be included in the analysis.

3. The Residual Jump:

This variable is measured by summing the absolute value of residual returns extracted by fitting Carhart's Four-Factor model. The residuals are accumulated conditional on the idiosyncratic volatility of the residuals. To isolate the Jump from the regular fluctuation in returns, two standard deviations is used as a threshold,

$$Jump_i = \sum abs\ (\mathcal{E}_{i,t}) > 2 * IVOL_i) \qquad (3)$$

By construction, this variable detects the extreme fluctuation beyond the standard deviation. Stocks with long-tailed distribution are expected to be more attractive for lottery-attracted traders, thus generating payoffs similar to lottery-like stocks.

4. The Price.

Several previous studies employ the low price as a proxy for the lottery-like stocks (see, for example, Han and Kumar, 2013). This classification is based on the investors' tendency to exaggerate the upside potential of the low-priced stocks, therefore they, illusively, perceive these stocks as lottery assets (Birru, 2016). Simply, the stock price is the closing price of the stock at the end of the past month.

5. Lottery Index (Lndx).

This index is created to represent the common variation in the four lottery-like proxies (IVOL, MAX, JUMP, and Price). This index is constructed following the method in Han and Kumar (2013). Firstly, the stocks are ranked into vigintile according to every single lottery-like proxy, separately. Then, the index is created as the average of the vigintile assignments according to the different lottery-like proxies divided by 20. By construction, the value of the index ranges from 0 to 1. Notice that, to match other lottery-like proxies, the stocks are ranked according to the inverse price (1/price) where the lowest-priced stocks take the 20^{th} rank, and so on.

2.3.2.2. Control Variables.

To isolate the lottery-like effect from other potential return predictors, the effect of the lottery-like features will be analysed after controlling for a selected set of these predictors. these control variables are as follows,

1. Market Beta: traditionally measured by regressing the stock's risk premium (R_i) on the market risk premium (R_m). To mitigate the impact of nonsynchronous trading, we follow Lewellen and Nagel (2006) and Cederburg and O'Doherty (2016) by adding four lags of the market premium to the regression,

$$R_{i,d} = \alpha_i + \beta_{i,0}*R_{m,d} + \beta_{i,1}*R_{m,d-1} + \beta_{i,2}*\{(R_{m,d-2} + R_{m,d-3} + R_{m,d-4})/3\} + \varepsilon_{i,d}, \quad (4)$$

$$\beta_{i,t} = \beta_{i,0} + \beta_{i,1} + \beta_{i,2} \quad (5)$$

Where R_i and R_m are the daily risk premium for the stocks i and the market portfolio, respectively, and $\beta_{i,t}$ is the estimated beta. Like the idiosyncratic volatility, the beta will be estimated using the daily returns over the past three months and re-estimated on a monthly basis. Past empirical work found a positive relationship between lottery features and the stock's beta.

2. Downside Beta (Dbeta): measured in a similar way to the market beta but the stock return is regressed only on the negative market returns rather than the whole market returns series. Therefore, unlike the Beta, this variable measures the systematic comovement with the market conditional on the negative market returns.
3. Co-skewness: This variable measures the association between the stock and the variation in the tail of the market portfolio. Following Harvey and Siddique (2000), to measure the co-skewness, the following quadratic form of the market model will be fitted,

$$R_{i,d} = \alpha_i + \beta_{i,d} * R_{m,d} + C_{i,d} * R^2_{m,d} + \varepsilon_{i,d} \quad (6)$$

where $C_{i,d}$ represents the co-skewness measure. Positive co-skewness indicates that the stock has a lower tail risk, and it is more probable to generate a positive return conditioning on the extreme fluctuations in the market returns.

4. The minimum return (Min5): similar to the MAX5, this variable is measured by averaging the lowest 5 daily return observations over the past three months. For ease of interpretation, the value is multiplied by -1, thus the higher value of this measure indicates a higher level of tail risk.
5. Size (MV): following the existing literature, firm size is measured by the market value of the equity (a stock's price times the number of shares outstanding) at the end of the past month. The previous empirical work found a negative relationship between the market value and the lottery-like features (see, for example, Kumar, 2009, and Bali et al., 2011).
6. Price to 52-week high (PH52): is the ratio of current price to the highest price over the past 52 weeks,

$$PH52 = \text{Current } P_i \,/\, \text{52-week high price} \quad (7)$$

Besides the past performance, this ratio was employed as a proxy for the anchoring bias (see, George and Hwang, 2004; and Hur and Singh, 2019). In particular, it has been found that the investors are more likely to produce erroneous expectations when the market price is far or near to their past 52-week high.

7. Med-term Momentum (Mom): following Jegadeesh & Titman (1993), the med-term momentum is defined as the cumulative return over the past 6 months after skipping a

month between the portfolio formation period and the holding period, i.e., cumulative return over month t–7 to month t–1.

8. Short-term reversal (Rev): following Jegadeesh (1990), this variable is measured using the stock return over the past month.
9. Turnover: is the monthly average of the daily stock turnover which is the stock volume in dollars divided by the number of shares outstanding.
10. Bid-Ask Spread (Spread): is the monthly average of the daily bid-ask spread. The daily bid-ask spread is the difference between the quoted bid and ask prices divided by the average of the two prices, as a following,

$$\text{Bid-Ask spread} = (Bid_{i,d} - Ask_{i,d}) / (Bid_{i,d} + Ask_{i,d})/2. \qquad (8)$$

This ratio is suggested by the literature as a market friction proxy and illiquidity measure. Lottery-like stocks are expected to be illiquid therefore have a high spread.

11. Amihud (2002)'s Illiquidity measure (Amih): In general, liquidity implies the ability to trade a large quantity of a certain asset quickly, at low cost, and without inducing a significant effect on the price level. Following Bali et al. (2011) and Amihud (2002), I measure the price impact of illiquidity as the monthly average of the daily absolute stock return to dollar trading volume ratio,

$$Amih_{i,t} = \Sigma \{|Ri, d| / VOLD_{i,d}\} \qquad (9)$$

Where Ri, t is the return of stock i in month t, $VOLD_{i,d}$ is the daily trading volume in the dollar for the stock i, in dollars. This liquidity measure serves as a proxy for the impact ratio and the effect of the order flow on the prices which is inspired by Kyle (1985).

12. ROA: is accounting profitability ratio of return on asset and it is measured by the ratio of earnings to the total asset.
13. BM: is the ratio of the book value to the market value.

2.3.3. Analysis Procedures.

This section describes the procedures performed to examine the effect of the speculative behaviour of the investors in the UK stock market. Firstly, the performance of the lottery-sorted portfolios is analysed by sorting the selected stocks into 10 deciles and then measuring their returns over the next month. Then, the performance of the lottery-based portfolios and the predictive power of the lottery-like features are analysed in a multivariate framework. Particularly, we conduct double-sorting analysis and the Fama and Macbeth cross-sectional regression to examine the effect of previously documented returns predictors on the ability of lottery-like features to predict future returns. The study employs these different analysis approaches to maintain a direct comparison with previous studies and to provide robust empirical results. In the following subsections, these procedures are discussed in more detail.

2.3.3.1. Single-sort Portfolio.

As mentioned before, through this analysis 10 portfolios are constructed by sorting the stocks in the sample into deciles with an equal number of shares in each decile. For instance, each month the stocks are ranked ascendingly according to the level of the lottery index and 10 lottery-based portfolios are created. The portfolios are rebalanced on a monthly basis. The motivation of this analysis is to check the cross-sectional variation in future performance and the other important characteristics of these portfolios. The performance of the lottery-based portfolios is represented by next month's returns. To investigate whether the performance of the lottery-like stock is different from that of non-lottery stocks, a zero-cost strategy is created by shorting the highest lottery-sorted portfolio and buying the lowest lottery-sorted portfolio. In addition to the raw value, the risk-adjusted alpha will be shown by adjusting the raw expected return to Carhart (1997)’s four-factor pricing model. This kind of analysis is plausible for some reasons. It is a practical approach to identify the profitable characteristic-based strategies. Also, the nonparametric nature makes this simple approach free of any functional form and requirements that restrict the alternative parametric methods, e.g., the multivariate regression approach.

However, the reported results under the sorting approach suffer some important pitfalls. Importantly, under this approach it is difficult to control for more than two or three different characteristics at a time. Accordingly, it is impossible to analyse the marginal effect of each potential returns predictors on the main variable in this study (i.e. the lottery-like features). Also, the sorting approach is too simple to examine the functional form of the relation between the average stocks returns and the firm feature. To address this issue, the multivariate cross-sectional regression of Fama and MacBeth (1973) is used besides the sorting approach.

2.3.3.2. Double-sort Portfolio.

In the single-sort analysis, the stocks are sorted according to single characteristics (i.e. the lottery-like features one at a time) while ignoring any other related features. To push the analysis one step further, the performance of the lottery-based portfolios will be analysed in the double-sort framework. Particularly, 9 portfolios are created by firstly sorting the stocks into 3 groups based on any of the selected anomalies, and then resorting the stocks within each of these groups into another 3 portfolios according to the lottery-related features. Similar to one-way sorts, the portfolios are rebalanced on a monthly basis. For example, each month, the stocks in the sample are ranked ascendingly by the level of the market capitalisation (or any other stocks characteristics) thus 3 groups of stocks with a different size level are created. Then within each size-based group, the stocks are resorted into another 3 groups according to any of the lottery-like proxies. The main motivation is to investigate the influence of the other determinants of stock returns on speculative-induced trading performance. To illustrate, if the lottery-related spread in the risk-adjusted performance changes across the different anomalies' levels, then this will be an indication of the association between the two characteristics. Similar to the one-way sorting approach, the performance of the constructed portfolios is measured by the risk-adjusted alpha of the zero-cost strategy within each anomaly level. The double-sort approach deeps our understanding of the pricing anomalies however it faces the same pitfalls as in the single sorting.

2.3.3.3. Fama-MacBeth Cross-sectional Regressions.

In the double-sorting approach, the portfolios are created by only controlling for two characteristics at a time. Therefore, this nonparametric analysis cannot explicitly control for other characteristics that may influence returns. For instance, sorting on three or more characteristics is impractical. To control for other possible mechanisms in a practical multivariate framework, the widely used Fama & Macbeth (1973) two-step cross-sectional analysis will be performed. Under the first step, the following cross-sectional regression will be estimated on a month-to-month basis,

$$R_{i,t} = \alpha_{i,t} + \beta_{lott}*LOTT_{i,t-1} + \Sigma\ \beta_x*X_{i,t-1} + \varepsilon_{i,t} \qquad (10)$$

Where $R_{i,t}$ is the stock i risk premium, LOTT is any of the employed lottery-like proxies, and X represents a set of the controlling variables. After estimating this model on a monthly basis, the averages of the estimated time-series coefficients are tested against the null hypothesis. In all of the Fama-Macbeth Regressions, the left-hand side of the equation is the monthly return of the individual stocks while the right-hand side contains the lottery-related proxies, one or more of them, and the other widely reported stock's returns predictors. Each regression estimated with Newey & West (1987)'s t-statistic adjusted for heteroscedasticity and autocorrelation.

Despite the powerful multivariate setting, the cross-sectional regressions face potential pitfalls. The imposed functional form is restrictive and could be incorrect. Moreover, the regression results are likely to be dominated by the extreme cases, for example, the microcaps (small capitalisation stocks) and extremely illiquid stocks. However, I tackle this issue in the robustness analysis section by redoing the analysis for different capitalisation groups and after excluding low-priced and illiquid stocks. Also, the tradition in the previous studies is to use a few portfolios as base assets in the Fama-MacBeth cross-sectional regressions. Ang et al. (2020) highlight the potential problem of information losing by aggregating the stocks into a few characteristic-based portfolios. To address this issue, I follow the suggestion to use the individual stocks rather than the portfolios as base assets in the Fama-MacBeth cross-sectional regressions.

Together the nonparametric stocks sorting approach and the parametric approach of Fama-MacBeth (1973) would provide a powerful analysis and robust empirical evidence on the nature of the lottery-like features pricing the UK stocks.

2.4. Empirical Results.

In this section, the empirical results will be reported. Firstly, the general statistics and the correlation of the selected variables will be presented. Secondly, the stocks will be sorted according to each lottery-related characteristic and the empirical results of the portfolio-level analysis will be presented. Thirdly, the empirical analysis of the double-sorted portfolios will be shown. Finally, the Fama-Macbeth cross-sectional regression analysis will be presented.

2.4.1. General Statistics and Correlation Analysis.

2.4.1.1. Descriptive Statistics.

Table 2.1 summaries the main statistical characteristics of the whole sample. The average return is -0.37% for the whole period. Comparing this negative performance with the positive performance of the value-weighted index (i.e., the all-share index), indicates that this negative performance is mainly generated by the small capitalisation stocks rather than the large ones. This negative return is reasonable performance for a period with two big market crashes, i.e. the Dot-com crash (from March 2000 to October 2002) and the 2008 global financial crisis (December 2007 to June 2009). The averages of the IVOL, Max is comparable to one reported by Walkshäusl (2014) for the European sample, Byun & Kim (2016) for the U.S sample, and Zhong & Gray (2016) for the Australian sample.

Table 2.1. Descriptive Statistics.

This table reports the general statistical characteristics of the pooled sample. All stocks are sampled together. EWRet: is the equally-weighted return of all stocks over the whole sampling period, VWRet is the value-weighted return of all stocks over the whole sampling period, IVOL: is the idiosyncratic volatility over the Past 3 months, MAX5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, Price: is the stocks market price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002) multiplied by 10^7, Spread: is the monthly average of the daily bid-ask spread, Turnover: is the number of share traded over the month to the number of shares outstanding, MV: is the market value of the firm at the end of the month (in million of pounds), BM : is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return. ROA: is the Return on the asset, CAPEX: is the ratio of capital expenditure to the total asset. The sample covers January 1991 to December 2017.

Variable	Obs	Mean	Std.Dev		Variable	Obs	Mean	Std.Dev
EWRet	199132	-0.37%	13.65		Coskew	199132	-3.00%	0.46
VWRet	199132	0.34%	4.11		ZDays	199134	0.16	0.14
IVOL	199132	2.44	1.82		Spread	197742	0.02	0.03
MAX5%	199132	5.49	4.02		Turnover	182440	8.19	11.25
Jump%	199132	22.93	19.35		Amih	192453	1.68	16.97
Price	199132	500	1780.64		PH52	199134	0.77	0.22
Lindx	199132	0.52	0.25		MOM6%	195372	4.21%	40.61
Min5%	199132	-4.93%	3.69		Rev%	199134	-0.02%	14.16
MV	199132	1906.53	5618.08		ROA	193272	-0.01	0.27
Beta	199132	0.89	1.15		CAPEX	191812	0.05	0.06
Dbeta	199132	0.77	1.15		BM	188965	0.66	0.76

2.4.1.2.Correlation analysis.

This section reports the analysis of the correlation coefficients between the variables. These coefficients are calculated in a cross-section of stocks. The analysis spans the period from January 1991 to December 2017.

Table 2.2 reports the correlation coefficients between the variables used in this study. The reported figures disclose some noteworthy relationships. All proxies of the lottery effect have the expected significant relationship with the next month's return. For example, the

Table 2.2. Correlation analysis

This table represents the correlation between the study variables. The correlation coefficients are estimated across the stocks and for the whole sampling period. Rett+1 is the return of stocks over the whole sampling period, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, 1/logP: is the reciprocal of the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of trading days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily bid-ask spread, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on the asset of the recent past accounting year. The sample covers January 1991 to December 2017.

	Ret_{t+1}	IVOL	MAX5	Jump	1/logP	Min5	LogMV	Dbeta	Coskew	Beta	Zdays	Spread	Amih	Rev	Mom	Ph52	ROA	BM
Ret_{t+1}	1																	
IVOL	-0.11	1																
MAX5	-0.09	0.92	1															
jump	-0.1	0.92	0.87	1														
1/logP	0.03	0.46	0.41	0.45	1													
Min5	-0.12	0.91	0.74	0.84	0.41	1												
LogMV	0.07	-0.56	-0.51	-0.58	-0.60	-0.48	1											
Dbeta	-0.01	0.063	0.09	0.04	-0.05	0.12	0.1	1										
Coskew	0.00	-0.04	-0.04	-0.05	-0.03	-0.03	0.05	-0.51	1									
Beta	-0.02	0.14	0.18	0.12	-0.01	0.19	0.03	0.35	-0.05	1								
Zdays	-0.02	0.18	0.18	0.27	0.35	0.11	-0.62	-0.13	-0.03	0.07	1							
Spread	-0.07	0.62	0.58	0.63	0.51	0.57	-0.70	-0.04	-0.03	0.02	0.50	1						
Amih	-0.01	0.11	0.09	0.114	0.09	0.12	-0.12	-0.03	0.00	-0.02	0.043	0.17	1					
Rev	0.08	-0.10	0.06	-0.09	-0.11	-0.26	0.11	-0.01	-0.01	-0.04	-0.00	-0.11	-0.04	1				
Mom	0.08	-0.13	0.11	-0.12	-0.14	-0.42	0.12	-0.02	-0.02	-0.04	0.005	-0.17	-0.06	0.56	1			
Ph52	0.12	-0.60	-0.49	-0.58	-0.40	-0.73	0.44	-0.06	0.00	-0.15	-0.14	-0.48	-0.11	0.40	0.57	1		
ROA	0.06	-0.39	-0.39	-0.37	-0.31	-0.32	0.35	-0.02	0.03	-0.05	-0.16	-0.39	-0.04	0.04	0.02	0.25	1	
BM	0.02	0.28	0.22	0.27	0.30	0.32	-0.26	-0.02	0.00	0.02	0.063	0.24	0.11	-0.14	-0.21	-0.34	-0.05	1

correlation coefficient between the IVOL and the expected return is approximately -11%. This inverse relation may serve as a preliminary indication of the existence of the lottery effect and the idiosyncratic volatility puzzle in the UK market. Moreover, this inverse relationship is consistent with evidence documented in previous empirical studies such as Ang et al. (2009) and Bali et al. (2011). Other interesting relationships are the ones between the different proxies of the lottery effect. Unsurprisingly, the table displays a high and significant positive bivariate relationship between IVOL, MAX5, Jump, and the inverse price which is consistent with the evidence reported in the previous works (see, e.g., Bali et al., (2011) and Zhong & Gray (2016). For instance, the correlation coefficient between IVOL and Max is 92% and statistically significant. (see, for example, Kumar 2009). This high and significant relationship between the employed proxies of the lottery effect may serve as an indication of an existing common component among them.

Generally, it seems that the lottery-like stocks are illiquid. There is an economically significant positive relationship between all proxies of lottery effect and the Bid-Ask spread and the Amihud's impact measure as liquidity proxies. For example, the correlation coefficients between the idiosyncratic volatility and the liquidity-related proxies, namely Bid-Ask spread and Amihud's impact measure, are 62% and 11%, respectively. In addition to liquidity, there is a significant association between the lottery-likeness proxies and the various left tail measures, namely the minimum (Min5), the down beta (Dbeta), and the co-skewness (Coskew).

Remarkably, there is a considerable positive correlation between these proxies and the left-tail risk. For example, the correlation between the inverse price and the minimum returns is -41%. Also, the negative correlation between the PH52 (ratio of current price to highest price over the past 52 weeks) and the lottery-like proxies confirms that the lottery-related stocks are more likely to be losers. The correlation between Max and the PH52 ratio is almost -49%. The reported results display a noticeable relationship between the size, measured by the market value, and the lottery-related characteristics, for example, the correlation coefficient between the IVOL and the LogMV is -56%.

All these reported relationships are consistent with the evidence in the previous studies (see, e.g., Bali et al., 2011, Han & Kumar, 2013, and Annaert et al., 2013). In summary, stocks with lottery-like features are more likely to be small, illiquid, and losers with a long left-tail. It is early to assume that, but all these remarkable bivariate relationships emphasise one of the widely accepted explanations for the lottery effect, namely, the mispricing of the hard-to-arbitrage assets. If the investors face difficulties in shorting small and illiquid stocks they would take a longer time to reflect the poor information regarding the expected losses (see, Stambaugh et al., 2015 and Atilgan et al., 2019). Thus, these stocks are more prone to overvaluation and it is expected to experience persistent losses as a result of slow price correction.

2.4.2. Performance and General Characteristics of the Lottery-like Stocks: One-way sorts.

Under this section, the results of the single-sort lottery portfolios analysis will be shown. Each month, the stocks are sorted into 10 portfolios according to their lottery-related features. Each time the stocks are sorted considering a single feature. To save the space and to summarise, the general characteristics are shown of the portfolios generated by sorting on lottery index rather than individual proxies. By construction, this index is built to represent the common variation of the employed lottery-likeness proxies. In the beginning, the characteristics of the generated 10 portfolios are shown, then, the subsequent-month returns are examined and discussed.

2.4.2.1 Descriptive Statistics of the Lottery-based Portfolios.

Under this subsection, the general characteristics of the lottery-based decile portfolios will be shown. For brevity, Table 2.3 will only show the characteristics of the portfolios based on the lottery-index.

Table 2.3 shows the characteristics of the 10 portfolios created to mimic the Lottery-likeness, sorted by the Lottery index (Lndx). All the reported figures are equal-weighted average. As mentioned, the reported figures represent the characteristics of these decile portfolios. P10 contains the stocks with the highest lottery rank while P1 contains the stocks with the lowest rank. The results displayed in Table 2.3 show many important patterns in the characteristics among the lottery-sorted portfolios.

By construction, the individual lottery-like proxies increase from P1 to P10. To illustrate, moving from the portfolio with the highest level of lottery-likeness (P10) to the lowest level portfolio (P1), the Maximum return (MAX5) increases from ≈12.7% to ≈2.3. The same pattern is found for the idiosyncratic volatility (IVOL), idiosyncratic tails (Jump), and the

Price (logP). Confirming the results shown in Table 2.2 of the previous section, the results in Table 2.3 shows that stocks with lottery-like features are more likely to be more vulnerable to

Table 2.3. Characteristics of the lottery-like stocks.

This table shows the characteristics of the 10 lottery-index portfolios. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, MAX5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars multiplied by 10^7 (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month (in million of pounds), BM: is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on the asset. The sample covers January 1991 to December 2017.

	P10	P9	P8	P7	P6	P5	P4	P3	P2	P1	P10-P1
Lndx	0.94	0.83	0.73	0.64	0.56	0.48	0.40	0.33	0.25	0.15	0.79
IVOL	5.81	3.70	3.05	2.37	2.03	1.77	1.56	1.38	1.19	0.95	4.87
MAX5	12.70	8.21	6.79	5.36	4.61	4.09	3.62	3.23	2.81	2.29	10.41
Jump	59.43	36.38	29.51	22.48	18.73	15.99	13.74	11.73	9.72	7.36	52.07
LogP	3.93	5.91	7.96	7.93	7.71	7.34	7.37	6.59	6.75	7.65	-3.73
Min5	10.97	7.13	6.02	4.83	4.19	3.74	3.38	3.04	2.68	2.19	8.78
DBeta	0.99	0.87	0.84	0.82	0.77	0.76	0.73	0.72	0.70	0.64	0.34
CoSkew	-0.10	-0.05	-0.04	-0.03	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01	-0.09
Beta	1.17	1.09	1.05	0.97	0.90	0.87	0.81	0.79	0.73	0.66	0.51
MV	92	265	451	754	1110	1517	2038	2737	3859	7559	-7467
Zdays	0.27	0.24	0.21	0.18	0.16	0.15	0.14	0.13	0.12	0.12	0.15
Spread	0.07	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.01	0.01	0.06
Turnover	27.10	18.32	15.31	11.36	10.56	8.24	7.99	7.45	7.23	6.56	20.54
Amih	25.02	7.40	12.69	4.35	5.20	1.71	1.95	2.72	0.73	0.43	24.60
Rev	-1.77	-0.36	-0.19	0.32	0.54	0.69	0.60	0.50	0.51	0.55	-2.33
Mom	-7.68	1.42	3.40	5.53	6.72	6.64	6.72	7.27	7.52	8.49	-16.17
PH52	0.54	0.66	0.70	0.76	0.80	0.82	0.85	0.86	0.88	0.90	-0.36
ROA	-0.54	-0.21	-0.05	-0.03	0.03	0.04	0.03	0.06	0.06	0.06	-0.60
Capex	0.06	0.06	0.06	0.06	0.06	0.06	0.06	0.05	0.05	0.05	0.01
BM	1.81	0.94	0.86	0.67	0.62	0.61	0.59	0.56	0.55	0.56	1.25

downside risk, loser, illiquid, and small in value. Going from the most speculative portfolio (P10) to the least speculative portfolio (P1), the minimum returns (Min5) increase from≈2.19% to ≈10.97%. Also, the differences in downside beta (Dbeta) and Co-Skewness (CoSkew) between P10 and P1 are 0.34 and -0.09 respectively. Empirical results in Bali et al. (2011), Han et al. (2015), and others show that stocks with lottery-related features are more likely to have lower returns over the past medium horizon. Consistent with evidence in these studies, the figures in Table 2.3 demonstrate similar patterns. On average, Lottery-like stocks generate losses over the past year. In particular, they generate negative momentum (return over the past 6-month) and a low PH52 ratio (ratio of current price to 52-week high price). In addition to market performance, these stocks are a loser in terms of fundamental-based performance, they had a negative return on assets (ROA). For example, comparing portfolio P10 with P1, the differences in momentum (Mom6) and ROA are approximately -16.17% and -0.6 respectively.

Besides being a loser and risky, previous studies found lottery-like stocks to be illiquid and small in value. Consistent with these studies, the observations in Table 2.3 show the tendency of the lottery-like stocks to be small in value and illiquid. As seen in Table 2.3, the average bid-ask spread of portfolio P10 is 0.07 and it is obviously higher than that for the portfolios with lower lottery-like characteristics. In sum, the results in Table 2.3 indicate that the lottery-like stocks are, on average, more likely to be a loser, risky, small in value, and illiquid.

In the following, the next month's performance of the lottery-based portfolios is examined through performing a single-sort analysis.

2.4.2.2. One-month Ahead Return of the Lottery-like Stocks.

Under this subsection, we will continue to examine the performance of lottery-sorted portfolios. We will push the issue one step further and the next month return performance across these portfolios is shown. In addition to the raw level, the risk-adjusted return is considered. To adjust the expected return for the potential common risk, Carhart’s four-factor model will be used.

Table 2.4 represents the next month's returns across the 10 lottery-sorted portfolios. For direct comparison with the previous studies, the returns of decile portfolios that are generated by sorting the stocks based on the idiosyncratic volatility (IVOL) and the past maximum daily returns (MAX5) are shown. Portfolio P10 consists of the stocks with the highest Lottery-like proxies (i.e. Lndx, IVOL, and MAX5) during the past 3 months, and Portfolio P1 consists of the stocks with the lowest lottery-like proxies. The results show the value-weighted and the equal-weighted returns for these portfolios during the period from January 1991 to December 2017. Under each of these trading strategies, the corresponding differential returns, both in raw value and in risk-adjusted value, and the Newey and West t-statistics are represented.

The results shown above in Table 2.4 confirm the baffling inverse relationship between the next month's return and the lottery-like features documented by the prior studies in the other markets around the world. Regardless of the employed lottery-like proxies, moving from the highest portfolio P10 to the lowest portfolio P1, the return over the subsequent month decreases dramatically. For instance, the difference in equal-weighted return between the highest Lndx-based portfolio P10 and lowest Lndx-based portfolio P1 is -2.74% per month and significant with a t-statistic of -4.33.

Table 2.4 One-month Ahead Return of the Portfolios Based on Lottery-like Index.

This table shows the next month's return of the lottery-based portfolios. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of the second-highest lottery proxy, and so on. t-stat is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Carh(α) is the Carhart four-factor model alpha.

Proxy	Lndx			IVOL			MAX5	
Ret	Ew	Vw		Ew	Vw		Ew	Vw
P10	-2.16	-1.74		-3.45	-2.86		-2.82	-2.09
P9	-1.10	-0.83		-1.28	-0.87		-1.08	-0.48
P8	-0.90	-0.82		-0.75	-0.70		-0.39	0.06
P7	-0.39	-0.14		-0.17	0.04		-0.45	-0.12
P6	0.09	0.44		0.25	0.15		0.19	0.28
P5	0.28	0.27		0.53	0.46		0.37	0.58
P4	0.62	0.58		0.63	0.49		0.49	0.48
P3	0.53	0.52		0.67	0.52		0.50	0.36
P2	0.44	0.38		0.74	0.54		0.55	0.35
P1	0.56	0.54		0.79	0.62		0.59	0.76
P10-P1	-2.74	-2.36		-4.24	-3.49		-3.41	-2.85
t-stat	**-4.33**	**-3.12**		**-5.74**	**-4.51**		**-4.58**	**-3.14**
Carh(α)	-3.09	-2.88		-4.66	-3.92		-3.87	-3.36
t-stat	**-5.97**	**-4.28**		**-9.58**	**-5.81**		**-8.26**	**-5.88**
P9-P2	-1.52	-1.19		-2.02	-1.41		-1.63	-0.83
t-stat	**-3.58**	**-1.91**		**-4.03**	**-2.17**		**-3.02**	**-1.31**
Carh (α)	-1.90	-1.46		-2.35	-1.74		-2.02	-1.24
t-stat	**-5.24**	**-2.80**		**-6.13**	**-2.84**		**-5.07**	**-2.29**

The natural next question is whether this significant inverse predictability is robust to adjusting for widely used risk factors. To answer this question, the raw returns are adjusted for risk by applying the widely used Carhart Four-factor model. The reported adjusted return in Table 2.4 reaffirms the negative difference in the next month's performance between the highest and lowest lottery-like portfolios. For example, considering the equal-weighted case, the four-factor alpha of shorting the highest Lndx-based portfolio P10 and buying long the lowest Lndx-based portfolio P1 is -3.09% per month and significant with a t-statistic of -3.12. The pattern is similar with respect to other lottery-like proxies. For both the IVOL and the MAX5, the highest portfolio P10 underperforms the lowest portfolio P1, even after adjusting for the risk factors in Carhart’s model. So far, this could be taken as strong evidence on the existence of the lottery-effect and the associated idiosyncratic volatility puzzle in the UK sample. These observations are consistent with results found in Ang et al. (2006, 2009), and Bali et al. (2011), among others. And obviously, it contradicts the rational behaviour of risk and returns trade-off that is assumed by the traditional finance literature. The weighting scheme is very substantial in evaluating the asset pricing regularities. Bali and Cakici (2008) show that weighting the returns by market value rather than equal weighting, alters the idiosyncratic volatility effect from insignificant to significant. Like equal-weighted returns, the value-weighted returns in Table 2.4 decrease in the lottery-related proxies which reconfirms that the lottery-like stocks earn lower returns than the other stocks in the markets and regardless of the inherent risk level.

Taking a closer look at the performance of the portfolios formed on lottery-like features, it is clear that the decreasing rate in returns across the portfolios is not monotonic. For all cases, going from the lowest lottery portfolio P1 through portfolios P2, P3, up to P4, the average returns are approximately stable. Taking the Lndx as an example, the value-weighted returns for portfolios P1-P4 are ranging from 0.56% to 0.62% per month. But the difference in returns starts declining dramatically from portfolio P6 to the highest lottery-like portfolio P10. For instance, the average value-weighted returns of the portfolios P6-10 formed by sorting based on the past maximum return (MAX5) are ranging from 0.28% to -2.09% per month. To examine the effect of this non-monotonic trend, the difference in returns between the second-highest lottery-formed portfolio (P9) and the second-lowest lottery-based portfolio is reported. However, except for the value-weighted spread for the MAX5-based strategy, all the cross-sectional spreads in the returns of P9 and P2 are significant, economically and statistically. Again, taking the lottery index (Lndx) as an example, the difference in value-weighted returns between P9 and P2 is -1.19% and significant with a t-statistic of -1.91. Removing out the risk-related component does not change the result, the value-weighted four-factor alpha is lower and more significant with a value equal to -1.46% and a t-statistic of -2.8.

Therefore, if the traditional risk factors are not helpful, what might be the reason(s) behind the anomalous behaviour that appeared in Table 2.4? To answer this question, it will be useful to combine the results in Table 2.4 with the patterns in the characteristics shown in Table 2.3, there are many informative observations. One of the most interesting observations, is that the next month's returns of the lottery-like portfolios are more likely to be attributed to the return continuation rather than the return reversal. Like the subsequent month returns, the pattern in the past returns, shown in Table 2.3, is inversely related to the lottery-like proxies. This continuation behaviour in the performance of the lottery-like portfolios are in contradiction with the evidence found in the US sample, where the reversal describes the trend in the performance of the lottery-like stocks (see, for example, Huang et al., 2009, Bali et al., 2011 and Han and Kumar, 2013). This persistence in the underperformance of the lottery-related portfolios gives a prominence for the behavioural explanation, namely, the under-reaction to news biases. A significant line of the behavioural literature claims that the under-reaction behaviour by the investors is what may lead to the continuation anomalies. For example, some studies argue that the midterm momentum anomaly is related to the investors' delay response to information (see, for example, Antoniou et al, 2013; Chen and Zhao, 2012; Verardo, 2009; and Doukas and McKnight, 2005). Also, Atilgan et al. (2020) argue that the investor’s under-reaction to bad news is the reason for the persistence of the left-tails performance. Another ingredient that is essential for the continuous trend to exist is the limit to arbitrage (see, Hong and Stein, 1999). As mentioned in the previous section, the Lottery-like stocks are more likely to be illiquid, small in size, and to have longer left-tail, which means that they are hard to arbitrage by the market, especially on the downstate. Stambaugh et al. (2015) and Gu et al. (2018) suggest that the idiosyncratic puzzle is a manifestation of the limited arbitrage and the associated persistent mispricing.

In summary, Tables 2.3 and 2.4 show acceptable evidence that the lottery-like stocks in the UK market are more likely to underperform other stocks in this market. Also, there are preliminary observations in support of the difficult to arbitrage mispricing behaviour.

2.4.3. The Association Between the Lottery-like Effect and other Market Anomalies: The Double-sort approach.

Previous empirical studies report much evidence on the significant association between the lottery-like features (e.g., IVOL and MAX) and many of the widely known market anomalies that have found to be priced by the investors in the market (e.g., liquidity effect, size effect, momentum, and reversal). In the previous section, some preliminary evidence of these relationships was reported (see. Tables 2.3 and 2.4). In this section, a deeper look at the overlapping between the reported lottery-effect and a selected set of widely studied anomalies. To this end, 9 portfolios will be constructed by sorting the stocks, firstly, on one of the anomalies, and then, dependently, by one of the lottery-like proxies. Specifically, in the first step, the stocks will be grouped into 3 levels according to one of the selected return predictors. And then, within each of these three groups, the stocks are resorted into another 3 groups according to one of the lottery-like proxies. The main aim of this analysis is to investigate the dependency of the reported anomalous behaviour of the lottery-like stocks on the anomalies documented by the previous empirical tests. For the sake of brevity, the results will only show the alpha of the lottery-index zero-cost strategy conditional on the level of the selected anomaly.

2.4.3.1. Left-tail Behaviour and the Lottery-like Effect.

As shown in Table 2.3, there is a clear association between the lottery-like features (Lndx, IVOL, and MAX) and the tail behaviour measures (Down-Beta, Co-skewness, and the minimum returns). Consequently, this section investigates the effect of the tail risk on the lottery-like stocks' subsequent performance. To do so, the stocks are dependently sorted firstly into terciles based on the left-tail risk and then into another terciles based on the lottery-like features. Hedging portfolios are built within each level of the left-tail risk by buying long the high-lottery portfolio and shorting the low-lottery portfolio and the risk-adjusted alphas of these portfolios are shown in Table 2.5. The goal is to compare the performance of lottery-like strategy payoffs across different levels of tail risk.

The results are shown in Table 2.5 highlight the strong association between the left-tail and the lottery-like strategy performance. Clearly, controlling for the past minimum returns (Min5), the negative relationship between the lottery-like proxies and the subsequent month's performance is the most intense for the stocks with the longest left-tail. Considering the lottery-index, for the lowest Min5 portfolio, the return predictability is insignificant, the value-weighted (equal-weighted) risk-adjusted alpha is only -0.15% with a t-statistic of -0.78 (-0.08% with a t-statistic of -0.61. A similar effect for the left-tail appears for idiosyncratic volatility (IVOL) and the past maximum returns (MAX), but the risk-adjusted alpha remains significant even for the low-Min5 portfolio. For instance, for the low-Min5 portfolio, the equal-weighted (value-weighted) alpha of the IVOL-hedge strategy is -0.32% with t = -2.26 (-0.40% with t = -1.93). This pattern is consistent with the risk-return puzzle. Although they have a higher left-tail risk, the lottery-like stocks underperform other stocks with lower left-tail risk.

Table 2.5 The association between the left-tail risk and the Lottery-like effect.

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the left-tail proxies and one of the lottery proxies. All portfolios are generated through sorting stocks in the sample into 3 groups (High, Medium, and Low) by one of the left-tail proxies (i.e., Min5, DDeta, and Coskew). Then resorting the stocks within each group into 3 portfolios by one of the lottery-like features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, MAX5: is the maximum daily return over the month. Min5: is the average of 5 lowest daily returns over the past 3 months multiplied by -1, DBeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns. The sample covers January 2000 to December 2017. Carh(α) is the Carhart's alpha of the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t-stat is the newey-west t-statistic with lags selected automatically.

			Lndx		IVOL		MAX5	
		Level	Carh(α)	t-stat	Carh(α)	t	Carh(α)	t-stat
Min5	Ew	H	-1.53	-4.11	-2.83	-8.67	-2.07	-5.62
		M	-0.42	-2.88	-0.78	-3.90	-0.63	-3.49
		L	-0.08	-0.61	-0.32	-2.26	-0.25	-1.67
	Vw	H	-2.23	-5.37	-2.68	-5.46	-2.50	-4.32
		M	-0.63	-2.68	-0.83	-3.89	-0.63	-2.88
		L	-0.15	-0.78	-0.40	-1.93	-0.58	-2.97
DBeta	Ew	H	-2.55	-6.71	-3.02	-7.40	-2.64	-6.54
		M	-1.70	-7.34	-1.97	-7.47	-1.69	-6.99
		L	-2.45	-7.24	-2.96	-8.72	-2.25	-6.71
	Vw	H	-1.75	-2.82	-1.97	-3.32	-1.54	-3.03
		M	-1.59	-5.63	-1.60	-6.36	-1.56	-4.81
		L	-1.90	-4.63	-2.41	-6.48	-2.21	-5.93
Coskew	Ew	H	-2.53	-6.68	-3.01	-7.77	-2.18	-6.00
		M	-1.57	-7.80	-1.93	-8.19	-1.62	-6.65
		L	-2.68	-7.27	-3.21	-8.10	-2.70	-6.77
	Vw	H	-1.93	-3.80	-2.23	-4.12	-1.61	-3.37
		M	-0.86	-4.17	-1.21	-3.96	-0.74	-2.30
		L	-1.65	-2.82	-2.28	-3.88	-1.34	-2.45

Both downside beta and the Co-skewness measure tail-risk by employing the joint distribution with the market returns rather than the total unconditional distribution. In particular, they used to proxy the association between a specific asset and the market conditioning on the extreme market states. Therefore, they represent a different aspect of information from that by Min5. Table 2.5 shows different results for the Down-beta and the Co-skewness. It appears that neither of these systematic tail-risk measures has a consistent effect on the lottery-like stocks' performance. For example, for all lottery proxies, the risk-adjusted alpha is almost equal for the low-risk and high-risk portfolios and higher than the alpha of the medium-risk portfolio. Consider the IVOL as an example, the equal-weighted risk-adjusted alphas of the hedging strategy for the low-down-beta portfolio and the high-down-beta portfolio are -2.45% and -2.55%, respectively. The same thing holds for the value-weighted risk-adjusted alpha.

2.4.3.2. Liquidity Level and Lottery-Like Effect.

In this section, the performance of the lottery-like strategy is examined after controlling for the illiquidity level. Liquidity is a multidimensional concept (see, Kyle, 1985). Therefore, to represent the liquidity, three different liquidity proxies will be employed. (Amihud (2002)'s price-impact ratio, the bid-ask spread, and the number of zero-return days. It is worth noting that the liquidity data is not available for all the stocks included in the sample, hence this may affect the results in some way.

The results reported in Table 2.6 represent the effect of the liquidity level on the performance of the lottery-like investment strategy. Like in the left-tail risk, the stocks are firstly sorted on the liquidity proxy, then within each liquidity level, a lottery-like hedge strategy is created.

The figures show the alphas and the associated t-statistics for the lottery-effect hedge strategy that was created within each liquidity level. Clearly, for all liquidity proxies, the alpha of the lottery hedge portfolios increases considerably with the level of the liquidity proxies. Take the Amihud's impact measure as a proxy of liquidity and the Lottery-index (Lndx) as a proxy for the lottery-like feature, the value-weighted alpha for the highest and the lowest level of Amihud liquidity are -3.12% and -0.84% with a t-statistics of -8.38 and -3.49, respectively. This sharp decreasing pattern in the performance highlights the influence of the illiquidity level on the underperformance of the lottery-like stock, hence the negative relation between the lottery-likeness and the subsequent-month return. In other words, being highly illiquid, generates a significant portion of the negative return for the lottery-like stocks. But regardless of the dramatic drop in the underperformance (the four-factor adjusted alpha) of the lottery-like portfolio, it remains significant for the lowest illiquidity level.

Table 2.6 The association between the Liquidity level and the Lottery-like effect.

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the liquidity proxies and one of the lottery proxies. All portfolios are generated by sorting the stocks in the sample into 3 groups (High, Medium, and Low) by one of the liquidity proxies (i.e., Spread, Amih, and Zdyas). Then, resorting the stocks within each group into 3 portfolios by one of the lottery-related features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, MAX5: is the maximum daily return over the month. ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price. The sample covers January 1991 to December 2017. Carh(α) is the Carhart's alpha of the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t-stat is the newey t-statistic with lags selected automatically.

Liquidity		Level	Lndx		IVOL		MAX	
			Carh(α)	t-stat	Carh(α)	t-stat	Carh(α)	t-stat
Spread	Ew	H	-2.42	-6.24	-3.84	-11.52	-2.97	-8.63
		M	-1.41	-4.95	-1.87	-7.95	-1.38	-4.91
		L	-0.78	-4.06	-1.03	-4.75	-0.80	-3.99
	Vw	H	-2.38	-6.23	-3.93	-8.76	-3.23	-7.89
		M	-1.57	-5.32	-1.84	-6.62	-1.53	-5.37
		L	-0.80	-3.40	-1.03	-4.21	-0.78	-2.91
Amih	Ew	H	-3.03	-8.07	-3.85	-10.20	-3.25	-8.15
		M	-1.87	-6.19	-2.40	-7.77	-1.86	-5.64
		L	-0.98	-4.32	-1.33	-5.11	-1.07	-4.22
	Vw	H	-3.12	-8.38	-3.94	-8.82	-3.38	-7.49
		M	-1.79	-5.13	-2.28	-7.64	-1.78	-5.68
		L	-0.84	-3.49	-1.14	-5.12	-0.88	-2.84
Zdyas	Ew	H	-3.23	-9.72	-3.37	-8.99	-2.76	-7.27
		M	-1.18	-5.94	-2.76	-7.40	-2.27	-6.70
		L	-1.34	-5.08	-1.83	-5.33	-1.73	-5.14
	Vw	H	-2.76	-4.28	-2.69	-6.43	-2.13	-5.02
		M	-0.94	-4.11	-2.29	-5.39	-1.91	-5.00
		L	-0.76	-3.51	-1.34	-5.01	-1.10	-2.85

The patterns outlined in Table 2.6 are not surprising and consistent with the evidence in the previous studies. Hou and Loh (2016) report a fractional ability for the market frictions, e.g., bid-ask spread, Amihud's impact ratio, and the fraction of days with zero returns, to explain the idiosyncratic volatility puzzle. Kelly (2014) states that stocks with low liquidity and high market frictions possess high trading costs and informationally uncertain therefore infrequently traded. Consequently, these stocks have a low association with the general market movements, thus have high idiosyncratic volatility. Previous works on the liquidity effect in the UK stock market document a puzzling inverse relation between the illiquidity level and the expected return (see, for example, Lu and Hwang, 2007, and Foran et al., 2015).

Prior works suggest different explanations for the association between speculative features and the liquidity characteristics. Han & and Lesmond (2011), Han et al. (2015), and Reza et al. (2015) all attribute the idiosyncratic volatility-puzzle to the microstructure biases, e.g., bid-ask bounce. Alternatively, this dependency between the idiosyncratic volatility puzzle and the severity of trading friction could be linked to the mispricing level. In the financial market studies, the higher the bis-ask spread and the illiquidity should lead to higher transaction costs and thereby more arbitraging difficulty. Doukas et al. (2010), Stambaugh et al. (2015), Zhong & Gray (2016), Hung & Yang (2018), Gu et al. (2018), and Kumar et al. (2018) are all examples of the studies that link the idiosyncratic volatility puzzle and the MAX-effect to the limits to arbitrage and the associated tendency to overvalue the costly-to-trade assets in the markets. Moreover, Millar (1977) and Stambaugh et al. (2015) suggest that the high information uncertainty induces intense disagreement between the investors in the market and raises the cost of the trade, in turn, the higher trading costs constraint the short seller from arbitraging the most overvalued stocks. Eventually, these stocks experience negative returns in the following period. Au et al. (2008) demonstrate that the short-selling activities in the UK stock market are less likely for the stocks with high idiosyncratic risk as a result of deterrent arbitraging costs. In summary, the substantial effect of the illiquidity level on the performance of the lottery-like stocks may support the mispricing explanation.

2.4.3.3. Past Returns and Lottery-like Effect.

Jegadeesh, (1990) and Jegadeesh & Titman (1993) document two of the most widely studied market anomalies, i.e., the short-term reversal and the mid-term momentum in return. Consistent with the results from the U.S. and other developed markets, the prior empirical results from the UK studies report strong evidence on the short-term market reversal and the mid-term momentum in returns (see, e.g., Hon & Tonks, 2003, and Antoniou et al., 2006).

Some previous empirical works report a significant association between the past and the future returns of the lottery-like stocks. For example, Huang et al. (2009) demonstrate that the stock's returns in the previous month can fully account for the underperformance of the

Table 2.7 The association between the past performance and the Lottery-like effect.

This table reports a performance analysis of the double-sorted portfolios formed by sorting stocks according to one of the past performance proxies and one of the lottery proxies. All portfolios are generated by sorting the stocks in the sample into 3 groups (winners, medium, and Losers) by any of the past performance proxies (i.e., the Momentum, the PH52, and the return over the past month). Then resorting the stocks within each group into 3 portfolios by any of the lottery-like features (Lndx, IVOL, and MAX5), IVOL: is the idiosyncratic volatility, MAX: is the maximum daily return over the month. PH52: is the ratio of the current price to the 52-week high price. Mom is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return. The sample covers January 1991 to December 2017. Carh (α) is Carhart's alpha for the zero-cost strategy that short high lottery stocks and buy long the lowest lottery stocks within each controlling variable. t-stat is the newey t-statistic with lags selected automatically.

Anomaly		Level	Lndx		IVOL		Max	
			Carh (α)	t-stat	Carh (α)	t-stat	Carh (α)	t-stat
Mom	Ew	W	-1.10	-3.88	-1.53	-5.91	-1.30	-4.48
		M	-1.19	-5.32	-1.54	-6.15	-1.19	-5.40
		L	-3.16	-9.72	-3.71	-11.86	-3.42	-9.08
	Vw	H	-0.84	-2.54	-1.33	-3.29	-1.08	-4.42
		M	-1.09	-2.62	-1.41	-3.64	-0.88	-3.02
		L	-2.40	-3.82	-2.22	-3.75	-2.76	-4.17
PH52	Ew	W	-0.24	-1.39	-0.54	-2.94	-0.48	-2.83
		M	-1.05	-4.96	-1.24	-5.26	-1.11	-4.92
		L	-2.92	-8.75	-3.96	-12.78	-3.49	-8.36
	Vw	W	-0.61	-3.60	-0.88	-5.32	-0.71	-3.08
		M	-1.23	-3.73	-1.44	-4.26	-1.21	-3.44
		L	-2.99	-5.78	-3.20	-5.02	-3.29	-4.46
Rev	Ew	W	-1.53	-4.75	-1.93	-6.01	-1.57	-4.66
		M	-1.59	-7.65	-1.87	-7.46	-1.57	-6.17
		L	-3.07	-8.46	-3.59	-8.53	-2.98	-6.74
	Vw	W	-0.95	-2.25	-1.09	-2.52	-0.65	-2.04
		M	-0.85	-3.80	-1.21	-3.96	-0.73	-2.45
		L	-2.68	-4.31	-2.91	-5.18	-2.43	-3.77

lottery-like stocks. Aboulamer and Kryzanowski (2016) argue that the short-term trend in the stocks' return (reversal vs continuation) is very important for the sign and the magnitude of idiosyncratic volatility and the MAX effect. Also, Arena et al. (2008) find a significant association between momentum and idiosyncratic volatility. In addition to the momentum effect, the ratio of current price to highest 52-week price (PH52) is related to one of the most important cognitive biases in the decision-making literature, namely, the Anchoring bias. Recently, some literature argued that the nearness of the current price to the past highest price creates a psychological barrier that leads to a more conservative reaction by the investors, which in turn leads to an underreaction to the value-related news (see, Birru, 2015). Motivated by the importance of these anomalies in determining the securities prices, the goal of this part of the analysis is to examine the association between these price anomalies and the speculative anomalies that this study seeks to test.

As expected, the results shown in Table 2.7 display a greater lottery effect within the stocks with extreme past losses than the stocks with extreme past gains. Taking the lottery index as example, for losers over the past 6-month (the momentum), the value-weighted risk-adjusted alpha of the lottery hedge portfolio is -2.40% (t = -3.82) while for the winners is only -0.84% (t = -2.54). This is consistent with the results of Bali et al. (2011), Conrad et al. (2014), and Annaert et al. (2013), they all show that stocks with a high probability to generate extreme payoffs are more likely to be loser stocks over the midterm horizon. What is interesting here is that the results in Table 2.7 reconfirm the short-term continuation trend in the returns of the lottery-like stocks. To illustrate, if we move from the losers group to the winner group the risk-adjusted alpha of the value-weighted (equal-weighted) MAX-hedge portfolio drops dramatically from -2.43% (t = -3.77) to -0.65% (t = -2.04). This short-term continuation in the performance of the lottery-formed portfolios is contrary to the reversal pattern that has been documented by the studies in the U.S. market and other parts of the world. Under this result, it seems eligible to exclude the reversal explanation suggested in Huang et al. (2009) and others. Rather it gives some legitimacy to the under-reaction channel.

The reversal in the return has been related to the level of microstructure noise. Consequently, Hou & Loh (2016) argue that the level of the lagged return can be used as a proxy for market friction. Their empirical results show the ability of the lagged return to attenuate the magnitude of the negative idiosyncratic volatility-return relation. Accordingly, the reported dependency between the lottery-like anomalies and the short-term performance anomaly may be explained by the inability of the investors to arbitrage the deficiencies in the value of these stocks as they are hindered by the high noise and trading costs. In a related study, Hong et al. (2000) shows that due to some friction the bad news diffuses gradually to the market. They argue that this slow diffusion is what causes the continuation pattern in return over the midterm horizon. Moreover, many works have shown the tendency shown by the manager of the companies to delay disclosure of the bad news to the market (see, e.g., Dye, 1985, Kothari et al., 2009). The main purpose of this control over the bad news is to stop, or at least to slow, the decline in the stock prices (Kim et al., 2011). Investigating the effect of the asymmetric flow of the information, many empirical works show a link between the likelihood to crash in the stock's price and the ability of the manager to slow or to hide the bad information from the investors' eyes (Hutton et al., 2009, Jin et al., 2006, and Chang et al., 2017). In addition, the evidence shows the tendency of the volatility to increase following disclosure of poor outcomes and a period of negative performance (Shin, 2003, and Patton & Sheppard, 2015). Moreover, Lamont (2012) argues that firms employ a variety of tools to impede the short seller from targeting their stocks in the market. Collectively, all these interrelated relationships might explain the relationship between the past performance and magnitude of the Lottery-like effect.

The effect of the PH52 anomaly on the anomalous behaviour of the lottery-like stocks is remarkable. The results in Table 2.7 show a substantial effect on the nearness from the highest price over the past 52 weeks. It is obvious that the Lottery effect almost concentrated in the group of stocks with a price far from its highest 52-week value. In other words, this anomaly explains a significant proportion of the Lottery effect. To elucidate, the equal-weighted alpha of the lottery hedge portfolio within the high PH52 group is only -0.26% and insignificant (t= -1.39). This result is consistent with the mispricing story behind the lottery effect. George and Huang (2004) document anomalous returns continuation behaviour when the stock price is near or far from its past 52-week high, and they argue a behavioural explanation for this continuation behaviour. Specifically, they argue that the investors, as decision-makers, are cognitively biased and anchored by the past extreme price observations. Consequently, if they use the past high and low prices as a reference point, they are more likely to inefficiently adjust the price for the relevant news, which in turn leads to the short-term under-reaction phenomenon. When the information is received by the market, the correction process starts and thus a continuation trend appears. Recently, numerous empirical works have confirmed the existence of PH52 (the 52-week high) momentum, for example, Liu et al. (2011), George et al. (2018), Li and Yu (2012), and Hur and Singh (2019). Also, similar anchoring bias is found in the analyst sample (see, Cen et al., 2013). To summarise, as the lottery-like stocks are more concentrated in the short-leg of the PH52-momentum strategy, it would be intuitive for these stocks to experience a persistent loss. Recall that these stocks are hard-to-value therefore to arbitrage (e.g. speculative, small, and illiquid). Therefore, the investors are less likely to reflect the bad news relevant to these stocks in a timely manner.

2.4.3.4. Effect of the Firm Size and Book to Market Value on Lottery-like Effect.

It has been widely reported by empirical studies that the market value can inversely predict the subsequent returns (i.e. the size effect). This size anomaly was documented by Banz (1981). Levis (1989), Andrikopoulos et al. (2008), and many others provide empirical evidence on the existence of the size-effect in the UK market. Fama and French (2008) show that many of the pricing deficiencies previously documented in the stock market are associated with the size effect. Furthermore, many empirical works have employed the market value as a proxy for the information uncertainty and arbitrage friction (for example see, Zhang, 2006). Arguably, higher information uncertainty would leave more room for various psychological biases. Therefore, firms with smaller market capitalisation are more susceptible to misevaluation. Another pervasive market anomaly is the value-effect, which states that the stocks with higher market value to book value ratio (the growth stocks) tend to underperform the stocks with the lower value of this ratio (the value stocks) (see, Rosenberg et al., 1985). A similar result for the UK market has been documented by many empirical works (see, e.g., Miles & Timmermann, 1996, and Clubb & Naffi, 2007). This ratio would be a suitable proxy for the mispricing by the investors. Hence, more related to the stock's prices tendency to reverse in the future. It has been found that the persistent underperformance of low book to market stocks is a manifestation of the mispricing induced by arbitrage difficulty (see, Ali et al., 2003; Doukas et al., 2010). Conard et al. (2014) relate this mispricing to the speculative component created by the lottery-like demand.

Unsurprisingly, the results outlined in Table 2.8 show the concentration of the lottery-like effect in the group of stocks with small market value and low book-to-market ratio. Clearly, the risk-adjusted alpha of the lottery-based hedge portfolio is considerably lower for these stocks. For example, within the group of small size stocks, the value-weighted risk-adjusted alpha of the lottery-hedge portfolio is -2.67% with a newey and west t-statistic of -8.05, while for the group of big size stocks this alpha is only -0.96% and with a t-statistic of -4.14. In the case of the low book-to-market ratio group, the result shows a similar pattern but with a more striking effect on the value-weighted strategy, especially for idiosyncratic volatility and the

MAX strategies. To illustrate, the value-weighted risk-adjusted alpha of the hedge portfolio for both strategies is not significant. For the high book-to-market group of stocks, the alpha is -0.69% with a newey and west t-statistic of -1.43 in the case of IVOL and -0.42 with a newey and west t-statistic of -0.99 in the case MAX. These patterns of the UK stock market are consistent with previous empirical evidence from other markets (see, e.g., Han & Kumar, 2013; Annaert et al., 2013; and Kang et al., 2014).

Table 2.8 The association between the valuation measures and the Lottery-like effect.

This table reports performance analysis of the double-sorted portfolios formed by sorting stocks according to market value or book-to-market ratio in the first step and then by lottery-related features. 9 portfolios generated through sorting stocks in the sample into 3 groups (High, Medium, and Low) by one of the valuation proxies (market value or book-to-market ratio). Then re-sorting the stocks within each group into 3 portfolios by one of the lottery-related features (Lndx, IVOL, and MAX). Lndx: is the lottery index, IVOL: is the idiosyncratic volatility, Max is the maximum daily return over the past 3 months. MV is the market value of the firm at the end of the month, BM is the book to market value ratio. The sample spans from January 1991 to December 2017. Carh (α): is alpha of the Carhart (1997)'s asset pricing model, t-stat is the newey t-statistic with 3 lags.

Anomaly		Level	Lndx		IVOL		Max	
			Carh (α)	t-stat	Carh (α)	t-stat	Carh (α)	t-stat
MV	Ew	B	-1.01	-4.57	-1.33	-5.48	-1.04	-3.89
		M	-1.80	-6.52	-2.16	-6.85	-1.83	-5.90
		S	-2.51	-7.07	-3.77	-10.50	-2.90	-8.13
	Vw	B	-0.96	-4.14	-1.27	-5.68	-0.90	-2.88
		M	-1.74	-6.67	-2.04	-7.19	-1.79	-5.86
		S	-2.67	-8.05	-3.77	-11.28	-2.78	-8.90
BM	Ew	H	-1.63	-4.25	-1.91	-4.79	-1.60	-4.36
		M	-1.90	-7.30	-2.07	-7.58	-1.78	-6.39
		L	-2.77	-7.72	-3.26	-8.50	-2.65	-7.18
	Vw	H	-0.82	-1.98	-0.69	-1.43	-0.42	-0.99
		M	-1.58	-3.90	-1.67	-5.01	-1.07	-2.60
		L	-2.24	-5.43	-2.54	-7.41	-2.11	-5.93

As mentioned, the small market value is widely considered as a sign of higher information uncertainty and limit to arbitrage. Thus, the small firms are more prone to misvaluation. Likewise, the Low book-to-market stocks was found to be more likely associated with mispricing. Therefore, it seems understandable why these stocks are more associated with the lottery-like effect. Another related explanation would be found in the distress risk anomaly. Contrary to the intuition, Campbell et al. (2008) show that firms with higher distress risk gain lower expected returns than other stocks with lower distress risk. The firms with the extremely low size or with very low book-to-market ratios are found to be the most likely to default in the near future (See, Campbell et al., 2008, and Gao et al., 2018). Furthermore, examining the size effect in the UK market, Andrikopoulos et al., (2008) show that the small-size stocks have been the most likely to go bankrupt and to de-list from the London Stock Exchange over the past time. Conrad et al., (2014) confirm the default risk anomaly and link it to the gambling behaviour of the investors in the market. They demonstrate that the investors consider the highly distressed companies with a low book-to-market ratio as a speculative investment and find that the negative premium is concentrated within the group of speculative distress risk with a high market-to-book ratio. In summary, the empirical observations in Table 2.8 suggest that the reported speculative behaviour in the UK market seems to be related to the interim mispricing by the investors hence highlight the likelihood of the behavioural interpretation of the anomalous performance uncovered so far in this study.

2.4.4. Fama-MacBeth Cross-sectional Analysis Results.

So far, the results reported in the previous sections show the existence of the lottery-related effect in the London Stock Exchange, that is, there is a negative relation between the lottery-like features and the subsequent month's performance. Also, the double-sort portfolios analysis shows a clear association between the previously documented return predictors such as liquidity, left-tail risk (i.g., the maximum historical losses), and the 52-week high momentum. However, these results only show the bivariate relationship between the investigated lottery-related anomalies and the other widely known anomalies. In this section, the widely used Fama and Macbeth procedures will be performed to investigate these relationships in a multivariate set. Under this method, a two-step approach is performed to estimate the returns' sensitivity to a selected set of candidate variables (see, Fama and Macbeth, 1973). In the first step, a cross-sectional regression of the return on the explanatory variables is done on a monthly basis. In the second step, the coefficients, estimated in the first step, are averaged and tested against the null hypothesis. Table 2.9 shows the results of Fama and Macbeth's cross-sectional analysis. The analysis spans the period from January 1991 to December 2017. Many different sets of multivariate relationships (model) are estimated to clarify the specific importance of the different anomalies in explaining the lottery effect.

The results shown in Table 2.9 uncover many interesting observations. Firstly, the results reconfirm the negative predictability for the returns by the different lottery-like proxies, the performance is decreasing in the lottery-like features. For example, under Model 1 (Model 2)

Table 2.9 Fama and Macbeth cross-sectional regressions results.

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV : is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom: is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on asset CAPEX: is the ratio of capital expenditure total asset. R2: is the R square. Obs: is the number of stock observations. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
Cons	1.45***	1.37***	1.19***	-4.5***	-2.94***	-3.7***	-4.13***	-2**	-2.6***	1.43***	1.5***	1.6***
Lndx	-3.6***			-1.2**			-1.01**			0.40		
IVOL		-0.79***			-0.44***			-0.48***			-0.07	
MAX			-0.32***			-0.17***			-0.18***			-0.045
PH52				5.9***	4.4***	5.22***	5.3***	3.35***	3.9***			
Mom							0.009***	0.011***	0.01***			
Rev							-0.021***	-0.013***	-0.01*			
Min5										-0.47***	-0.40***	-0.40***
Dbeta												
Coskew												
Zdyas												
Amih												
Spread												
LogMV												
Beta												
ROA												
CAPEX												
BM												
Rsq	0.03	0.0357	0.032	0.0523	0.056	0.0561	0.0672	0.0707	0.0702	0.0467	0.0455	0.0469
Obs	199132	199132	199132	199132	199132	199132	195370	195370	195370	199132	199132	199132

Continued

	Model 13	Model 14	Model 15	Model 16	Model 17	Model 18	Model 19	Model 20	Model 21	Model 22	Model 23	Model 24
Cons	1.32***	1.4***	1.5***	0.98***	1.22***	1.04***	0.27	0.76*	-0.049	-2.14**	-1.5	-1.33
Lndx	0.45			-1.84***			-2.4***			0.93***		
Ivol		-0.05			-0.60***			-0.68***			-0.11	
MAX			-0.045			-0.20***			-0.22202			-0.05*
PH52										2.74***	2.67***	2.48***
Mom										0.011***	0.012***	0.013***
Rev										-0.029***	-0.023***	-0.02***
Min5	-0.48***	-0.42***	-0.41***							-0.28***	-0.18***	-0.20***
DBeta	0.16**	0.13*	0.17**							0.149***	0.149**	0.17***
Coskew	-0.08	-0.12	0.05							-0.27	-0.22	-0.14
Zdyas				2.7***	1.2***	1.62***				0.31	0.14	0.16
Amih				-0.02	-0.03	-0.02				-0.25	-0.28	-0.30
Spread				-43.4***	-22.1***	-33.3***				-13.7***	-10.7**	-10.5**
LogMV							0.056	0.006	0.09**	-0.012	-0.06	-0.06
Beta							-0.07	-0.003	-0.011	-0.011	0.02	0.03
ROA							2.5***	1.7***	2.02***	1.27***	1.08**	1.1**
CAPEX							-1.54*	-1.4*	-1.67**	-1.42**	-1.44**	-1.46**
BM							0.78***	0.84***	0.78***	1.13***	1.12***	1.12***
Rsq	0.0582	0.0568	0.0582	0.0537	0.0554	0.0527	0.0659	0.071	0.0683	0.1295	0.1301	0.1304
Observations	199132	199132	199132	192404	192404	192404	183815	183815	183815	176128	176128	176128

coefficients of the lottery-like index (the idiosyncratic volatility) is -3.6 (-0.79) and the newey and west t-statistic is highly significant at α=1%. Secondly, controlling for the 52-week high momentum substantially affects the predictability power of the lottery-related proxies. For instance, the magnitude of the coefficient of the Lndx (MAX) reduced markedly, from -3.6 (-0.37) to -1.2 (-0.17). However, they retain their significance in predicting the future performance of the lottery-like strategies. Thirdly, the results reaffirm the ability of the left-tail proxy (the Min5) to fully explain the so far observed negative relation between the lottery-like proxies and the future performance. In particular, models 10, 11, and 12 of Table 2.9 show that, after controlling for the effect of the Min5, the pricing coefficients of the employed lottery-like proxies are turned statistically and economically insignificant. Consider the IVOL as an example, the coefficients are reduced to only -0.07. This result highlights the close link between the lottery effect and the recently documented persistent left-tail momentum, where the investors found to underreact to left tail information (see, Atilgan et al., 2019). It is noteworthy that this result is inconsistent with Bali et al. (2011), as they report the inability of the left-tail measure to explain the lottery effect. Lastly, the other controlling variables such as the liquidity proxies and the accounting fundamentals (e.g., ROA) can explain the lottery-like anomaly but partially. For instance, models 15-17 show that the liquidity proxies, jointly, can explain only a small part of the lottery-like effect. Numerically, their inclusion reduces the IVOL coefficients from -0.79 to -0.6, with no effect on its statistical significance.

To summarize, in the multivariate framework, the results of the cross-sectional regression indicate the existence of the lottery effect in the UK stock market. Contradicting the standard risk-return trade-off, the lottery-like stocks in the UK market underperform other stocks, although they are vulnerable to a higher level of risk. Moreover, the results in Table 2.9 reveal the ability of the left-tail proxy to fully explain the negative relation between future performance and the lottery-like features. In addition, the cross-sectional analysis shows that the 52-week high momentum partially explains the lottery effect.

In the light of these empirical observations and as we ruled out the ability of the widely used risk factors in explaining the underperformance of the lottery-like stocks, it seems that the behavioural story is more plausible. Previous empirical works propose an asymmetry in the response of the investors to the bad news (see, Easterwood and Nutt, 1999; Hong et al., 2000; and Chan et al., 2003). Kothari et al. (2009) argued that some firms hold bad news which causes initial underreaction and asymmetric response to this information when they were announced. Similar evidence found for the UK market, Tuan et al. (2018) analyses the UK market and argue that the information uncertainty gives a suitable environment for the companies to withhold bad news, which in turn leads to higher forecasting error by the analyst. Also, Clubb and Wu (2014) analyse the UK companies' earnings data and demonstrate that the ability to predict the next earning is negatively related to the earning variability. In addition, Artikis and Papanastasopoulos (2019) argue that investors in the UK market and highlight the underperformance of the stocks with bad news, they argue that the illiquidity that characterised these stocks is the main driver of this mispricing. Of course, if we combine all this evidence with the limited arbitrage proposition and the more likely erroneous expectation triggered by the anchoring bias, a sensible story is built to explain the observed underperformance for the lottery-like stocks. That is, the Lottery-like stocks are more likely to represent the stocks with bad news (e.g., losers in term of return and accounting earning), that trade at price near to the past 52-week high price, if the investors are susceptible to anchoring bias, then they will underestimate the left-tail of these stocks. And remember that these highly fluctuated stocks are small and illiquid which may deter the short seller from arbitraging the apparent mispricing. Consequently, the underperformance of the lottery-like stocks persists, and the nonstandard inverse risk-return relationship appears in the market.

2.5. Robustness tests.

As shown in the previous sections, the lottery-like features are inversely related to the next month' return across the UK stocks. Moreover, so far, the results in this chapter show that this lottery-like effect is explainable by cross-sectional differences in the left-tail (i.e., the minimum daily returns in the past months). As a natural step, it is important to check the robustness of these results against the different methodological specifications. Therefore, this section examines the consistency of the evidence obtained above in this study in the face of some alterations to the analysis procedures. Han and Lesmond (2011) show that the idiosyncratic puzzle is merely a manifestation of liquidity bias such as bid-ask bounce. Also, Bali and Cakici (2008) demonstrate that the pricing of the idiosyncratic risk in the US market is not robust to different samples and weighting schemes. Furthermore, many market anomalies have found to be attenuated in recent years (Chordia et al., 2014). And others indicate the effect of the different Market states on the return predictability (Cooper et al., 2004).

2.5.1. Skipping the First Month after the Portfolio Formation.

To investigate whether microstructure issues affect the reported lottery-like effect within the UK market, we re-conduct the analysis after skipping one month and examine the predictability of the lottery-like features for the two-month-ahead return. Table 2.10 shows the two-month-ahead returns and the corresponding Carhart Four-Factor alpha of the lottery-sorted portfolios.

Table 2.10 Two-month-ahead returns of the lottery-like stocks.

This table shows the two-month ahead returns of the lottery-based portfolios. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of the second-highest lottery proxy, and so on. The sample covers January 1991 to December 2017. Carh (α) is the Carhart four-factor model alpha. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

Decile	Lndx		IVOL		MAX	
	Ew	Vw	Ew	Vw	Ew	Vw
P10	-2.31	-2.27	-3.01	-2.06	-2.62	-2.24
P9	-1.35	-0.90	-1.36	-1.09	-0.93	-0.54
P8	-0.94	-1.00	-0.82	-0.54	-0.65	-0.03
P7	-0.58	-0.26	-0.23	-0.17	-0.30	-0.02
P6	0.02	0.10	0.20	0.34	0.24	0.52
P5	0.43	0.60	0.47	0.57	0.32	0.21
P4	0.62	0.49	0.57	0.58	0.38	0.39
P3	0.47	0.31	0.70	0.58	0.56	0.45
P2	0.64	0.52	0.75	0.70	0.59	0.62
P1	0.57	0.55	0.83	0.57	0.50	0.74
P10-P1	-2.9***	-2.8***	-3.8***	-2.6***	-3.1***	-3.0***
Carh (α)	-3.2***	-2.9***	-4.2***	-2.95***	-3.7***	-3.3***
P9-P2	-2.0***	-1.4**	-2.1***	-1.8***	-1.5***	-1.2*
Carh (α)	-2.3***	-1.6***	-2.5***	-2.1***	-1.82***	-1.7***

Table 2.10 reconfirms the reported underperformance of the lottery-like stock against the non-lottery stocks. Skipping the first month next to the portfolio formation, the raw return and the risk-adjusted alpha of the highest lottery-based portfolio are lower than the ones for the lowest portfolio. For example, considering the lottery index, the value-weighted alpha of the lottery-hedge portfolio is -2.9% and highly significant. This result rules out the potential

effect of the microstructure biases on the reported findings on the existence of the lottery-like effect in the UK stock market.

In addition to the portfolios' performance analysis, Table 2.11 shows Fama and MacBeth cross-sectional regression results in the case of a two-month-ahead return.

Table 2.11 Fama and MacBeth cross-sectional regressions of two-month-ahead returns.

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the two-month ahead stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the Past 3 months, Max5: is the average of 5 highest daily returns over the past 3 month, Jump: is the sum of the absolute returns over the 2 standard deviation, logP: is the logarithm of the stock price at the end of the month, Min5: is the average of 5 lowest daily returns over the past 3 month multiplied by -1, Dbeta: is the downside beta of the stocks, Coskew: is the co-skewness between the stock's returns and the general market returns, Beta: is the market beta measured by using CAPM as a pricing model, ZDays: is the percentage of days with zero returns, Amih: is the ratio of absolute monthly return to the monthly trading volume in dollars (liquidity measure inspired by Amihud, 2002), Spread: is the monthly average of the daily spreads between the bid price and the ask price, Turnover: is the monthly average of the daily traded shares to the number of shares outstanding, MV: is the market value of the firm at the end of the month, BMV : is the book to market value ratio, PH52: is the ratio of current price to the 52-week high price. Mom: is the monthly cumulative return over the period from t-7 to t-2. Rev: is the one lagged month return, ROA: is the Return on asset CAPEX: is the ratio of capital expenditure total asset. Rsq: is the R square. Obs: is the number of stock observations. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Mod1	Mod2	Mod3	Mod4	Mod5	Mod6
Cons	1.4***	1.2***	0.98***	-3.4***	-2.8***	-2.6***
Lndx	-3.4***			0.5*		
IVOL		-0.68***			-0.01	
MAX			-0.26***			-0.07
PH52				3.8***	3.5***	3.4***
Mom				0.008***	0.01***	0.011***
Rev				0.005	0.01*	0.0135**
Min5				-0.13***	-0.06	-0.065*
DBeta				0.15**	0.15**	0.17**
Coskew				0.020765	0.13	0.20
Zdyas				0.6	0.41	0.30
Amih				0.06	0.09	0.06
Spread				-18.0***	-16.5***	-13.9***
LogMV				-0.015	-0.046	-0.046
Beta				-0.007	0.000322	0.012
ROA				1.6***	1.5***	1.37***
CAPEX				-1.6**	-1.6**	-1.56**
BM				1.1***	1.1***	1.07***
Rsq	0.03	0.033	0.03	0.125	0.125	0.125
Obs	199134	199134	199134	176129	176129	176129

Confirming with the portfolio analysis, the cross-sectional regression results outlined in Table 2.11 show the pricing of the lottery-related features across the stocks in the UK market. The average slope coefficients for all three lottery-like proxies are negative and significant economically and statistically. Consider the MAX as an example, the average of slope coefficients is -0.26 and significant at α=1%. These results reinforce the evidence reported in the main body of this study on the existence of the lottery-like effect in the UK market.

2.5.2. Subsamples Analysis.

In addition to microstructure issues, it is also important to check the robustness of the reported lottery-like effect across different samples. In this regard, previous literature shows the effect of sample filtering on the payoffs of many widely reported market anomalies. For example, previous research shows the concentration of the lottery-like effect in the small, low price, and illiquid stocks (for example, see Bali and Cakici, 2008, Kumar, 2009). Also, it is important to highlight the performance of the lottery-like strategy over the different sampling periods.

2.5.2.1. Filtering Out the Small-size, the Illiquid, and the Penny Stocks.

Under this section, the effect of penny price, small size and illiquid stocks exclusion on the lottery strategy payoffs will be shown. The double-sort portfolios analysis in section (5) outlined some of the related observations. Particularly, the results in Tables 2.6 and 2.8 show that the performance of the lottery-based strategy is negative and significant in the most liquid and the big market value groups. Therefore, in this section, the Fama and MacBeth cross-sectional regression will be conducted, but after filtering out the stocks with a price less than 10 pounds, the stocks with a market value lower than the median of the sample, and the stocks with Amihud's impact ratio higher than the sample' median. One of these criteria will be filtered at a time.

Table 2.12 represents the cross-sectional regression after filtering out the mentioned stocks. In this table, two different models are shown. In models 1, 3, 5 the regression of the stocks' returns on one of the lottery-like features at a time. While in models 2, 4, and 6, in addition to the lottery features, the control variables are included. For brevity, only the constant and the average slope coefficients of the different lottery-like features are shown in the table.

Table 2.12 Filtering-out the small-size, the illiquid, and the penny stocks.

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index. IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. R2: is the R square. Obs: is the number of stock observations. Panel A shows the stocks with prices higher than £10; Panel B shows stocks with lower than the sample-median Amihud's price impact measure, and Panel C shows stocks with a market value higher than the sample-median. The full model indicates a model consists of a lottery-like effect with a set of control variables. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A	stocks with Price > £10					
Const	1.4	-1.9	1.42	-1.12	1.2***	-0.95
Lndx	-3.4***	0.95**				
IVOL			-0.81***	-0.11		
MAX					-0.32***	-0.051*
Full Model		Yes		Yes		Yes
Rsq	0.028	0.1311	0.034	0.132	0.03	0.132
Obs	191213	169797	191213	169797	191213	169797
Panel B	Liquid stocks					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const	0.93***	0.42	1.3***	0.71	1.1***	0.76
Lndx	-2.1***	0.78**				
IVOL			-.68***	-0.066		
MAX					-0.24***	0.0
Full Model		Yes		Yes		Yes
Rsq	0.0334	0.1904	0.0377	0.1914	0.038	0.1921
Obs	96225	89401	96225	89401	96225	89401
Panel C	Big stocks					
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Const	0.83	-0.34	1.14***	-0.23	0.91***	-0.21
Lndx	-1.83***	0.85**				
IVOL			-0.59***	0.13		
MAX					-0.20***	0.06
Full Model		Yes		Yes		Yes
Rsq	0.028	0.18	0.032	0.182	0.033	0.182
Obs	99564	91439	99564	91439	99564	91439

Although it is weaker in comparison to the results presented in the whole sample, the lottery effect appears to persist in the filtered sample. The results in Table 2.12 indicate that the coefficients of the lottery effect are negative and significant. For example, model 1 of Panel A shows that after filtering the low-priced stocks, the coefficient of the lottery index remains significant with a value of -3.4. These results can be generalised to big-size and liquid stocks. Thus, under these observations, the effect of the subsampling on the lottery-like effect could be ruled out. Therefore, the so far reported evidence indicates the robustness of the lottery effect within the UK sample.

2.5.2.2. Different Sampling Periods.

Kumar (2009) shows that the demand for lottery-like stocks is higher in the downturn state. This means that the lottery-like stocks are more prone to misvaluation in the bear market. Walkshausl (2014) demonstrates that the returns of the lottery strategy (i.e., the MAX effect) are lower in periods of crisis. Therefore, in this subsection, the performance of the 10 deciles portfolios sorted on the lottery features (e.g., the Lottery index, the IVOL, and the MAX) is shown for three different sub-periods.

The first sub-period spans from 1991 to 2000 and the second sub-period spans from 2001 to 2007, while the third sub-period spans from 2008 to 2017. The purpose behind this subsampling is to highlight the performance of the lottery stocks through the period of crisis, for example, the dot-com crash and the recent financial crisis.

It is clear from the observations outlined in Table 2.13, that the reported lottery-like effect is a prominent phenomenon in periods of crisis. The difference between the returns of the highest decile portfolio and the lowest decile portfolio is considerably low during periods dominated by a rising market. To clarify, although they remain negative, the differential return and alpha of the lottery-like strategy are substantially very low during the period 1991-2000. Through this period the financial markets over the world witnessed the so-called dot-com bubble. During this bubble, the record shows that the UK stock market rose like a rocket to a historical level. Regardless of the upmarket, the lottery-like stocks had generated, on average, a lower return than the non-lottery counterpart, the four-factor alpha is significantly negative in most cases. For example, the alpha of the lottery-index-based strategy is -1.97% and significant at α=1%. In comparison to the bubble period, the lottery effect was dramatically strong during the period of crash market 2000-2017. This empirical observation is in line with the evidence in Kumar (2009) and Walkshausl (2014).

Table 2.13 Subperiod analysis:1991-2000, 2001-2007, and 2008-2017.

This table shows the next month's return of the lottery-based portfolios over a different period. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of the second-highest lottery proxy, and so on. t- Statistic is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Carh(α) is the Carhart four-factor model alpha. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

Port	Lndx			IVOL			MAX		
	1991 to 2000	2001 to 2007	2008 to 2017	1991 to 2000	2001 to 2 007	2008 to 2017	1991 to 2000	2001 to 2007	2008 to 2017
P10	-0.28	-4.04	-2.85	-0.71	-4.90	-3.63	-0.14	-4.16	-2.60
P9	0.42	-2.08	-1.65	0.83	-2.08	-1.75	0.65	-1.46	-0.93
P8	0.49	-1.70	-1.26	-0.10	-1.45	-0.78	0.73	-0.42	-0.28
P7	0.53	-1.11	-0.75	0.66	-0.82	0.01	0.43	-0.84	-0.18
P6	0.89	-0.18	0.23	0.87	0.29	-0.68	1.04	-0.16	-0.19
P5	1.00	0.17	-0.46	1.17	0.00	0.05	1.12	0.22	0.29
P4	1.28	0.46	0.14	1.11	0.89	-0.43	0.96	0.15	0.24
P3	0.62	0.28	-0.17	0.81	1.07	-0.16	0.96	0.51	-0.35
P2	1.20	0.33	0.30	1.14	0.08	0.25	0.57	0.47	0.05
P1	0.73	0.24	0.42	1.05	0.19	0.48	0.82	0.79	0.68
P10-P1	-1.01	-4.16***	-3.35***	-1.76*	-4.95***	-4.2***	-0.96	-4.86***	-3.34***
Carh(α)	-1.79***	-3.69***	-3.87***	-2.63***	-4.54***	-4.84***	-2.0**	-4.25***	-4.15***
P9-P1	-0.79	-2.45**	-1.91*	-0.31	-2.18**	-1.98*	0.08	-1.9	-1.0
Carh(α)	-1.37**	-1.98***	-2.25***	-1.1*	-1.7*	-2.46**	-0.87	-1.17	-1.65*

2.5.3. Effect of the Investors Sentiment and Market Liquidity.

As shown in the previous sections, there is a robust lottery effect in the UK market. In addition, the evidence indicates that this effect is most likely to be explained by the behaviour of the left-tail. Also, the evidence indicated that the pricing of the lottery stock is related to the anchoring bias of the continuous trend due to the erroneous expectation by the investor. The behavioural literature relates this erroneous valuation by the investor to overconfidence (Daniel and Hirshleifer, 2015). Furthermore, many works link overconfidence and other cognitive biases to excessive trading states. Statman et al. (2006), Lou and Shu (2017), and Han et al. (2019) all argue and demonstrate that mispricing is more probable in times of high trading volume and liquid market. Also, Baker and Stein (2004) developed a model with liquidity as a proxy for the sentiment. In this section, we shed some light on the effect of excessive trading and investor sentiment on the lottery effect in the UK market. For that, in this section, the excessive trading regime of the market should be represented by the market aggregate turnover and the Economic Sentiment Indicator (ESI) will be used as a proxy of the investor sentiment. Combining both indices would serve as a suitable proxy of a mispricing environment. Three different activity states will be created, the OPTIMISTIC state in which the liquidity and sentiment are above the median value, MILD in which the only one of the two variables, the liquidity or the sentiment is above the median, and lastly the PESSIMISTIC state where both variables are below the median value.

To test whether lottery-like stocks' performance is affected by the trading activity state and the level of sentiment, we regress the time series of monthly payoffs to the zero-cost strategy of lottery-like features on 3 dummy variables for the OPTIMISTIC, MILD, and PESSIMISTIC state, with no intercept. Also, Fama and MacBeth cross-sectional regressions will be presented for each different activity level.

Table 2.13 displays the performance analysis of the lottery-based portfolios for the three different activity levels. As expected, the findings in Table 2.13 support the projected inverse association between sentimental trading and the lottery-based strategy performance. Regardless of the employed lottery-likeness proxy, the difference in the value-weighted returns and the risk-adjusted alpha are always lower following the time of pessimistic and low activity state. For example, following the pessimistic state (low liquidity and low sentiment) the difference in the returns of the high IVOL (MAX) decile and the low IVOL (MAX) decile is only -1.1% (-0.23%) and statistically insignificant. Also, in most cases, the lottery payoffs are considerably lower flowing periods with high investor sentiment and excessive liquidity. This finding is in line with the previously conjectured mispricing story. In particular, it appears more likely for the investors in the UK market to overvalue the lottery-like stocks when their trading is driven by the optimistic emotion and having access to liquidity.

This interpretation is highly possible especially if we deal with stocks that are characterised by arbitraging difficulties (see, Baker and Wurgler, 2007). Moreover, the results are consistent with the active investing puzzle, which states that after excessive trading the investors are more likely to lose money (Odean, 1999; Daniel and Hirshleifer, 2015).

Table 2.14 Effect of sentiment state and general market liquidity on the Lottery-like stocks' performance.

This table shows the next month's return of the lottery-based portfolios through different periods of emotional trading. Optem: is a period of high sentiment and high liquidity, Pessem: is the period of low sentiment and low liquidity. Mild: consists of all other periods that don't belong to either Optem or Pessem. Each month the stocks are grouped into deciles according to any of the lottery proxies, then each portfolio is held for the subsequent month. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 months. P10 is the portfolio of the highest lottery proxy, P9 is the portfolio of the second-highest lottery proxy, and so on. t- Statistic is the newey and west t-statistic with lag selected automatically. The sample covers January 1991 to December 2017. Carh(α) is the Carhart four-factor model alpha. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

Lottery	Lndx			IVOL			MAX		
	Optem	Mild	Pessem	Optem	Mild	Pessem	Optem	Mild	Pessem
P10	-5.22	-2.10	0.15	-6.56	-2.73	0.09	-4.75	-2.31	1.06
P9	-3.41	-1.02	1.20	-2.80	-0.78	0.55	-2.26	-0.44	0.78
P8	-2.90	-0.56	0.48	-1.84	-0.76	0.77	0.49	-0.35	1.02
P7	-1.71	-0.59	1.58	-0.96	-0.12	1.18	-1.41	-0.34	1.89
P6	-0.63	0.15	1.92	-0.43	-0.10	1.48	-0.55	0.15	1.35
P5	-0.35	0.11	1.38	-0.39	0.32	1.66	-0.51	0.58	1.64
P4	0.20	0.54	1.29	0.13	0.24	1.33	0.30	0.34	1.13
P3	-0.21	0.02	1.31	0.35	0.33	1.19	-0.18	0.18	0.99
P2	0.43	0.38	1.36	-0.30	0.43	1.49	0.13	0.19	0.81
P1	-0.05	0.41	1.05	-0.11	0.59	0.99	0.31	0.74	1.08
P10-P1	-5.2***	-2.5***	-1.1	-6.5***	-3.3***	-1.1	-5.1***	-3.0***	-0.23
Carh(α)	-3.8***	-3.1***	-2.1**	-5.2***	-3.97***	-2.1*	-3.7**	-3.7***	-1.5
Obs	53	196	53	53	196	53	53	196	53

In the following, the cross-sectional regression analysis is performed for each different trading activity state.

The results outlined in Table 2.14 confirm the general results that have been reported in this study about the mispricing of lottery-like stocks. Generally, the magnitude and the significance of the lottery-like effect vary across different sentimental activity regimes. Comparing the low-sentiment regime to the high-sentiment regime, the coefficients of lottery-like proxies are less in magnitude and insignificant. For example, moving from a high sentimental trading regime to a low sentimental regime reduces the IVOL effect from significant -1.18 to insignificant -0.3.

Table 2.15 Effect of sentiment state and general market liquidity: the Fama and MacBeth cross-sectional regression.

This table represents the average estimated coefficients from monthly Fama-Macbeth cross-sectional regressions for each level of sentimental activity. All stocks are sampled together. The left-side of the equation is the stocks' risk premium. Lndx: is the lottery-index, IVOL: is the idiosyncratic volatility over the past 3 months, Max5: is the average of 5 highest daily returns over the past 3 monthR2: is the R square. Obs: is the number of stock observations. No control indicates regressions with only the lottery proxies as independent, while under the Control column the models add the set of the controlling variables. The sample covers January 1991 to December 2017. Note that *** indicate t-statistic significant at 1%, ** significant at 5% and * significant at 10%.

	No control			Control		
Panel A	High Sentiment					
Cons	1.4**	1.1*	0.6	-4.8*	-4.0	-3.8
Lndx	-6***			0.59		
IVOL		-1.18***			-0.41**	
Max			-0.41***			-0.16***
Rsq	0.03	0.041	0.035	0.11	0.11	0.114
Obs	35503	35503	35503	32173	32173	32173
Panel B	Mild Sentiment					
Cons	1.44***	1.43***	1.3***	-1.33	-0.66	-0.42
Lndx	-3.52***			1.1**		
IVOL		-0.75***			-0.09	
Max			-0.31***			-0.05
Rsq	0.031	0.035	0.032	0.13	0.13	0.13
Obs	122007	122007	122007	108095	108095	108095
Panel C	Low Sentiment					
Cons	1.57***	1.43***	1.25**	0.27	0.51	0.4
Lndx	-1.6			0.68		
IVOL		-0.3			0.03	
Max			-0.1			0.02
Rsq	0.021	0.025	0.024	0.12	0.12	0.122
Obs	34337	34337	34337	30429	30429	30429

Another interesting finding is the ability of the IVOL and the MAX to retain their predictability power in the period of high sentiment. Referring to the whole sample analysis displayed in Table 2.7, the Lottery-like proxies lost their effect in favour of the left-tail effect (i.e., the MIN). However, the results in Table 2.14 indicate that in the high sentimental regime, the IVOL and the MAX effect retained their ability to inversely predict the next month's returns across the stocks in the UK market, even after controlling for the MIN and the other selected returns predictors. In particular, the results in Panel A of Table 2.14 show that the IVOL’s (MAX’s) coefficient is -0.41 (-0.16) and significant at α=0.05 level. In sum, the mentioned lottery-like effect disappears after the period of low active sentimental trading and the robust after the period of active sentimental trading.

2.6. Summary and Concluding Remarks.

Recently, an increasing number of studies have reported the investors' tendency to speculate and hence to prefer lottery-like stocks that have high potentials for extreme payoffs in the future (see, e.g., Kumar, 2009; and Bali et al., 2017). Consequently, the empirical evidence from the U.S. and the other stock markets document a puzzling low performance for the portfolio of stocks with high idiosyncratic volatility and extreme fluctuation. However, there is still an ongoing debate on the main drivers of the documented lottery effect. This study contributes to this debate by investigating lottery-like trading in the UK market.

The empirical findings in this study are consistent with the previous empirical evidence. Particularly, the lottery-like stocks are found to underperform the other stocks group in the UK stock market. Also, this underperformance appears to be concentrated in the crisis periods and persists after controlling for other returns predictors such as size, momentum, and systematic downsize risk. However, the forces behind this poor performance are different from the ones found by the studies in the US and other stock markets over the world. The empirical observations shown in this study imply that the left-tail measure subsumes the reported lottery effect in the UK stock market. In addition, the findings in this study indicate that the poor performance of the lottery stocks is partially explained by the anchoring effect and the limited arbitrage proxies. In total, it seems that the lottery effect exists in the UK market, and it is merely a manifestation of the investor underreaction to left-tail duration, which is magnified by the arbitrage frictions and the investors sentimental trading.

CHAPTER THREE

Underreaction and the Risk-based Anomalies: Evidence from the UK

Abstract

Stocks with high left-tail risk and idiosyncratic risk have been found to be overvalued by the investor, hence, underperforming the market benchmark (see, Ang et al., 2006; and Atilgan et al., 2020). This study contributes to the existing literature by studying the behaviour of these risk-based anomalies in the UK stock market through the period of January 1996 to December 2017. Also, the study examines the investor's inattention as a reason behind these pricing anomalies. Contradicting the standard risk-averse behaviour, the empirical findings indicate the ability of the left-tail risk (i.e. the expected short-fall) and the idiosyncratic volatility to inversely predict the stock returns over the next midterm (i.e. next 6 months) in the UK market. Furthermore, after controlling for the information uncertainty and the illiquidity, the results revealed that the suggested limited attention behaviour is a significant contributor to the magnitude of the left-tail momentum and idiosyncratic risk puzzle.

Keywords: Return Predictability; Risk-seeking; Underreaction behaviour; Limited Attention; Limited Arbitrage.

3.1. Introduction.

The standard theory of asset pricing in finance assumes that investors are risk-averse and hence rationally require a systematic compensation to hold risky financial assets. A representative example of this theory is the capital asset pricing model of Sharpe (1964). Under this model, the investor is rational risk-averse who diversifies his/her investment among the available investment alternatives. Consequently, the unsystematic risk is cancelled out thus only the systematic risk is compensated by the market. Regardless of the theoretical appeal of these assumptions, the ongoing empirical evidence has been not supportive. Empirical efforts in the equity market have documented many pricing irregularities that imply movements in asset prices are predictable by non-risk features.

The advocates of rational markets argue that the priced features are a signal for misspecification of the single factor model (i.e. the CAPM) hence additional pricing factors would fill this drawback. For example, Fama and French (1993) extend the single factor model by adding two additional factors, namely the size, and the book-to-market ratio. Also, Carhart (1997) adds the momentum factor to the Fama and French three-factor model. They argue that these additional characteristics are priced by the investors as risk-related factors.

Recently, asset pricing literature has uncovered more striking evidence on the misspecifications of the standard model of asset pricing. The unsystematic risk is priced by the investors and there is an inverse relationship between the risk and returns. Ang et al. (2006) document an inverse relationship between the idiosyncratic volatility (IVOL effect) and the subsequent returns of the stocks in the U.S stock market. In addition, Atilgan et al. (2020) find a negative relationship between the downside risk and the subsequent returns in the U.S market. These results mean investors prefer stocks with higher risk rather than low-risk stocks. Moreover, these results form a direct challenge to the rational theory of asset pricing and the risk-return trade-off.

Failure of the rational pricing hypothesis to explain the movements in the prices of the stocks, encourages the transition to the behavioural pricing theory. Under this theory, the investors' decision-taking processes are cognitively biased, and they have preferences for a non-risk basis (e.g. preference for lottery-like returns). Cognitive biases by the investors lead to erroneous expectations regarding the stock's prospects and therefore the investors overreact and/or underreact to the news flow to the market (see, for example, DeBondt and Thaler, 1985, Grinblatt and Han, 2005, and Hou et al, 2009). Consequently, continuation and reversal patterns appear in the market.

Behavioural finance has borrowed many conceptual terms from the psychology field. For example, representative heuristic bias and the investor's overconfidence could explain the reported overreaction and the reversal in the prices of the stocks (DeBondt and Thaler 1985, and Odean 1998). Also, cognitive biases such as limited attention, conservative bias, anchoring bias have been proposed by the literature as an explanation for the observed continuation patterns (e.g. midterm momentum).

Stocks with high volatility and extreme losses are hard-to-value and more vulnerable to behavioural biases (Baker & Wurgler 2006, and Kumar 2009). Therefore, behavioural explanations could offer an alternative channel that would explain the underperformance associated with these investments. Indeed, prior empirical investigations have found a close link between the behavioural biases and the negative returns of the high idiosyncratic volatility and the extreme losses. For example, sentimental-driven trading and speculative behaviour lead the investors to overvalue the stocks with high idiosyncratic volatility (Brandt et al. 2010, Stambaugh et al. 2015, and Bali et al. 2011). Also, Bi and Zhu (2020) find that sentimental trading induces the left-tail momentum anomaly documented by Atilgan et al. (2020). This evidence indicates that the underperformance of these risky assets is the result of a reversal in the prices of overvalued stocks. The momentum-like behaviour of the strategies based on the IVOL and the left-tail risk make the underreaction-related behaviour a possible channel that could explain at least part of these anomalies.

This work contributes to the literature by adding evidence on the behaviour of the IVOL effect and the left-tail momentum from the UK market. In the previous chapter of this academic work, the results report significant abnormal returns for the strategy that goes long on the stocks with low idiosyncratic volatility and short on the stocks with high idiosyncratic volatility. In addition to the idiosyncratic risk, the analysis is extended by adding evidence on the relationship between the left-tail risk and the returns over the next 6 months across the stocks in the UK market. Also, and more importantly, the work adds evidence on the behavioural explanation of these anomalies. In particular, the link between the underreaction-related behaviour and the IVOL effect and the left-tail momentum is tested.

Underreaction is an implicit variable and there is no consensus on the measurement of this behaviour, thereby it is difficult to be measured. In this work, to measure this behaviour, different four variables and their common index are used to proxy the undereaction behaviour. Particularly, this behaviour is represented by the 52-week high ratio, the standardised change in volume, the continuous information index, and the delay response measure. These variables are selected to represent different aspects of the underreaction behaviour that have been reported in behavioural finance studies. In addition to these individual measures, an index of their common movement is built by conducting the principal component analysis (PCA). Each one of these underreaction-related proxies will be explained in more detail in the methodology section.

The results show that, in addition to the IVOL effect, the left-tail momentum also exists in the UK market. Therefore, contradicting the standard theory of finance, the investors in the UK stock market accept lower returns to invest in stocks with high left-tail risk. Moreover, the findings reveal that this anomalous behaviour persists over the next midterm horizon and shows up in the market at least over the next 24 months. Therefore, the left-tail momentum behaviour reported in this study is stronger than that in U.S. stocks.

The results from the bivariate portfolio analysis and the Fama-MacBeth cross-sectional regression show that the underreaction-related behaviour has a significant effect over the reported IVOL effect and the left-tail momentum. The negative relation between the future returns and the IVOL and the left-tail risk is stronger when the investors are less attentive. This result is robust to different specifications and subsamples.

The remainder of the work is organised as follows. Section 2 reviews the related literature. Section 3 describes the data and the methodology. Section 3 presents the empirical results. Section 4 presents a battery of robustness tests.

3.2. Underreaction behaviour and persistent mispricing.

3.2.1. Theoretical Background of the Underreaction Behaviour.

Today behavioural finance is a diverse field. Psychological-based literature suggests various mechanisms that could explain the persistent pricing anomalies. However, this diversity can be described under specific parsimonious forces, such as Cognitive limitations, beliefs, and preferences (Hirshleifer, 2015, and Barberis, 2018). The suggested psychological-based mechanisms could generate the reversal and the continuation patterns observed in the financial markets. For example, some of the proposed behavioural models argue that the investors, for different reasons, underreact to news, thereby the current returns positively predict the future performance thus the continuation-based anomalies such as the price momentum anomaly (see, Hong et al, 2000).

The intuitive ability of the limited cognitive biases and the associated underreaction behaviour to explain the continuation pattern in the financial markets makes them a potential explanation for the persistent underperformance of the high-risk anomalies (e.g. the idiosyncratic puzzle). Therefore, the focus of this section is to review the literature related to the underreaction mechanisms. It will not be a comprehensive review of the literature, rather, the focus will be on the most important and widely cited models.

Many of the predictable patterns in the stock’s returns are a manifestation of price continuation with different horizons (see, Jagadeesh and Titman, 2011, and Atilgan et al., 2020). Psychology-based pricing literature has suggested diverse models that could explain such positive autocorrelation in stock prices (Barberis, 2018). Underreaction to the news has been suggested as a natural explanation for this positive autocorrelation and persistent drift in the stock prices. Under this approach, the investors underreact to current trends in news due to their limited cognitive ability to process the information or/and the slow diffusion of the information itself (Hong et al, 1999). The underreaction models have suggested various reasons for assuming limited information processing ability by the investors in the financial markets. For instance, the evidence shows that investors are prone to anchoring bias and conservatively adjust their valuation to the relevant news (Tversky and Kahneman, 1974, and Epley and Gilovich, 2001). Also, some studies show that the investors in the financial markets demonstrate different capabilities to interpret various kinds of information and different states of the world (Karlsson et al. 2009, Hirshleifer et al. 2011).

Underreaction-driven mispricing is an important ingredient of many behavioural-based pricing models. Going back to the earliest attempts, Barberis et al (1998) and Hong et al (1999) develop two distinct behavioural theories to explain the observed predictable pattern in returns. Although they can successfully explain the observable short-run continuation and long-run reversal patterns, these two models differ in the exact mechanism that leads to return predictability patterns. Model of Barberis et al. (1998) relies more on cognitive biases such as *representativeness bias* (introduced by Kahneman and Tversky, 1974) and *conservatism bias* (introduced by Edwards, 1968). On the other hand, Hong et al. (1999) rely less on the cognitive biases, instead, they assume that the investors are heterogeneous in their ability to process the different sources of information and information diffuse slowly. Each one of these different cognitive biases can slow the information reflection and impede price discovery. Consequently, the ultimate explicit manifestation in the short run is the price continuation.

In their heuristic learning model, Barberis et al. (1998) assume that the market is dominated by the investors who employ some heuristic rules to update their beliefs about the market prospects. In particular, investors are prone to representativeness and conservatism biases. Under the representativeness heuristic, the investors ignore the law of probability and extrapolate the current patterns in the cash flows to the future, while under the conservatism heuristic the investors prefer to be closer to their old expectations about the cash flow and update slowly toward the new real value. Accordingly, if the investor fails to update his beliefs sufficiently the information will take a longer time to be reflected in the securities prices. Therefore, the price continuation pattern appears in the short-run. In their model, Barberis et al. (1998) assume that the earnings follow a random walk process. Ignoring the real process behind the earnings, the investor’s beliefs that earnings follow two states of the world, namely mean-reverting state and trend state. Under conservatism, the investors underreact to the mild persistent sequence of earnings by understating the weight of new information. Furthermore, this underreaction behaviour can explain the observed short-run continuation in the return such as price momentum, earnings momentum, and drift in returns observed after seasoned equity offerings. Lastly, under the limited arbitrage hypothesis, like the one introduced by De Long et al., (1990), the underreaction-driven misvaluation persists, at least in the short run.

Following a different approach, Hong et al, (1999) develop a behavioural model that could explain the short-run price continuation and the long-run reversal. Rather than assuming a single representative agent who suffers some psychological biases, they posit a heterogeneous agent with bounded rationality and who faces an environment where firm-specific news diffuses gradually to the market. Particularly, the market is dominated by two different groups of investors, namely, "News Watchers" and "Momentum Traders". Each one of these groups observes a different subset of the available information universe. The news-watchers process only the information they privately observe. On the other hand, momentum traders condition only on a partial history of prices. Assumptions of bounded rationality and slow diffusion of information could cooperatively drive the underreaction behaviour and the positive autocorrelation in the stock's prices.

Another way to think about the continuation phenomenon is found in studies of Rabin (2002) and Rabin and Vayanos (2010). Particularly, they argue that investors suffer from the gambler fallacy in their expectations. Gambler fallacy is an example of "law of small number" heuristic bias, which states that the investor erroneously believes that a small sample will simply reflect the properties of the whole data generating process (see, Tversky and Kahneman, 1981). Therefore, under the gambler fallacy, the investor in the financial markets expects the subsequent returns to be of the opposite sign of the current one. This fallacious belief, that the short-run sequence of returns is more likely to reverse at the next time, drives the investor to underreact to the current sequence, bad or good, of performance by the financial assets. Like conservatism bias in Barberis et al. (1998), the investor fails to update his belief about the future fundamentals and returns of the stocks due to the gambling fallacy.

Cognitive resources are scarce thus attention is limited and selective (Kahneman, 1973). In the face of uncertainty and complex tasks, people resort more to heuristic and simplifications (Simons, 1955, Kahneman and Tversky, 1973). Therefore, a vague environment could lead the cognitively-limited investors to ignore the value-relevant information, thereby the underreaction-driven pricing anomalies (Hirshleifer et al. 2011). Peng (2005) analyses the effect of limited attention and learning constraints on the decision of representative investors. She shows that in an uncertain environment, the investor optimises her consumption and portfolio decisions by allocating her limited attention between the multiple sources of uncertainty. Accordingly, if the assets have heterogeneous information environments, fundamental shocks will be incorporated into their prices at different speeds. Therefore, limited attention leads to a slower reaction to fundamental shocks and firms' announcements. Peng and Xiong (2006) show that limited attention induces investors to category-learning behaviour. Under their model, the investors first process information about the market and industries before processing firm-specific information. Accordingly, during market turmoil, the investors turn their attention to analyse market-wide information and ignore firm-specific ones. Hirshleifer et al. (2011) develop a model that explains both underreaction and overreaction to different earnings components in the context of investor's inattention. They posit that as a result of attention cost, investors with limited attention focus on a specific subset of earning components while ignoring others. In general, limited attention may slow the reflection of the information in the market and impede the efficient price discovery process. Consequently, the returns of financial assets are predictable, at least in the short-run.

3.2.2. Empirical Evidence on the Underreaction Behaviour.

In the above section, different theoretical mechanisms that could plausibly underlie return predictability in the financial market have been reviewed. Under these variant psychological-based mechanisms, the investors are cognitively biased and, consequently, their decisions are imperfect. As shown, cognitive biases, such as limited attention and conservatism, combined with limited arbitrage hypothesis, can generate the observed underreaction to news and the associated price continuation anomaly. Under this section, empirical evidence in support of the underreaction-based pricing mechanisms is reviewed.

The aforementioned underreaction-based theories have been validated in a growing number of empirical works. Besides the plausible theoretical intuition, the underreaction-related mechanisms, such as conservatism, anchoring, limited attention, and information uncertainty, have shown a considerable empirical ability to predict returns across assets and over time. In an early empirical test, Hong et al. (2000) investigate the slow diffusion hypothesis of Hong et al. (1999). Particularly, they investigate the ability of this underreaction-based hypothesis in explaining the price momentum anomaly. They argue that the information is more likely to diffuse slowly for stocks with small market capitalisation and low analyst coverage. Therefore, price momentum, as an example of continuation behaviour, should be higher for the small stocks and stocks with low coverage. Indeed, they find that the momentum strategy generates higher payoffs within the group of stocks with lower market value and lower coverage. More interestingly, they document an asymmetric effect for the slow diffusing channel on the continuation behaviour. In specific, the results in their study show that the returns of loser stocks exhibit more persistent behaviour.

In addition to the gradual information hypothesis of Hong et al. (1999), Doukas and McKnight (2005) test the investor conservatism hypothesis of Barberis et al. (1998). They investigate the validity of both hypotheses to explain the momentum anomaly in 13 European markets. Similar to Hong et al. (2000), they proxy the information flow by the market value and analyst coverage. Also, they employ the analyst forecast dispersion as a proxy for the weight of the new information. They argue that a more accurate earnings forecast has a higher statistical weight. According to Barberis et al (1998) model, rationally-bounded investors fail to update their beliefs about these stocks. Thus, if the investor conservatism hypothesis of Barberis et al. (1998) is valid, stocks with accurate analyst forecasts would generate stronger momentum. The empirical results support both hypotheses, therefore they argue that the information diffusion channel and conservatism bias show some successful ability to explain the continuation in the stock's prices.

Recently more efforts have been dedicated to examining the validity of limited attention, as a source of underreaction to information. These efforts have produced much empirical evidence in support of limited attention behaviour. In general, they found that the investors, due to many reasons, have a limited capacity for information processing. Consequently, the investor response with delay thus the continuation behaviour in the stocks' prices appears. Limited attention is a non-observable variable. Quantifying this behavioural phenomenon, the researchers employed different proxies. For example, some of them employ the trading activity measures, such as turnover, as a proxy for the amount of attention paid by the investors. While others used the speed of response to the information by the investors as a suitable proxy for the underreaction behaviour.

Hou and Moskowitz (2005) argue that the delay in price response to the market-wide information is a manifestation of the limited recognition of the firm by the investors. To operationalise the delay response, they develop a parsimonious measure that reflects the fraction of the current price explained by the lagged market information. Particularly, they posit that if the firm is less recognised by the investors, their price would respond significantly to the lagged market returns. They demonstrate that their measure of the delay in response is a measure of market frictions and limited attention in general. Hou and Moskowitz (2005)'s measure of firm recognition has been employed in many works (see, for example, Hou, 2007; Bris et al., 2007; Boehmer and Wu, 2013; Wang and Yu, 2013; Callen et al., 2103). For example, Wang and Yu (2013) employ this measure of price delay as an underreaction behaviour proxy and examine its ability to explain the profitability premium.

Another interesting empirical proxy of the investor attention level is the trading activity. If the investor pays little attention to a specific stock, they will trade it less frequently. In the financial market, the trading activity can be easily expressed by the volume or turnover. As an attention proxy, trading volume and turnover have been employed in many empirical studies. For example, Gervais et al. (2001), Barber and Odean (2008), Hou et al. (2009), Loh (2010), Lin et al. (2014), Cheng et al. (2015), Chang et al. (2018), and Chen et al. (2019). Hou et al. (2009) found that the continuation in price associated with earnings news is higher among stocks with low volume. They explain this relation between volume and earnings momentum as an underreaction behaviour. Cheng et al. (2015) show that compared to firms with high prior turnover, the firms with low prior turnover underreact to the purchase announcements, and therefore experience larger positive long-run excess returns following such events.

Theoretically, anchoring bias is considered as one of the plausible explanations for the price continuation anomalies in the financial market. George and Hwang (2004) find that the stocks with prices near to (far from) their past 52-week high price experience higher (lower) returns in the future. They suggest that the investors anchored to the 52-week high price level hence they erroneously underreact to the current news. When the price is near the 52-week high price, the investors are less willing to push the price beyond this psychological barrier, and vice versa. In particular, they posit that the stock with a price near to its 52-week high will initially underreact to good news, while the stock with a price furthest from its 52-week high will initially underreact to bad news. George et al. (2015) support this view and show that post-earnings-announcement drift is stronger for stock with price near (far from) its 52-week high and positive (negative) earnings surprise arrive. Also, Li and Yu (2012), Goh and Jeon (2017), Hur and Singh, (2019), Huang et al., (2020), and Byun et al. (2020) are all examples of studies that suggest the 52-week high ratio as a proxy for the limited investor attention.

Da et al. (2014) develop an index that distinguishes stocks with continuous information from discrete information cases. Particularly, they posit that the investors are more likely to miss the information that arrives continuously in small pieces. Thus, stocks with a series of frequent gradual changes show more persistent returns than stocks with dramatic salient changes. Empirically, they found price momentum is stronger and more persistent for stocks with continuous information. Chang et al. (2018) used this information index as an attention proxy and found it to capture investor underreaction in Japan.

The underreaction hypothesis has been supported by much other empirical evidence in the financial literature. Recently some papers employ the search frequency in google (volume search index (SVI)) or other searching engines as a proxy for the investors' attention. Of those are Da et al (2011), Chapman, (2018), Chen et al., (2019), Wen et al., (2019), Choi et al (2020). Chemmanur and Yan (2009) and Lou, (2014) use the change in advertising expense as an attention-grabbing feature. DellaVigna and Pollet (2009) and Hirshleifer et al. (2009) show that investors pay less attention to news that is released on Fridays and days with many competing announcements. Moreover, Karlsson et al. (2009) provide empirical support to the "ostrich effect" in the financial market environment, they found investors to underreact more to the news in the down-market state. They contend that the investors avoid the adverse news in the down-market state and "put their heads in the sands" which may cause more persistent continuation in the prices. Hou et al. (2009) show that underreaction-related behaviour is more evident in the down-market state.

Regardless of the employed attention proxies, the aforementioned empirical evidence agrees that, on average, the investors are exposed to underreaction-related biases that lead them to respond slowly to the value-relevant news. The ultimate result of these behavioural biases is the appearance of continuation-related anomalies such as price momentum, post-announcement drift, and left-tail momentum.

3.2.3. Underreaction-related Behaviour in the UK Stock Market.

Similar to the studies in the US market, the literature from the UK stock market shows evidence of behavioural biases by various practitioners, i.e., individual investors and stocks analysts (Constantinou et al., 2003). Stock prices behave in predictable patterns that challenge the widely used models of asset pricing, such as the CAPM and Fama-French three-factor model.

Liu et al. (2003) provide empirical evidence on the existence of the post-earnings-announcement drift in the UK stock market. Using a sample of 835 shares from January 1988 to May 1998, they found a significant post-earnings-announcement drift in the UK market. This drift is robust to risk factors and market microstructure effects. Liu et al. (1999), Hon and Tonks (2003), and Siganos (2007) all provide evidence on the existence of price momentum in the UK market. Liu et al. (2011) studied the credibility of the 52-week high strategy in an international sample, including the UK, and found this strategy to generate a significant abnormal return in the UK market. This evidence of the continuation pattern suggests that the UK market responds inefficiently to information.

Also, investors in the UK market have been found to overvalue stocks with high credit risk (Agarwal and Taffler, 2008; and Godfery and Brooks, 2015). Agarwal and Taffler (2008) link the credit risk puzzle to the continuation in returns (price momentum), and they argue that both anomalies are a manifestation of underreaction to financial distress risk. Godfery and Brooks (2015) attribute the continuous poor performance of the financially distressed stocks to limit-to-arbitrage factors that hinder the ability of the investors to incorporate the information on a timely basis. Similar to the stocks with high credit risk, financially weak stocks have been found to earn a negative abnormal return in the UK market. Kumsta and Vivian (2019) document a puzzling underperformance of the financially weak stocks in the UK market. Moreover, they find that illiquidity enhances this puzzling pricing behaviour.

Reviewing the aforementioned literature highlights some interesting points. Although it is one of the largest and most important stock markets in the world. The UK stock market, compared to the U.S. market, has received little attention from the financial behaviour studies. For instance, there is a lack of investigation into the behaviour of left-tail-based strategy and IVOL-based strategy in the UK market. There is little evidence on the ability of the underreaction-related features to explain the predictability of the returns in the UK stock market. Therefore, this study contributes to the literature by examining the existence of the left-tail momentum anomaly and the idiosyncratic volatility puzzle in the UK stock market. Also, this study adds to the existing studies by examining whether the underreaction-related biases can explain the return predictability by the left-tail risk measure and the idiosyncratic volatility, if any.

3.3. Variables Definitions, Data, and Methodology.

This section describes in brief details the proxies that are employed to represent the variables in this study, the data sample, and the methodology.

3.3.1. Variable Definitions.

Similar to other financial-economic concepts, the left-tail risk, and the underreaction-related features have no explicit measures and are difficult to quantify. To represent them various proxies have been employed by the financial literature. In the following, the employed proxies of these variables are described.

3.3.1.1. Risk-based anomalies.

1- Left-tail Risk (ES).

Previous literature has adopted different metrics to proxy the left-tail risk (see, for example, Bali et al. 2009; Atilgan et al, 2019; Huang et al, 2012; and Bali et al, 2014). For instance, some of these metrics are intended to gauge the systematic part rather than the total left-tail distribution. Moreover, they differ in the estimation methods, paramedic vs non-parametric. In this study, for the sake of simplicity, we will follow Bali et al. (2009) and Atilgan et al. (2019) by measuring the total left-tail risk non-parametrically. In particular, the left-tail risk will be represented by the Expected Shortfall (hereafter, ES). Under the ES, the tail risk is the average amount of losses conditional on a given threshold (Artzner, 1999). For example, the ES can be measured by averaging the negative returns under the 5-percentile of the realised distribution. There is no specific rule to select the threshold under which the ES is calculated. Therefore, in this study, the left-tail risk will be calculated as the average of returns under the 5-percentile over the past three months and the past 1-year (250 days), as follows,

$$ES\alpha\% = 1/N \sum Ri < \alpha\% , \qquad (1)$$

Where Ri is the daily returns of stock i over the past days (past 60 or 250 days), α% is the selected threshold (5% in this study), and N is the number of observations less than α% level. The higher the ES, the higher the risk of losses. Notice, that in the primary analysis, we will show the results of the ES with 5% over the past 60 days. In a later analysis, the ES5% are estimated over the past 250 days used in the robustness test. For the 60-day measure, at least 35 observations are required. These measures are re-estimated on a monthly basis.

2- Idiosyncratic Volatility (IVOL).

The findings in the second chapter demonstrate a close link between the idiosyncratic volatility and the left-tail risk. In the financial literature the idiosyncratic volatility serves as a proxy for different features. Some argue that IVOL is a proxy for the lottery-like feature (e.g. Bali et al. 2011), while others link this variable to the arbitrage cost (e.g. Cao and Han, 2016). To measure the idiosyncratic volatility, we follow Ang et al. (2006). In specific, over the past three months, we run the following Carhart's model,

$$R_{it} - rf_t = \alpha_i + \beta_m * (R_{mt} - rf_t) + \beta_{smb} * SMB_t + \beta_{hml} * HML_t + \beta_{umd} * UMD_t + \varepsilon_{it}, \quad (2)$$

Where R_{it} is the return of stock i on day t, R_{mt} is the market return on day t, rf_t is the risk-free rate, SMB_t is the small market capitalisation minus big market capitalisation factor, HML_t is the high minus low factor, UMD_t is the winner minus loser factor, and ε_{it} is the unexplained component of returns of stock i. Also, α_i, β_m, β_{smb}, β_{hml}, and β_{umd} are the estimated parameters. After estimating the model, the idiosyncratic volatility is calculated as the standard deviation of the residuals. Empirically, this measure is designed to represent the unsystematic part of returns variation. The investors are more likely to misvalue stocks with high unsystematic volatility (see, Kumar 2009). To mitigate the effect of nonsynchronous trading we require a minimum of 35 observations to estimate Carhart's four-factor model. These procedures are re-estimated on a monthly basis therefore monthly series of idiosyncratic volatility is estimated for each individual stock. The data for Carhart's four-factor model is obtained from the following http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/. For more details about the factors construction procedures, please, refer to Gregory et al. (2013).

3.3.1.2. Limited Attention Proxies.

like other financial behavioural terms, the limited attention and the associated under-reaction behaviour have no direct and explicit measure. To address this issue, this work employs several proxies to represent the under-reaction behaviour. In particular, the under-reaction is proxied by four different measures. These measures are the delay to past market information, the abnormal change in volume, the information continuation index, and the 52-week high ratio. These proxies are motivated by much empirical and theoretical evidence in the literature. In the following, each one of these proxies is described in detail.

1- Delayed response.

Hou and Moskowitz (2005) argue that market frictions may lead the investors to respond with delay to market-wide information. They argue that for firms with obstructive frictions, the investors would face recognition problems hence inefficient price discovery processes. To operationalise this recognition problem, they employ the market past returns as a proxy for the market-wide information and run the following regression:

$$R_{i,t} = \alpha_i + \beta_{i,t} * R_{m,t} + \sum_{n=1}^{4} \beta_{i,t-n} * R_{m,t-n} + \varepsilon_{i,t}\,, \qquad (3)$$

Where R_{it} is the return on stock i and $R_{m,t}$ is the return on the general market index at time t. They claim that if the investors respond with delay to market information, the lag terms of the market return in equation (3) would significantly predict the return at time t. Thus, adding the lagged market returns over the past short-term period should substantially improve the predictive power of the restricted market model that includes only the contemporaneous market return at time t. Under this logic, their main delay response measure is the fraction of the contemporaneous individual stock returns explained by the lagged market returns,

$$\text{Delay}_i = 1 - \frac{R^2_{unrestriscted}}{R^2_{restricted}}\,, \qquad (4)$$

Where R^2 is the fraction of return explained by the corresponding model. According to equation (4), the delay index of stock i (Delay_i) ranges from 0 to 1. The higher value of Delay_i indicates a higher predictive ability for the past information therefore the investors are less attentive to the information and respond with delay.

To keep aligned with the main goal in this study, we follow Boehmer and Wu (2013) and focus our interest on the left side of the information distribution. Thus, we will apply the above measure conditioning on the past negative market returns. We estimate the Delay_i using daily returns over the past three months. In the robust analysis, we measure the above delay measure using weekly observations over the past year (52 weeks).

2- Abnormal volume.

Low abnormal trading volume signals low visibility of stocks (Gervais et al., 2001). Moreover, much empirical evidence links the low volume to limited attention features, for example, lower analyst coverage (see, Lee and Swaminathan, 2000, and Lin et al, 2014) and firm size (see, Lo and Wang, 2000; Chordia and Swaminathan, 2000). Motivated by this, an increasing number of empirical works has employed the trading volume as a reliable proxy of investors' attention, an example of these works are Barber and Odean (2008), Hou et al. (2009), Loh (2010), Cheng et al. (2015), Chang et al. (2018) and Chen et al. (2019). Following these works, the abnormal volume is employed as a second proxy of the underreaction. Specifically, the abnormal volume of stock i in month t is,

$$ABnVol_i = (Volume_{it} - \sum_{n=1}^{12} \text{Volume}_{it-n}) / \text{Std}(\text{Volume}_i) \qquad (5)$$

Where Volume is the pound trading volume in month t, Std is the standard deviation of the volume over the past 12 months. Equation (5) allows us to define the degree of drop and rise in the trading activity of a particular stock. According to this equation, if they pay little attention to stocks i, they should trade this stock less frequently.

3- Continuous information.

Da et al. (2014) develop an attention measure to test a frog-in-the-pan (FIP) hypothesis in the financial market context. Particularly, they posit that the investors are more likely to miss the information that arrives continuously in small pieces. Thus, stocks with a series of frequent gradual changes show more persistent return continuation than stocks with dramatic salient changes. To test this hypothesis, they suggest the following measure,

$$ID_i = \text{sgn (PRET)} * [\%\text{neg}-\%\text{pos}] \qquad (6)$$

where sgn (PRET) is the sign of the cumulative return over the formation period, %neg is the percentage of negative-return days over the formation period, and %pos is the percentage of days with a positive return. According to equation (6) is that if the return over the past period is generated by a large number of small returns with consistent sign, then the return is generated by continuous information. In contrast, if the return over the formation period is generated by a few large returns of the opposite sign, then the return is generated by discrete information. In this study, we used a decomposed measure of the above ID measure. In particular, we classify the sample into the following three groups,

$$ID_i = \begin{cases} \%pos - \%neg & if\ sng(PRET) = sgn(pos\% - \%neg) \\ 0 & otherwise \end{cases} \qquad (7)$$

The above classification aims to give separate values for the negative and positive continuous news. To illustrate, if the stock i return over the formation period is negative and generated by the frequent negative daily returns, then there is continuous negative information and the measure will take a negative value (%neg>%pos). The same logic applies to the positive return. Notice that the stocks with discrete information will fall in the middle of the distribution with a value of 0. Building on the FIP hypothesis, the past performance of the stocks with the negative ID and positive ID are more likely to continue in the future. Therefore, we conjecture that the left-tail momentum and idiosyncratic volatility effect will be stronger if they have negative ID. The ID is calculated using the daily return and one year as a formation period.

4- Price to 52-week high (PH52).

Anchoring bias states that the investors underreact to new information, as they stick to the old reference point in their valuation. George and Hwang (2004) claim that the price momentum associated with a 52-week high strategy is a manifestation of the anchoring bias. Also, Li and Yu (2012), George et al. (2015), and Hur and Singh, (2019) all suggest the 52-week high ratio as a proxy for the limited investor attention. Following these studies, the 52-week high ratio will be used as the fourth proxy for limited attention. This ratio is calculated as follows,

$$PH52 = P_{i,t} / \text{52-week high price} \qquad (8)$$

where $P_{i,t}$ is the current closing price for stock i and denominator is the highest price for over the past 52 weeks. According to the anchoring bias and the revealed empirical evidence, the investors are more likely to miss out on the news of the stocks with a closing price far from or near to the past 52-week high price are more likely mispriced. Therefore, we expect the continuation behaviour in the returns of the left-tail and idiosyncratic volatility strategies to be stronger for the stocks with a price far from the past 52-week high.

5- Attention index.

In addition to the above four attention proxies, a fifth measure is created by weighting them into one joint index. To this end, we employ the so-called principal component analysis (PCA) to weight the various measures of attention and extract the common attention index. Particularly, each month, we apply the PCA to the four proxies and extract the first common component. This component will be used as the attention index. In this step, we conjecture that the extracted first component measures the joint variation in the four proxies, which is generally assumed to be related to attention behaviour.

3.3.1.3. Information Uncertainty Index.

The uncovered nonstandard behaviour and the judgmental biases in the financial market have been found to be stronger in a vague environment. Moreover, it is more likely for individual investors to pay less attention to complex and difficult-to-process information (Hirshleifer et al. (2017). Zhu et al. (2019) found that both limited attention and information uncertainty are important in explaining the documented fundamental-based anomaly. Thus, information uncertainty could be the mechanism through which limited attention has the force to deter the efficient price discovery process. To explore this potential channel, we employ 5 different proxies of information uncertainty. These proxies are firm size, firm age, and turnover uncertainty, return synchronicity, and the bid-ask spread. Similar to the attention index, we employ the PCA to extract the first common component of these proxies which will be used as the index of information uncertainty.

1- firm size:

For many intuitive reasons, small firms are supposed to have less value-related information available than large firms (Zhang, 2006). For example, investing in small firms might require a higher cost of information acquisition and the small firm might be exposed to relatively high disclosure preparation costs. Thus, small firms are more likely to receive lower invigilation rates than large firms. Following Zhang (2006), the firm size is represented by the market value of the firm which is the number of shares outstanding multiplied by the closing price.

2- Age:

Firm's age is another intuitive proxy of information asymmetry and uncertainty. Practically, the young firms have less information available for valuation. Empirically, the Firm's age has been employed by many works as a plausible proxy of information uncertainty, for example, Zhang (2006), Jiang et al. (2005), Kumar, (2009). In this study, the Firm's age is the number of months since the firm's initial appearance in the DataStream database.

3- Turnover volatility:

Liquidity uncertainty in liquidity is found to be negatively related to information transparency in some recent studies (see, for example, Lang and Maffett, 2011; and Ng, 2011). Also, George and Hwang (2010) demonstrate that stocks with high turnover volatility are more likely to be overvalued due to the high information uncertainty that they suffer from. Therefore, we will use the turnover volatility as an information uncertainty proxy. Turnover is the volume in dollars divided by the number of shares outstanding. To evaluate the turnover uncertainty, the standard deviation of the daily turnover over the past 12 months is considered.

4- Return Synchronicity:

Theoretically, co-movement in stocks' prices reflects co-movement in their fundamentals. Higher synchronicity is found to be a result of an informative environment with lower information uncertainty (see, for example, Piotroski and Roulstone, 2004; Chan & Hameed, 2006; Dasgupta et al., 2010; and An and Zhang, 2013). For example, An and Zhang (2013) show that stocks with dedicated monitoring by institutional investors exhibit higher return synchronicity. In their categorical learning model, Peng and Xiong (2006) link the return co-movement to the limited attention capacity by the investors. Following these studies, we define stocks with lower return synchronicity as ones with high information uncertainty. To measure return synchronicity, on a monthly basis, for each stock, we first estimate the R^2 of the following market model over the past 3 months of daily data,

$$R_{i,t} = \alpha_i + \beta_{i,t} * R_{m,t} + \varepsilon_{i,t}, \qquad (9)$$

where $R_{i,t}$ and $R_{m,t}$ are the return for the firm i and the market, respectively, on time t. The return synchronicity is the logistic transformation of the R^2.

$$\text{Synch} = \text{Log}\left(\frac{R^2}{1-R^2}\right). \qquad (10)$$

5- Bid-Ask spread:

If there is a high information uncertainty about the true value of the financial assets, there would be a higher gap in the valuation between the various market participants (Roll, 1984; and Karpoff, 1984). Kim and Verrecchia (1994) and Gregoriou et al. (2005) show, empirically, that the bid-ask spread is positively related to information asymmetry features. Godfrey and Brooks (2015) employ the bid-ask spread as a limit to arbitrage proxy. They found stronger momentum for stocks with a high bid-ask spread. Thus, the bid-ask spread is a suitable proxy of information uncertainty. This spread is represented by the monthly average of the daily bid-ask spread over the past month. The daily bid-ask spread is the difference between the closing bid and ask prices divided by the average of their mid-point, as follows,

$$\text{Bid-Ask spread} = (\text{Bid}_{i,d} - \text{Ask}_{i,d}) / (\text{Bid}_{i,d} + \text{Ask}_{i,d})/2. \qquad (11)$$

Where Bid and Ask are the closing bid and ask prices. We take the average of daily bid-ask spread over the past month.

3.3.1.4. Liquidity Measures.

Lack of liquidity is another potential channel through which continuation in the securities' prices shows up in the financial market.

1- Amihud (2002)'s Illiquidity measure (Amih):

Liquidity generally implies the ability to trade a large number of certain assets quickly, at low cost, and without inducing a significant effect on the price level. Following Bali et al. (2011) and Amihud (2002), we measure the price impact of illiquidity as the monthly average of the daily absolute stock return to dollar trading volume ratio,

$$Amih_{i,t} = \Sigma \{|R_{i,d}| / VOLD_{i,d}\}, \qquad (12)$$

Where Ri, t is the return of stock i in month t, $VOLD_{i,d}$ is the daily trading volume in dollars for the stock i. This liquidity measure serves as a proxy for the impact ratio and the effect of the order flow on the prices which is inspired by Kyle (1985).

2- Zero-return days: is the number of days with zero returns divided by the total number of trading days during the past three months.

3.3.1.5. Other Variables.

To isolate the potential effect of other return predictors, we control for a set of return predictors that are widely documented in the financial literature. This set of control variables is as follows,

1- Market Beta: traditionally measured by regressing the stock's risk premium (R_i-r_f) on the market risk premium (R_m). To mitigate the impact of nonsynchronous trading, we follow Lewellen and Nagel (2006) and Cederburg and O'Doherty (2016) by adding four lags of the market premium to the regression, as a following,

$$Rp_{i,t} = \alpha_i + \beta_{i,t} * Rp_{m,t} + \sum_{n=1}^{4} \beta_{i,t-n} * Rp_{m,t-n} + \varepsilon_{i,t}, \qquad (13)$$

$$\beta_i = \beta_{i,t} + \sum_{n=1}^{4} \beta_{i,t-n} \qquad (14)$$

Where Rp_i and Rp_m are the daily risk premium for the stocks i and the market portfolio, respectively, and β_i is the estimated beta. Similar to the idiosyncratic volatility, the beta will be re-estimated on a monthly basis using the daily returns over the past three months.

2- Downside Beta (Dbeta): is a systematic left-tail risk measure, measured in a similar way to the market beta but the stock return is regressed only on the negative market returns rather than the total market returns series. Therefore, the downside beta is designed to measure the association between the stock and the market conditioning on the market downstate.
3- Co-skewness: is another measure of the association between the stock and the market conditioning on the extreme fluctuations in the market return. Following Harvey and Siddique (2000), to measure the co-skewness, the following quadratic form of the market model will be fitted,

$$R_{i,d} = \alpha_i + \beta_{i,d} * R_{m,d} + C_{i,d} * R^2_{m,d} + \varepsilon_{i,d}\,, \qquad (15)$$

where $C_{i,d}$ represents the co-skewness measure. Positive co-skewness indicates that the stock has a lower tail risk, and it is more likely to generate a positive return conditioning on the tail of the market returns distribution.
4- Midterm Momentum (Mom): following Jegadeesh & Titman (1993), med-term momentum is defined as the cumulative return over the past 12 months after skipping a month between the portfolio formation period and the holding period, i.e., cumulative return over month t–12 to month t–1.
5- PosRC: the positive return consistency is a dummy variable that takes one if the stocks generate a positive return at least in 8 months out of the past 12 months.
6- NegRC: the negative return consistency is a dummy variable that takes one if the stocks generate a negative return at least in 8 months out of the past 12 months.
7- Short-term reversal (Rev): following Jegadeesh (1990), this variable is measured using the stock return over the past month (1-month return).
8- ROA: is the return on asset and measured by the ratio of earnings to the total asset.
9- BMV: is the ratio of the book value to the market value.
10- DY: is the dividend yield, the ratio of dividend to the current closing price.

3.3.2. Data.

To test the main relationships in this study, a sample of all common stocks from the London stock exchange is used. The stocks' data is updated on monthly basis and the sample is selected to consist of both the currently traded stocks and the delisted stocks in a way to mitigate the well-documented survivorship bias that found to affect the cross-sectional asset pricing tests (e.g., see, Shumway, 1997). The whole pre-filtering sample includes 5414 stocks. The data include daily and monthly prices and other trading data of the selected stocks and spans the period from January 1996 to December 2017. To mitigate the problem of non-synchronous trading, stocks with less than 35 trading days will be excluded. Also, we rule out any stocks with a price less than 3 pounds and any stocks with no turnover data. The last sample of stocks includes a varying monthly number that ranges from 303 in March of 1996 to 868 in September of 2007. The data source is Thomson Reuters DataStream. Following asset pricing literature in the UK, the sample will include only the common equities (see e.g. Florackis et al., 2011). In addition to the daily and monthly trading data from Thomson Reuters DataStream, data of the Fama-French Three-Factor model and the momentum factor are obtained from Gregory et al., (2013).

3.3.3. The Analysis Procedures.

This section describes the procedures performed to examine the behaviour of the left-tail momentum and the IVOL puzzle in the UK stock market. Firstly, the performance of the stocks based on the left-tail risk and idiosyncratic volatility is analysed by sorting the selected stocks into 10 deciles. Then, the performance of the created portfolios and the predictability of these risk features are analysed in a multivariate framework. Particularly, we conduct double-sort analysis and the Fama and MacBeth cross-sectional regression to analyse the effect of previously documented returns predictors on the ability of ES and IVOL to predict the returns. In the following subsections, these procedures are discussed in more detail.

3.3.3.1. Single-sort Analysis.

The basic goal of this work is to analyse the future performance of the investment strategies based on the left-tail risk and the idiosyncratic risk in the UK market. To achieve this step, decile portfolios are created by ranking the stocks on ES5% and the IVOL. Particularly, each month, 10 portfolios are constructed by sorting the stocks in the sample into deciles, with an equal number of shares in each decile. For instance, each month, the stocks are ranked ascendingly according to the level of ES5% or IVOL and 10 portfolios are created. The portfolios are rebalanced on a monthly basis. The performance of these portfolios is weighted by value and equally. The motivation of this analysis is to check the cross-sectional variation in future performance and the other important characteristics of these portfolios. The performance of these portfolios is represented by returns over the next month and the next six months. To investigate whether the left-tail momentum exists in the UK market, a zero-cost strategy is created by shorting the highest ES5%-sorted portfolio and buying long the lowest ES5%-sorted portfolio. Similarly, the IVOL puzzle is examined by creating a zero-cost strategy by shorting the highest IVOL-sorted portfolio and buying the lowest IVOL-sorted portfolio. In addition to the raw returns, the risk-adjusted alpha is shown by adjusting the raw return to the Carhart (1997) four-factor pricing model.

3.3.3.2. Double-sort Analysis.

In the single-sort analysis, the stocks are sorted according to single characteristics (i.e., the ES5% or IVOL one at a time) while ignoring any other related features. To push the analysis one step further, the interaction between the underreaction-related features and the performance of the ES5%-based and IVOL-based portfolios are analysed by conducting a double sorting procedure. Particularly, 9 portfolios are created by firstly sorting the stocks into 3 groups based on any of the attention proxies, and then within each of these groups, the stocks are resorted into another 3 portfolios according to the ES5% or IVOL. Similar to one-way sorts, the portfolios are rebalanced on a monthly basis and the performance is weighted by value and equally. For example, each month, the stocks in the sample are ranked ascendingly by the level of the delay measure, hence 3 portfolios of stocks with different delay response levels are created. Then, within each delay-based group, the stocks are sorted into another 3 groups according to the level of ES5% or the IVOL. Over the next six months, the spread in the returns between the extreme tercile portfolios within each attention-based level is calculated to represent the left-tail momentum and the IVOL puzzle. The main motivation is to investigate the ability of the underreaction-related features to explain the Left-tail momentum and the IVOL puzzle. To illustrate, our main interest if this risk-adjusted left-tail momentum varies significantly across the different attention levels. Similar to the one-way sorting approach, the performance of the constructed portfolios is measured by the risk-adjusted alpha of the zero-cost strategy within each attention level.

3.3.3.3. Triple-sort Analysis.

Continuation anomalies have been found to be amplified by the information uncertainty environment and the illiquid position. The triple sorting analysis is conducted to examine how the attention level interacts with other potential sources to generate the continuation in the stock's performance. Specifically, we will create 27 portfolios (3×3×3 dependent sorting) by firstly sorting the stocks into 3 groups according to the information uncertainty proxy or illiquidity proxy. Then, within each of these levels, the stocks resort into another 3 levels based on the attention proxy. In the last step, the stocks within each portfolio, created in the first two steps, are re-sorted into another three groups according to ES5% or IVOL. After creating the mentioned 27 portfolios, the performance of the ES5%-based and IVOL-based strategies is analysed within each interaction level of attention with information uncertainty or illiquidity. Similar to the double sorting analysis, the performance is analysed by the value and equal-weighted average return over the next six months. Also, the performance is adjusted to Carhart's four-factor model.

It should be noted that the above-mentioned sorting techniques have some advantages and pitfalls. Sorting the stocks is suitable to mimic the practical investment styles in the market. To illustrate, to generate a profitable trading strategy, the investors would allocate their capital according to the potential return's predictors (e.g. the earnings-price ratio). Also, the nonparametric nature makes this simple approach free of any functional form and requirements that could restrict the alternative parametric methods, e.g., the multivariate regression approach. Therefore, to address this issue, the multivariate cross-sectional regression of Fama and MacBeth (1973) is used besides the sorting approach.

3.3.3.4. Fama-MacBeth Cross-sectional Regressions.

In the sorting approach, the portfolios are created by only controlling for two or three characteristics at a time. Therefore, this dependency analysis cannot explicitly control for other characteristics that may influence returns. For instance, sorting on three or more characteristics is impractical. To control for other possible mechanisms in a practical multivariate framework, the widely used Fama & Macbeth (1973) two-step cross-sectional analysis is performed. Under the first step, the following cross-sectional regression is estimated on a month-to-month basis,

$$R_{i,t+2-t+7} = \alpha_{it} + \beta * ES5\%_{i,t} \text{ (or IVOL)} + \Sigma\, \beta_x * X_{i,t} + \varepsilon_{i,t}\,, \qquad (17)$$

Where $R_{i,t+2-t+7}$ is the stock i risk premium over the next 2-7 months, $ES5\%_{i,t}$ is the expected short-fall, IVOL is the idiosyncratic volatility proxy, and X represents a set of the controlling variables. After estimating this model on a monthly basis, the averages of the estimated time-series coefficients are tested against the null hypothesis. The controlling variable list includes the attention proxy, the information uncertainty proxy, the illiquidity, and the other controlling variables. We run the regression without or with control for these effects. The main purpose is to check the significance of the tested continuation anomalies while controlling for the attention level and other potential mispricing sources. Each regression estimated with the Newey-West t-statistic adjusted for autocorrelation and heteroskedasticity.

Despite the powerful multivariate setting, the cross-sectional regressions face potential pitfalls. The imposed functional form is restrictive and could be incorrect. Moreover, the regression results are likely to be dominated by the extreme cases, for example, the microcaps (small capitalisation stocks) and extremely illiquid stocks. However, I tackle this issue in the robustness analysis section by redoing the analysis for different capitalisation groups and after excluding low-priced and illiquid stocks. Also, the tradition on the previous studies is to use a few portfolios as base assets in the Fama-MacBeth cross-sectional regressions. Ang et al. (2020) highlight the potential problem of information losing by aggregating the stocks into a few characteristic-based portfolios. To address this issue, I follow the suggestion to use the individual stocks rather than the portfolios as base assets in the Fama-MacBeth cross-sectional regressions.

Together the nonparametric stocks sorting approach and the parametric approach of Fama-MacBeth (1973) would provide a powerful analysis and robust empirical evidence on the nature of the examined features pricing the UK stocks.

3.4. Empirical Results.

Under this section, the empirical results are shown. Firstly, the general description of the variables used in this study and the bivariate correlation coefficients between these variables are presented. Then, single-sort portfolio analysis is performed by ranking the stocks into deciles according to the left-tail and idiosyncratic volatility. This analysis aims to show the expected return and the general characteristics of these single-sort portfolios. Thirdly, the double-sort technique and the cross-sectional regression are performed to analyse the effect of the proposed under-reaction channels on the predictive power of left-tail measure and idiosyncratic volatility in the UK market. The main goal is to answer the main questions regarding the ability of the left-tail risk and the idiosyncratic to predict the future performance of the UK stocks and the effect of the underreaction-related behaviours on this predictability.

3.4.1. Descriptive Statistics and Correlation Analysis.

In Table 3.1, we will have a glance at the general description of the variables employed in this work. This table displays the averages, the standard deviations, the minimum, and the maximum statistics of each variable. The data spans the period of January 1996 to December 2017. To mitigate the effect of the outlier the data winsored at 1% level.

Table 3.1. Descriptive Statistics.

This table represents the descriptive statistics for each variable used in this paper. All variables, except for VWret and EWret, the return in month t+1, are computed for individual stocks at the end of the formation month (month t). ES5% denotes the expected-shortfall that corresponds to the average of return observations under the 5th percentile daily returns in the past 3 months. IVOL is the standard deviation of residuals subtracted from the Carhart four-factor model. MAX5 is the average of the five highest daily returns over the past three months. Rev is the monthly return over the past month. Mom12 is the return over the past 12 months. Spread is the average daily bid-ask spread over the past month. Amih is the price impact measure over the past month. Zdays is the ratio of days with zero return to the total number of days over the past three months. PH52 is the ratio of current price to the 52-week high price. Delay is the Hou and Moskowitz (2005)'s delay measure estimated from the daily returns over the past three months. ID is the information discreeteness index calculated from the daily returns over the past 12 months. DSVol is the standardised abnormal volume over the past month. MV is the market value at the end of the past period (in millions of pounds). Age is the number of months since the firm appears on the DataStream. Synch is synchronisation measure calculated from the explanatory power of the market model. Trvol is the volatility of the turnover over the past 12 months. Beta is the market beta with respect to the market index. Dbeta is the systematic tail risk measure calculated as the sensitivity of the stock returns to market returns over the downstate. Coskew is the coefficient of the squared market return as in Harvey et al. (2000). Iskew is the skewness of the stock daily returns over the past three months. The sample covers the period from January 1996 to December 2017.

Variable	Obs	Mean	Std. Dev.	Min	Max	Variable	Obs	Mean	Std. Dev.	Min	Max
VWret%	169,345	0.3	4.1	-18.5	11	delay	169,345	0.6	0.3	0	1
EWret%	169,345	-0.4	5.3	-27.9	21.1	ID	169,345	0	0.1	-0.6	1
ES5%	169,339	-5.5	3.8	-0.5	-39.9	DSVol	169,345	0.1	1.1	-2.4	3.4
IVOL	169,345	2.4	1.7	0.4	18	MV	169,345	2069	6089	2.2	57349
MAX5%	169,345	5.7	4	0.2	58.8	Age	168,720	214.2	176.6	3.4	634.5
Rev%	169,345	0	14.1	-128.4	109.3	Synch	169,345	-3.2	2.3	-14.1	1.5
Mom12%	169,344	5.3	57.3	-390.8	325.9	Trvol	169,307	0	0	0	0.1
Spread	169,228	0	0	0	0.3	Beta	169,345	0.9	1.3	-8.5	9
Amih	168,356	0	0	0	0	Dbeta	169,345	1.1	2	-11	16.6
Zdays	169,345	0.1	0.1	0	0.5	Coskew	169,345	0	0.4	-5.3	4.2
PH52	169,345	0.8	0.2	0.02	1						

Table 3.2 outlines the bivariate correlation coefficients between the variables of the study. The analysis spans the period of January 1996 to December 2017. As expected, the figures

Table 3.2 Correlation analysis.

This table represents the correlation matrix among the variables used in this paper. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from a Carhart four-factor model. MAX5 is the average of the five highest daily returns over the past three months. Price is the market price at the end of the formation month. Rev is the monthly return over the past month. Mom12 is the return over the past 12 months. Spread is the average of daily bid-ask spread over the formation month. Amih is the amihud price impact measure over the formation month. Zdays is the ratio of days with zero return to the total number of days over the past three months. PH52 is the ratio of the current price to the 52-week high price. Delay is the Hou and Moskowitz (2005)'s delay measure calculated from daily returns over the past three months. ID is the information discreetness index calculated from daily returns over the past 12 months. DSVol is the standardised abnormal volume over the past month. MV is the market value at the end of the formation period. Age is the number of months since the firm appeared on the DataStream. Synch is synchronisation measure calculated from the explanatory power of the market model. Ivvol is the volatility of the turnover over the past 12 months. Beta is the market beta with respect to the market index. Dbeta is the systematic tail risk measure calculated as the sensitivity of the stock returns to market return over the downstate. Coskew (coskewness) is the coefficient of the squared market return as in Harvey et al (2000). The sample covers the period from January 1996 to December 2017.

	ES5%	IVOL	MAX5	ID	Delay	PH52	DSvol	logMV	Synch	Age	Ivvol	Sp	Zdays	Amih	Beta	Dbeta	Cosk	ISK	MOM12
ES5%	1																		
IVOL	0.88	1																	
MAX5	0.68	0.88	1																
ID	-0.4	-0.36	-0.29	1															
Delay	0.12	0.25	0.18	-0.11	1														
PH52	-0.72	-0.62	-0.46	0.68	-0.11	1													
DSvol	-0.1	0	0.06	0.24	0.06	0.3	1												
logMV	-0.46	-0.54	-0.47	0.3	-0.47	0.42	0.06	1											
Synch	-0.13	-0.26	-0.19	0.1	-0.75	0.1	-0.06	0.48	1										
Age	-0.24	-0.28	-0.25	0.11	-0.2	0.19	0.01	0.35	0.2	1									
INTA	0.09	0.1	0.08	-0.05	0.01	-0.07	-0.02	-0.07	-0.01	-0.05									
HL	0.74	0.78	0.71	-0.34	0.09	-0.57	0.03	-0.37	-0.09	-0.2									
Ivvol	0.17	0.22	0.2	-0.07	0.11	-0.12	0.06	-0.19	-0.12	-0.18	1								
Sp	0.52	0.59	0.52	-0.29	0.34	-0.45	-0.08	-0.69	-0.34	-0.27	0.12	1							
Zdays	0.14	0.2	0.18	-0.17	0.4	-0.15	0	-0.64	-0.41	-0.26	0.1	0.54	1						
Amih	0.32	0.31	0.25	-0.17	0.13	-0.28	-0.11	-0.35	-0.14	-0.1	-0.01	0.45	0.25	1					
Beta	0.2	0.17	0.19	-0.07	-0.23	-0.16	-0.03	0	0.22	-0.03	0.04	0.05	-0.05	0.02	1				
Dbeta	0.1	0.13	0.12	-0.07	0.14	-0.1	-0.01	-0.18	-0.17	-0.08	0.05	0.14	0.17	0.07	0.62	1			
Cosk	-0.02	-0.04	-0.04	-0.01	0.11	0	-0.01	0.06	0.05	0.04	-0.02	-0.04	-0.05	-0.01	-0.06	-0.08	1		
Isk	-0.32	-0.03	0.25	0.07	0.03	0.24	0.12	-0.05	-0.06	-0.04	0.04	0.03	0.11	-0.03	-0.01	0.02	-0.05		
MOM12	-0.44	-0.32	-0.17	-0.68	0.02	0.74	0.30	0.17	0.01	0.02	-0.02	-0.22	-0.04	-0.20	-0.06	-0.04	-0.02	0.23	1
Rev	-0.26	-0.08	0.07	-0.23	-0.018	0.39	0.24	0.10	-0.03	0.03	0.003	-0.09	-0.01	-0.16	-0.04	-0.01	-0.01	0.27	0.30

show a highly significant relationship between the left-tail proxies (the expected short-fall) and the lottery proxies (e.g. the idiosyncratic volatility and the Max effect). The ES5% has a high positive and significant correlation with the IVOL and MAX5, the correlation coefficients are 88% and 68%, respectively. As shown in the previous chapter of this work (Chapter 2), inverse predictability of return by the lottery-like features, such as idiosyncratic volatility, is a manifestation of the left-tail predictive power. Specifically, stocks with lottery-like features have longer left-tail and persistent underperformance (i.e. past losers).

Another interesting observation is the significant relationship between the attention proxies and the left-tail measures. Stocks with longer left-tail and higher idiosyncratic risk are negatively related to Idneg, PH52, and DSVol, while positively related to Delay. For example, the correlation coefficients between the Idneg, PH52, and DSVol on one side and the ES5% on the other side, are -40%, -72%, and -10%, respectively. Also, the correlation between the ES5% and Delay is significant with a value of 12%. Accordingly, in the case of stocks with longer left-tail and higher IVOL, the investors are more likely to pay little attention to the value-relevant news. Thus, the performance of these stocks is more likely to show continuation behaviour, therefore, stronger price momentum.

Also, the figures shown in Table 3.2 indicate a significant association between the ES5% and the features related to information uncertainty. Stocks with higher ES5% and IVOL are more likely to be small, young, and have highly uncertain liquidity (higher Trvol) and lower synchronisation index. For example, the ES5% has a significant negative relationship with the size and the age, the coefficients are -46% and -24% respectively. As mentioned before, information uncertainty is another channel that could exacerbate the biased reactions by the investors. Therefore, prices of these stocks are more likely to underreact to the relevant-news hence continuation behaviour is highly probable for these stocks (see, Zhang, 2006 and Kumar 2009).

In the next, we will turn to the portfolio analysis to inspect the characteristics and the performance of the trading strategies that are based on the left-tail risk (ES5%) and the idiosyncratic volatility (IVOL).

3.4.2. Single-Sort on the idiosyncratic volatility and Expected Short-fall.

Under this subsection, the performance and the characteristics of the portfolios created based on the left-tail measures (i.e. the expected short-fall) and the IVOL are considered by performing the so-called single sort analysis. To this end, each month, the stocks are sorted into deciles based on the levels of the IVOL or ES5%. Then, the most important features of these portfolios are shown by equally averaging over the stocks included in each decile. To inspect the performance persistence, in addition to the first subsequent month, the performance is analysed over the next six months, skipping the first month after portfolio formation. The returns of these portfolios are weighted equally or by the market value.

3.4.2.1. General Characteristics of the Single-sort portfolios.

Table 3.3 represents the features of ES5%-sorted portfolios. As expected, idiosyncratic volatility increases monotonically with the value of left-tail risk, which rises from 1.13 for the lowest decile to 5.74 for the highest decile. Consistent with this result, the stocks with the highest left-tail risk are more likely to be considered as a lottery-like stock, in particular, MAX increases monotonically with the ES5% value. Also, on average, the stocks with higher left-tail risk (higher ES5%) are past losers. For example, price momentum (i.e. the return over the past 12 months) drops from 19.76% for the lowest decile of ES5% to -40.58% for the highest decile of ES5%.

Consistent with the correlation analysis outlined in Table 3.2, the results outlined in Table 3.3 show that the stocks with the highest left-tail risk are more susceptible to slow response from the market. The observations show that the decile with the highest ES5% has the lowest IDneg, Dsvol, and PH52 values. Also, this decile has the highest Delay value. For example, going down with ES5%, the DSvol decreases from 0.16 to 0.04. This means that investors in the UK stock market are less attentive to the stocks with longer left-tail. Therefore, these stocks are expected to show persistent poor performance.

In addition to inattention, Table 3.3 shows another probable impediment to fast price discovery in the highest ES5%-decile. Stocks with a long left-tail suffer a more uncertain information environment and severe illiquidity. In terms of uncertain information, the top decile consists of small, young stocks with high fluctuated prices and turnover. For example, the top decile age, on average, is 124 months vs 269 months for the lowest decile. On the liquidity side, spread, Amihud impact measure, and zero-return days all score the highest value for the top decile.

The empirical observations in Table 3.2 and Table 3.3 highlight the apparent association between the left-tail risk (ES5%) and proposed impediments of price discovery especially the inattention indicators.

Table 3.3 Characteristics of the ES5%-based portfolios.

This table represents the characteristics of the ES5%-based decile portfolios. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from a Carhart four-factor model. MAX5 is the average of the five highest daily returns over the past three months. Price is the market price at the end of the formation month. Past is the monthly return over the formation month. Mom12 is the return over the past 12 months. Spread is the average daily bid-ask spread over the formation month. Amih is the amihud price impact measure over the formation month. Zdays is the ratio of days with zero return to the total number of days over the past three months. PH52 is the ratio of the current price to the 52-week high price. Delay is Hou and Moskowitz (2005)'s delay measure calculated from daily returns over the past three months. ID is the information discreteness index calculated from daily returns over the past 12 months. DSVol is the standardised abnormal volume over the past month. MV is the market value at the end of the formation period. Age is the number of months since the firm appeared in the DataStream. Synch is a synchronisation measure calculated from the explanatory power of the market model. Trvol is the volatility of the turnover over the past 12 months. Beta is the market beta with respect to the market index. Dbeta is the systematic tail risk measure calculated as the sensitivity of the stock returns to market return over the downstate. Coskew (coskewness) is the coefficient of the squared market return as in Harvey et al (2000). Iskew is the skewness of the stock daily return over the past three months. The sample covers the period from January 1996 to December 2017.

Prt	ES5%	IVOL	MAX	Mom12	Past	ID	PH52	DSvol	Delay
Low	2.08	1.13	2.98	19.76	2.77	0.03	0.92	0.16	0.56
P2	2.81	1.36	3.49	17.27	2.14	0.02	0.89	0.15	0.52
P3	3.3	1.54	3.87	16.37	1.94	0.02	0.87	0.15	0.53
P4	3.77	1.69	4.17	14.26	1.42	0.02	0.85	0.12	0.54
P5	4.26	1.9	4.62	12.92	1.11	0.01	0.82	0.12	0.55
P6	4.83	2.13	5.1	10.56	0.75	0	0.79	0.11	0.57
P7	5.56	2.43	5.74	7.08	0.07	0	0.75	0.07	0.59
P8	6.58	2.9	6.76	2.7	-0.69	-0.01	0.7	0.07	0.62
P9	8.28	3.68	8.39	-7.48	-2.4	-0.03	0.62	0.04	0.66
High	13.43	5.74	11.47	-40.58	-7.52	-0.05	0.47	0.04	0.72
Prt	logMV	Trvol	Age	Synch	Sp	Amih	Zdays	BM	ROA
Low	6.9	0.38	269	-2.98	0.01	0.01	0.15	0.54	0.06
P2	6.76	0.38	266	-2.73	0.01	0.01	0.12	0.54	0.06
P3	6.58	0.39	258	-2.79	0.01	0.02	0.12	0.56	0.05
P4	6.42	0.4	253	-2.86	0.01	0.02	0.12	0.58	0.05
P5	6.19	0.43	240	-3.01	0.02	0.03	0.13	0.59	0.03
P6	5.93	0.44	221	-3.12	0.02	0.04	0.13	0.61	0.02
P7	5.61	0.48	198	-3.27	0.02	0.05	0.15	0.64	-0.01
P8	5.16	0.5	171	-3.51	0.03	0.07	0.17	0.68	-0.06
P9	4.59	0.56	143	-3.83	0.04	0.11	0.19	0.75	-0.13
High	3.85	0.7	124	-4.37	0.06	0.2	0.21	0.94	-0.19

As shown in Tables 3.2 and 3.3, stocks in the top ES5% decile are past losers with lottery-like features and high impediments to the price discovery process such as slow response by the investors. Therefore, it is expected that the investors will underreact to the past losses of the top ES5% decile thus it will show momentum in the performance. In the next, through the single sort analysis, we will check the future performance of the ES5%-based portfolios and the IVOL-based portfolios.

3.4.2.2. Persistent IVOL Puzzle and Left-tail Momentum.

The observations outlined in Table 3.3 show that the stocks with the highest left-tail risk suffer from extreme losses in the past recent months. Contradicting the rational pricing paradigm, Atilgan et al. (2020) and Bi and Zhu (2020) show that the past poor performance of the stocks with high left-tail risk exhibits momentum in the next midterm. Table 3.4 outlines the performance analysis of the IVOL- and ES5%-based deciles. The performance is measured by the return over the next month and the next 6-month and weighted equally and by the market value (measured at the end of the last month of the formation period). In addition to the raw return, the alpha corresponding to the Carhart (1997) model is shown.

Table 3.4 The 6-month ahead return of the IVOL- and ES5%-based portfolios.

This table represents the performance of the decile portfolios based on ES5% and IVOL. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from a Carhart four-factor model. Each month the stocks are sorted into 10 groups based on the ES5% or IVOL, then the performance of these portfolios is measured by the next-month return and the average of monthly returns over the next 2-7 months. The performance is weighted by the market value and equally. α^{carh} is the alpha of the Carhart four-factor model. t-stat is newey-west t-statistic. The sample covers the period from January 1996 to December 2017.

	ES5%				IVOL			
	t+1		t+2 to t+7		t+1		t+2 to t+7	
Prt	EW	VW	EW	VW	EW	VW	EW	VW
p10	-3.56	-2.42	-3.41	-2.52	-2.83	-1.53	-2.84	-1.94
p9	-1.64	-0.75	-1.36	-0.97	-1.73	-0.90	-1.66	-1.23
p8	-0.91	-0.77	-0.86	-0.61	-1.09	-0.75	-1.01	-0.66
p7	-0.22	-0.30	-0.40	-0.30	-0.47	-0.10	-0.48	-0.42
p6	0.28	0.51	0.19	0.12	-0.04	0.08	-0.01	0.23
p5	0.44	0.43	0.42	0.31	0.21	0.22	0.30	0.24
p4	0.62	0.31	0.61	0.43	0.41	0.26	0.40	0.30
p3	0.64	0.41	0.64	0.42	0.50	0.45	0.47	0.46
p2	0.67	0.50	0.62	0.47	0.69	0.63	0.59	0.53
p1	0.83	0.76	0.69	0.58	0.67	0.57	0.57	0.45
P10-P1	-4.65	-3.44	-4.36	-3.36	-3.75	-2.35	-3.66	-2.64
t-stat	-7.84	-4.88	-6.89	-4.21	-9.17	-4.86	-8.66	-5.38
P10-P1 α^{carh}	-4.58	-3.25	-4.33	-3.46	-3.65	-2.36	-3.67	-2.85
t-stat	-10.34	-5.73	-8.73	-5.07	-11.73	-5.68	-10.06	-6.19
P9-P2 α^{carh}	-2.54	-1.42	-2.21	-1.68	-2.68	-2.05	-2.55	-2.21
t-stat	-6.88	-2.75	-5.27	-2.60	-10.61	-5.30	-8.07	-5.12

Observations in Table 3.4 confirm the expected negative future performance of the top ES5% and IVOL deciles. In particular, either weighted equally or by market value, the past trend in the returns associated with the ES5%-based decile portfolios continues in the near midterm horizon. Weighted equally, the differential return between the top and bottom deciles of ES5%-rank is -4.65% and significant with a newey west t-statistic of -7.84. This poor performance continues up to the near midterm. On average, over the next 6-month horizon, the differential return is -4.36% and highly significant with a t-statistic of -8.89. Weighting the return by the market value and adjusting it for the Carhart four-factor model confirms the persistent poor performance of the top ES5% deciles (i.e., P8-P10). For example, the value-weighted alpha (α^{carh}) of the zero-cost ES5%-based strategy is -3.46% with a newey-west t-statistic of -5.07. Consistent with the reported results in the previous empirical chapter (Chapter 2), Table 3.4 shows that the same results hold for the IVOL case. The IVOL puzzle observed over the next month persists to the next midterm horizon (i.e., the next 6 months, skipping the first month following the formation). This persistent underperformance of the IVOL-based strategy highlights the possible role of the underreaction behaviour and the limited arbitrage in generating this anomaly.

The empirical findings outlined in Table 3.4 confirm the previous finding in the U.S and the international market (see, Atilgan et al., 2019, and Bi and Zhu, 2020). Regardless of the higher risk, the UK stocks with higher left-tail risk generate lower returns in the next midterm horizon. This result is puzzling and contradictory to the mean-variance theory of asset pricing. Therefore, the revealed results cast doubt on the pricing efficiency in this market.

Prior evidence from the UK market shows a significant price momentum (see, for example, Hon and Tonks 2003 and Morelli 2014). This raises the question of whether the revealed pattern is driven by the well-known midterm price momentum or an independent phenomenon. To answer this question, in the next section, the bivariate sorting analysis will be performed to check the association between the uncovered left-tail momentum and the traditional price momentum.

3.4.2.3. The Association Between Traditional Momentum and Left-tail Momentum.

Price momentum is a universal phenomenon that challenges the standard asset pricing models (e.g., the CAPM and the F-F three-factor model). Showing similar behaviour to the price momentum suggests that the left-tail-induced momentum process might be generated by the same force. Moreover, price momentum is found to be highly associated with the idiosyncratic volatility puzzle (see, Arena et al. 2008). Based on these observations, it is intuitive to empirically test whether the continuation behaviour associated with the left-tail risk would be a unique process and therefore it is not generated by the widely-known price momentum. To do so, we will double sort on both momentum strategies to check how the performance of the left-tail induced momentum will be affected by the level of the price momentum (i.e., the level of past midterm returns). In specific, firstly, the stocks will be sorted into three portfolios (winner, medium, and loser) according to the level of price momentum (i.e., the returns over the past 12 and 6 months), then, within each price momentum level, the stocks are re-sorted into another three groups (low, medium and high) according to the levels of ES5%.

Table 3.5 Association between the price momentum and the left-tail momentum.

This table represents the performance of the portfolios based on ES5% and past performance. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 3 months. Mom12 (Mom6) is the cumulative return over the past 12 (6) months. Each month the stocks are sorted into 3 groups based on the momentum, then within each group of momentum, the stocks are resorted into another three groups based on the ES5%. The performance of these portfolios is measured by the next month's return or the average monthly returns over the next 2-7 months. EW is the equally weighted return. VW is the value-weighted return. Carh α is the Carhart model alpha. t-stat is newey-west t-statistic. The sample covers the period from January 1996 to December 2017.

		Mom12											
		t+1						t+2 to t+7					
		EW			VW			EW			VW		
		L	M	W	L	M	W	L	M	W	L	M	W
ES5%	L	-0.11	0.61	1.01	0.05	0.68	0.53	-0.21	0.63	0.72	-0.01	0.65	0.61
	M	-1.10	0.45	0.84	-1.01	0.51	0.77	-1.17	0.40	0.32	-1.04	0.30	0.43
	H	-3.33	-0.60	-0.31	-1.86	-0.10	-0.04	-2.54	-0.54	-0.91	-1.05	0.10	-0.38
Carh α		-3.471	-1.6	-1.92	-2.061	-1.36	-1.4	-2.42	-1.46	-2.27	-1.33	-1.07	-1.7
t-stat		-11.24	-6.99	-6.12	-4.81	-4.65	-4.2	-10.1	-8.07	-6.57	-4.64	-3.9	-4.1
		Mom6											
ES5%	L	0.05	0.59	0.92	0.16	0.53	0.56	-0.19	0.63	0.72	-0.10	0.61	0.62
	M	-0.99	0.44	0.86	-0.67	0.47	0.58	-1.28	0.39	0.45	-0.91	0.38	0.39
	H	-3.21	-0.87	-0.36	-1.70	-0.12	0.18	-2.56	-0.59	-0.86	-1.20	0.06	-0.30
Carh α		-3.49	-1.82	-1.72	-2.00	-1.13	-1.16	-2.50	-1.47	-2.22	-1.53	-0.97	-1.86
t-stat		-11.54	-8.70	-5.93	-4.61	-3.76	-3.46	-9.85	-9.02	-7.68	-4.94	-3.91	-4.74

Observations outlined in Table 3.5 represent the returns of the portfolios sorted jointly according to the past momentum and ES5%. The performance will be shown for the subsequent month and next 2 to 7 months and will be adjusted to the factors suggested by Carhart (1997). Whatever the level and the horizon of the momentum strategy, the trend in the performance of the ES5%-based portfolios keeps the same direction. Clearly, the empirical evidence in Table 3.5 highlights the poor performance of the stocks in the top ES5% tercile. Practically, shorting the stocks in the highest ES5% tercile and buying long the stocks in the lowest ES5% tercile generates a significant negative Carhart's alpha. For example, within the 6-month momentum strategy, the equally weighted ES5%-based hedging alpha of the next-month returns is -3.49% with a newey and west t-statistic of -11.54 within the loser group and -1.72% with a newey and west t-statistic of -5.93 within the winner group. The same result holds if we weighted the returns by the market value or extending the performance analysis up to the next 7th month. For example, considering the 12-month momentum, the value-weighted alpha of the next 2-7 months is -1.33% with a newey and west t-statistic of -4.64 within the loser group and -1.7% with a newey and west t-statistic of -4.1 within the winner group.

In summary, the observed continuation behaviour associated with the magnitude of the left-tail risk is independent of the widely known price momentum anomaly. Thus, the left-tail momentum document in Table 3.4 is a unique anomaly that adds a challenge to the validity of the standard asset pricing theory in the UK market. In other words, the observations in the left tail of the return's distribution provide useful information regarding the future performance independent from that signalled by the price momentum.

Uncovering the continuous underperformance of the stocks with high IVOL and left-tail risk (ES5%), the following section examines whether these patterns are attributed to the investors' underreaction-related behaviour.

3.4.3. Effect of the investors' limited attention on the left-tail momentum, and the IVOL puzzle.

So far, the empirical evidence in this study has shown an anomalous poor behaviour for the stocks with extreme left-tail risk and high IVOL. The observed poor performance of these stocks is robust and remains significant, economically and statistically, even after adjusting for the widely used Carhart's four-factor model. Hence, it is intuitive to look for justification outside rational pricing literature. As discussed in the literature review section, behavioural finance offers alternative explanations that seem plausible to explain behaviour of the stock market. One of the most important of these explanations is the underreaction-related mechanisms. Specifically, if the investors pay a little attention and hence underreact to the coming news, they will create a continuation in the securities prices. Consistent with this hypothesis, Atilgan et al. (2019) and Bi and Zhu (2020) show that price momentum associated with extreme left-tail is more likely to be a result of the investors' irrational behaviour. To this end, this subsection of the empirical analysis is devoted to examine the effect of the investor's limited attention on the behaviour of the observed performance momentum associated with the ES5%-based strategy. In addition, we will examine the effect of the limited attention behaviour on the returns of the IVOL-based strategy. For this purpose, the limited attention is represented by five various proxies, namely, information discreteness, standardised abnormal volume, farness from the past 52-week high, price delay, and the common index of these four individual proxies. Noteworthy, that all these proxies are created in a way to distinguish delayed response to bad information.

For this purpose, a double sort approach is conducted by sorting the stocks sample into 3 groups according to the limited attention proxies, and then resorting the stocks within these initial groups into another 3 levels according to the ES5% or IVOL. Therefore, we will have 9 different portfolios for each different interaction. Our main interest is the difference in the performance ES5%-based (IVOL-based) strategy between the lowest and the highest level of attention. We expect the poor performance associated with the high ES5% (IVOL), in the UK market, to be higher for the stocks with inattentive investors. The results are shown in Table 3.6. For brevity, the results are only shown for the lowest and the highest levels of the attention proxies. The analysis spans the period from January 1996 to December 2017. Table 3.6 shows the differential return and the adjusted alpha of the ES5%-best portfolios at different levels of investor attention. The difference in the performance between the two extreme attention levels is tested by the newey-west t-statistic with 6 lags to adjust for overlapping in returns. The table highlights many interesting observations. Albeit of different magnitude, all attention proxies have a significant influence on the size of the ES5%- and IVOL-based payoffs. The left-tail momentum and the IVOL puzzle are stronger for the stocks with stronger underreaction-related features. In particular, the poor performance observed for the stocks with high left-tail risk and idiosyncratic risk is stronger if the stocks have lower volume (lower DSVol), continuous negative information (lower ID), a price far from its 52-week high, and higher delay response (high Delay). For example, Considering the PCA_{Att}, the equally weighted (value-weighted) payoff for the ES5%-based strategy is -2.4% (-1.67%) for the stocks with low PCA_{Att} compared to -0.44% (-0.27%) for the stocks with high PCA_{Att}. Therefore, the difference in the performance between the two extreme levels of PCA_{Att} is -1.96% (newey and west t-statistic= -7.9) if weighted equally and -1.4% (newey and west t-statistic= -3.8) if weighted by value. Similar results hold for the IVOL puzzle.

Table 3.6 Investors' limited attention and the behaviour of the IVOL puzzle and the left-tail momentum.

This table represents the performance of the portfolios based on attention proxies and the ES5% or IVOL. Each month the stocks are sorted into 3 groups based on an attention variable, then within each group of attention, the stocks resort into another three groups based on the ES5% or IVOL. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from the Carhart four-factor model. PH52 is the ratio of the current price to the 52-week high price. Delay is Hou and Moskowitz (2005)'s delay measure calculated from daily returns over the past three months. ID is the information discreteness index calculated from daily returns over the past 12 months. DSVol is the standardised abnormal volume over the past month. The performance of these portfolios is measured by the next month's return and the average monthly returns over the next 2-7 months. The performance is weighted by market value and equally. α^{FF} is a Fama-French three-factor alpha of a zero-cost portfolio. α^{Carh} is Carhart four-factor alpha of a zero-cost portfolio. Diff is the difference in the performance of the ES5%-based and IVOL-based zero-cost strategy, controlling for level of attention. t-stat is newey-west t-statistic. The sample covers the period from January 1996 to December 2017. a, b, and c indicate significance at the 1%, 5%, and 10% percent level, respectively.

		ES5%						IVOL					
		EW			VW			EW			VW		
		H-L	α^{FF}	α^{Carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}
Delay	L	-2.6^{a}	-3.2^{a}	-2.8^{a}	-1.9^{a}	-2.7^{a}	-2.5^{a}	-2.5^{a}	-3^{a}	-2.7^{a}	-1.86^{a}	-2.54^{a}	-2.4^{a}
	H	-1.6^{a}	-2.2^{a}	-1.7^{a}	-1.0^{b}	-1.8^{a}	-1.4^{a}	-1.44^{a}	-2.06^{a}	-1.6^{a}	-1^{b}	-1.76^{a}	-1.37^{a}
Diff		-1.06	-1	-1.1	-0.9	-0.9	-1.1	-1.1	-0.97	-1.1	-0.86	-0.78	-1.06
t-stat		-3.99	-4.52	-5.03	-2.11	-2.25	-2.94	-4.4	-4.69	-5.14	-2.44	-2.29	-3.26
		H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}
ID	L	-2.7^{a}	-3.2^{a}	-2.8^{a}	-2.1^{a}	-2.87^{a}	-2.64^{a}	-2.6^{a}	-3.1^{a}	-2.8^{a}	-2.1^{a}	-2.8^{a}	-2.4^{a}
	H	-0.63^{b}	-1.16^{a}	-1.18^{a}	-0.35	-1^{a}	-1.07^{a}	-0.46	-0.95^{a}	-1.1^{a}	-0.34	-0.9^{a}	-1.0^{a}
Diff		-2.04	-2.04	-1.6	-1.7	-1.88	-1.57	-2.16	-2.17	-1.7	-1.74	-1.8	-1.4
t-stat		-9.41	-9.14	-6.93	-4.93	-5.27	-4.4	-9.52	-8.94	-6.64	-4.69	-4.34	-3.3
		H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}
PH52	L	-2.0^{a}	-2.3^{a}	-2.25^{a}	-1.1^{a}	-1.42^{a}	-1.4^{a}	-2.2^{a}	-2.5^{a}	-2.6^{a}	-1.7^{a}	-2^{a}	-1.9^{a}
	H	-0.4^{c}	-0.85^{a}	-1.1^{a}	-0.2	-0.75^{b}	-1.2^{a}	-0.31	-0.76^{a}	-1.0^{a}	-0.25	-0.74^{b}	-1.1^{a}
Diff		-1.6	-1.45	-1.14	-0.87	-0.67	-0.2	-1.9	-1.75	-1.6	-1.5	-1.25	-0.79
t-stat		-7.56	-6.83	-4.71	-2.22	-1.64	-0.52	-8.48	-7.76	-5.66	-3.44	-2.52	-1.32
		H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}
DSVOL	L	-2.6^{a}	-3.2^{a}	-2.6^{a}	-1.6^{a}	-2.33^{a}	-1.7^{a}	-2.55^{a}	-3.2^{a}	-2.6^{a}	-1.78^{a}	-2.5^{a}	-2^{a}
	H	-1.77^{a}	-2.35^{a}	-2.14^{a}	-0.9^{b}	-1.67^{a}	-1.5^{a}	-1.63^{a}	-2.13^{a}	-2^{a}	-1.28^{a}	-1.9^{a}	-1.8^{a}
Diff		-0.8	-0.86	-0.4	-0.72	-0.66	-0.19	-0.92	-1.04	-0.57	-0.5	-0.6	-0.23
t-stat		-3.69	-4.44	-1.99	-2.89	-2.59	-0.7	-4.01	-5.03	-2.57	-1.95	-2.25	-0.69
		H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}	H-L	α^{FF}	α^{carh}
PCA_{Att}	L	-2.4^{a}	-2.8^{a}	-2.5^{a}	-1.67^{a}	-2.25^{a}	-1.9^{a}	-2.45^{a}	-2.84^{a}	-2.7^{a}	-1.9^{a}	-2.4^{a}	-2.06^{a}
	H	-0.44^{c}	-0.95^{a}	-1.16^{a}	-0.27	-0.85^{a}	-1.1^{a}	-0.3	-0.76^{a}	-1^{a}	-0.32	-0.88^{a}	-1.2^{a}
Diff		-1.96	-1.85	-1.3	-1.4	-1.4	-0.82	-2.2	-2.08	-1.7	-1.56	-1.5	-0.9
t-stat		-7.9	-7.19	-4.9	-3.8	-3.71	-2.13	-9	-8.32	-5.7	-3.8	-3.38	-1.77

To some extent, adjusting the returns to the widely used risk factors attenuates the attention-based variation in the performance of the investment strategies based on ES5% and IVOL.

However, this variation remains, economically and statistically, significant for most cases. Again, consider the PCA_{Att} as example, the difference in the value-weighted Carhart's alpha is -0.82% (newey-west t-statistic = -2.13) for the ES5%-based strategy and -0.9 (newey-west t-statistic = -1.77) for the IVOL-based strategy. It should be noted that this attenuation in the effect of the attention level is related to the rule of momentum factor in pricing the continuation-related anomalies.

This significant difference in the next 6-month performance varies from one attention proxy to another. To illustrate, considering the IVOL-based strategy, the difference in the value-weighted performance is -1.74% (t-statistic = -4.69) in the case of ID compared to only -0.5% (t-statistic = -1.95) in the case of DSvol. This disparity in the effect of the attention proxy on the performance of strategies, based on the left-tail risk (ES5%) and IVOL, may be related to the ability of the proxy to separate the stocks according to the past performance. By construction, ID and PH52 are built to separate the stocks based on their past performance.

The results reported in Table 3.6 line up with the previously documented evidence on the mispricing of the stocks with high left-tail risk and idiosyncratic risk (see, for, example, Stambaugh et al., 2015, Cao and Han, 2016, Atilgan et al., 2019, and Bi and Zhu, 2020). Underreaction-related features appear to partially explain these risk-based anomalies. In the UK market, stocks with high left-tail risk and idiosyncratic risk underperform in the future. And according to the result in Table 3.6 part of this underperformance is driven by the investor's inattentive action.

Previous studies have demonstrated that information uncertainty amplifies the continuation of the high-risk anomalies (Zhang 2006, and Kumsta and Vivian 2020). After shedding some light on the nature of this persistent poor performance and linking it to the underreaction behaviour, in the following, the role of the arbitrage deterrents, i.e., information uncertainty and illiquidity, will be examined.

3.4.4. Investors' Attention and Information Uncertainty Level.

Vogue environment has been accused of exacerbating the investor's cognitive biases (Tversky and Kahneman, 1974). This hypothesis has been supported in the context of the financial markets in many empirical works (see, for example, Zhang, 2006a; and Kumar, 2009). It may be thought that information risk influence is limited to individual investors. However, Zhang (2006b) and Hribar and McInnis (2011) demonstrate that the stock analyst is also susceptible to biases in an uncertain environment. Thus, the information uncertainty offers a possible channel through which the price continuation occurs. Therefore, this subsection intends to examine whether the information uncertainty is the channel through which the attention affects the IVOL puzzle and the left-tail momentum. It is projected that the observed underperformance momentum will be stronger for stocks with high information uncertainty.

We begin by analysing the effect of the information uncertainty on the price continuation associated with the ES5% and the IVOL. To this end, we will conduct a double sorting analysis. We create 9 portfolios by first sorting the stocks on the information uncertainty and then resorting each of these groups into another three levels based on the ES5% or the IVOL. To proxy the information risk, we will employ an index created from 5 different proxies of information uncertainty. For more details refer to the methodology section.

To examine the effect of the information uncertainty as an intermediary link between the attention level and the risk-related anomalies, a triple sort procedure is performed. In specific, 27 portfolios are created by sorting the stocks on the risk information index, the attention index, and the ES5% (or the IVOL), dependently and in order. The purpose of this analysis is to show how the effect of the attention level on the continuation behaviour changes with the level of information uncertainty.

Table 3.7 displays the left-tail momentum and the idiosyncratic puzzle conditioning on the level of the information uncertainty. As expected, the differential return between the extreme levels of ES5% and IVOL is highly concentrated in the group of stocks with high information uncertainty. In unadjusted terms, stocks in the lowest tercile of the information uncertainty rank show weak evidence of the examined continuation anomalies. For example, the difference in the unadjusted value-weighted return between the highest and the lowest level of IVOL is -0.47% and insignificant for the low information uncertainty level, while it is -2.42% and significant for the highest level of information uncertainty. The same result holds for the equal-weighted case and the ES5%-based strategy. The observations in Table 3.7 show that the difference in the spread between the high and low levels of information uncertainty is significant, economically, and statistically, for all different cases. Take the IVOL as an example, the difference in the value-weighted Carhart's alpha is -1.7% with a t-statistic of -4.02.

Adjusting the return to the widely used pricing factors (i.e., F-F three factors and the momentum factor) widens the spreads within the lower information uncertainty portfolio. For example, the value-weighted spread of the ES5%-based strategy rises from insignificant of -0.45% to -1.07% which is highly significant (α = 1%). This implies that even if the stocks have more certain information, they will fail to compensate the investors for the higher level of risk.

In summary, the information uncertainty explains a substantial part of the left-tail momentum and the IVOL puzzle in the UK market. This result is consistent with the results reported in Table 3.6 of this study and previous studies, which consider the left-tail momentum and the IVOL puzzle as a mispricing behaviour.

Table 3.7 Effect of information uncertainty on the performance of the IVOL puzzle and the left-tail momentum.

This table represents the performance of the portfolios based on information uncertainty and ES5% or IVOL. Each month the stocks are sorted into 3 groups based on the information uncertainty index, then within each group of uncertainty, the stocks resort into another three groups based on the ES5% or IVOL. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5[th] percentile of daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from Carhart four-factor model. InfRisk is the information uncertainty index that represents the first principal component of five employed uncertainty proxies. The performance of these portfolios is measured by the next month's return and the average monthly returns over the next 2-7 months. The performance is weighted by market value and equally. α^{FF} is Fama-French three-factor alpha of a zero-cost portfolio. α^{Carh} is Carhart four-factor alpha of a zero-cost portfolio. Diff is the difference in the performance of the ES5%-based and IVOL-based zero-cost strategy, controlling for level of attention. t-stat is newey-west t-statistic. The sample covers the period from January 1996 to December 2017. a, b, and c indicate significance at the 1%, 5%, and 10% percent level, respectively.

		ES5%						IVOL					
		EW			VW			EW			VW		
		H-L	α^{FF}	α^{Carh}	H-L	α^{FF}	α^{Carh}	H-L	α^{FF}	α^{Carh}	H-L	α^{FF}	α^{Carh}
InfRisk	L	-.47^{C}	-1.07^{a}	-.72^{a}	-0.45	-1.16^{a}	-1.07^{a}	-0.37^{C}	-0.95^{a}	-0.63^{a}	-0.47	-1.2^{a}	-1.1^{a}
	H	-2.9^{a}	-3.4^{a}	-3.1^{a}	-2.67^{a}	-3.3^{a}	-2.95^{a}	-2.68^{a}	-3.12^{a}	-2.93^{a}	-2.42^{a}	-3^{a}	-2.8^{a}
Diff		-2.43	-2.32	-2.37	-2.22	-2.13	-1.88	-2.31	-2.17	-2.3	-1.96	-1.78	-1.7
t-stat		-11.96	-12.05	-12.68	-7.09	-6.04	-5.01	-10.67	-9.84	-9.88	-6.13	-5.02	-4.02

Now we will turn to examine how the interaction between the information uncertainty and the attention level determines the left-tail momentum and the IVOL puzzle. Table 3.8 represents the result regarding this goal. Table 3.8 represents the triple-sort analysis of the interaction between the information uncertainty and the attention level to influence the left-tail momentum and the IVOL-puzzle. Several points about this interaction relationship are worth noting. Firstly, in the level of low information uncertainty, the left-tail momentum and the IVOL puzzle are significant only for the low attention level. For example, Table 3.8 shows that within the low level of information uncertainty, the equal-weighted left-tail momentum for the medium and high attention levels are -0.19% and -0.12%, respectively, and none of them is significant. Moving to the highest level of information uncertainty, the left-tail momentum and the IVOL puzzle are highly significant for all levels of attention. For instance, within the group of stocks with high information uncertainty, the value-weighted IVOL-based spreads for the three levels of attention are ranging from -1.4% to -1.87%, which are all significant, economically and statistically.

Table 3.8 Joint effect of information uncertainty and attention on the performance of the IVOL puzzle and left-tail momentum.

This table represents the triple sort analysis on information uncertainty, attention index, and the ES5% or IVOL. Each month the stocks are sorted into 3 groups based on information uncertainty index, then within each group of uncertainty the stocks are resorted into another three groups based on the attention index, thirdly, within each of 9 groups generated in the previous two, the stocks resort into another 3 groups based on ES5% or IVOL. .ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from Carhart four-factor model. InfRisk is the information uncertainty index that represents the first principal component of five employed uncertainty proxies. ATT is the attention index that represents the first principal component of four employed attention proxies. The performance of these portfolios is measured by the next month's return and the average monthly returns over the next 2-7 months. The performance is weighted by market value and equally. α^{FF} is the Fama-French three-factor alpha of a zero-cost portfolio. α^{Carh} is Carhart four-factor alpha of a zero-cost portfolio. Diff is the difference in the performance of the ES5%-based and IVOL-based zero-cost strategy, controlling for level of attention. The sample covers the period from January 1996 to December 2017. a, b, and c indicate significance at the 1%, 5%, and 10% percent level, respectively.

ES5%							
		EW			VW		
		InfRisk					
		L	M	H	L	M	H
ATT	L	-0.73^{a}	-1.82^{a}	-1.66^{a}	-0.81^{b}	-1.87^{a}	-1.25^{a}
	M	-0.19	-0.93^{a}	-1.77^{a}	-0.17	-1.10^{a}	-1.85^{a}
	H	-0.12	-0.76^{a}	-1.52^{a}	-0.10	-0.93^{b}	-1.53^{a}
Diff		-0.62^{b}	-1.10^{a}	-0.14	-0.71^{b}	-0.94^{b}	0.28
α^{FF}		-0.68^{b}	-1.13^{a}	0.11	-0.95^{a}	-0.86^{c}	0.61
α^{Carh}		0.01	-0.33	0.30	-0.36	0.00	0.98^{c}
IVOL							
		InfRisk					
		L	M	H	L	M	H
ATT	L	-0.54^{b}	-1.57^{a}	-2.02^{a}	-0.56	-1.55^{a}	-1.87^{a}
	M	-0.13	-0.86^{a}	-1.72^{a}	-0.07	-1.08^{a}	-1.80^{a}
	H	-0.00	-0.71^{b}	-1.43^{a}	-0.09	-0.94^{a}	-1.40^{a}
Diff		-0.53^{c}	-0.86^{b}	-0.59^{b}	-0.47	-0.61	-0.47
α^{FF}		-0.58^{c}	-1.0^{a}	-0.40	-0.67^{c}	-0.64	-0.22
α^{Carh}		0.06	-.17	-0.36	-0.10	0.14	-0.12

Except for the value-weighted IVOL-strategy, the attention levels produce significantly different levels of left-tail momentum and IVOL-spread, only within the low and medium information uncertainty. To elucidate this point, consider the value-weighted left-tail momentum, Table 3.8 shows that the difference between the lowest and the highest levels of attention is -0.71% within the low uncertainty level and -0.94% within the high uncertainty level, both are significant at α = 5%. In contrast, for the highly uncertain stocks, the influence of the attention level on the left-tail momentum is substantially attenuated and insignificant.

Regardless of the weighting scheme, the attention-related difference in the ES5%-based raw spread (Diff) is statistically not different from zero for the highest level of information uncertainty. Numerically, this equal-weighted spread is -0.14%, while it is 0.28% if weighted by the market-value. For the value-weighted IVOL cases, the effect of the attention on the short-long spread is not significant, despite the level of information uncertainty.

Similar to double-sort analysis, adjusting the results to Carhart's four-factor model largely attenuates the attention-related variation in the left-tail momentum and the IVOL puzzle. This result is due to the momentum factor which is constructed to price the continuation behaviour in the stocks prices.

In summary, for the low and medium tercile of information uncertainty, the low attention features amplify the future poor performance associated with the high ES5% and high IVOL. For the stocks with high information uncertainty, the attention level appears to add nothing. Unsurprisingly, investors are more likely to avoid stocks with costly information. However, for the stocks with low or medium information uncertainty, the underreaction behaviour provides extra information to that included in the information uncertainty regarding the stocks' prices.

3.4.5. Investors' Attention and Liquidity Level.

Illiquidity is an important impediment to the efficient price discovery process (Chordia et al., 2008, and Bali et al., 2014). Illiquidity has been found to amplify the under-reaction behaviour. Lin et al. (2014) show that illiquid stocks have a slower response to information. In the UK market, Mazouz et al. (2012) demonstrate that stocks with higher systematic risk underreact to current shocks thus show price continuation behaviour. Moreover, Kumsta and Vivian (2019) study the financial strength anomaly in the UK market. They find that illiquidity is more closely related to this anomaly than information uncertainty. Therefore, illiquidity could offer another potential channel through which the low attention level generates a stronger and more persistent continuation pattern.

Under this section, we examine whether illiquidity provides the inattentive behaviour a hand to produce a stronger left-tail momentum and the IVOL puzzle. For this purpose, we conduct a triple sorting procedure (3×3×3) similar to that outlined in Table 3.8, however this time the information uncertainty is replaced by the illiquidity. To proxy illiquidity, the well-known Amihud's price impact measure is employed. It is expected that the illiquidity is highly correlated to the information risk proxies, which both are considered as arbitrage impediments. Thus, maybe they both have the same relationship with the attention level. To address this issue, Amihud's measure is orthogonalised to the information uncertainty proxy, by running a monthly cross-sectional regression. In addition to the standard Amihud's measure, the residual from this cross-sectional regression is used as an uncertainty-independent liquidity measure in a separate analysis. Table 3.9 represents the 6-month-ahead performance of the zero-cost portfolios based on ES5% and IVOL with different levels of attention and illiquidity.

In Table 3.9, the effect of attention level on the left-tail momentum and IVOL puzzle within each level of liquidity is shown. In Panel A of Table 3.9, the standard Amihud's measure is employed as a liquidity proxy. Similar to the information uncertainty, the left-tail momentum and the IVOL puzzle are weakened as we move toward the portfolio of stocks with higher liquidity (lower Amihud measure) and higher attention level. Panel A of Table 3.9 reports that, for the high liquidity level, the left-tail momentum and IVOL puzzle significantly exist only for low attention levels. For example, the equal-weighted (value-weighted) left-tail momentum within the group of stocks with low Amihud ratio and low limited attention index is -1.56% (-1.15) and highly significant at α=1% level.

Except for the value-weighted ES5% portfolio within the high illiquidity, the variation in the level of attention generates a significant variation in the left-tail momentum and IVOL puzzle. The low attention level produces stronger left-tail momentum and IVOL puzzle. For the more liquid stocks (Low Amihud), the difference in IVOL-based raw spread (Diff) between the lowest and the highest level of attention is -1.37% if weighted equally and -1.03%, if weighted equally. Both are significant at α=1%. For the illiquid stocks, this difference in IVOL-related spread is -0.93% (significant at α=1%) if weighted equally and -0.56% (significant at α=10%) if weighted by market-value. Except for the value-weighted strategy within the highest Amihud tercile, similar results hold for the ES5% strategy. Adjusting the performance to the Fama-French three-factor model re-emphasises the significant ability for the underreaction features to generate a stronger left-tail momentum and IVOL puzzle. The difference in the F-F alpha between the lowest and the highest levels of attention index stays significant for most cases. Again, the attention-related variation in the adjusted performance of strategy based on the ES5% and IVOL is higher for the stocks with high liquidity. For the value-weighted F-F alpha of the IVOL-based strategy, the difference between the low-attention portfolio and the high-attention portfolio is -1.38% for the low

Table 3.9 Joint effect of liquidity and attention on the IVOL puzzle and left-tail momentum returns.

This table represents the triple-sort analysis on amihud illiquidity measure, attention index, and the ES5% or IVOL. Each month the stocks are sorted into 3 groups based on amihud price impact ratio, then within each group of uncertainty the stocks are resorted into another three groups based on the attention index, thirdly, within each of the 9 groups generated in the previous two, the stocks resort into another 3 groups based on ES5% or IVOL. Amih is the amihud price impact ratio. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 3 months. IVOL is the standard deviation of error terms calculated from Carhart four-factor model. ATT is the attention index which represents the first principal component of four employed attention proxies. The performance of these portfolios is measured by the next month's return and the average monthly returns over the next 2-7 months. The performance is weighted by market value and equally. α^{FF} is the Fama-French three-factor alpha of zero-cost portfolio. α^{Carh} is the Carhart four-factor alpha of a zero-cost portfolio. Diff is the difference in the performance of the ES5%-based and IVOL-based zero-cost strategy, controlling for level of attention. The sample covers the period from January 1996 to December 2017. a, b, and c indicate significance at the 1%, 5%, and 10% percent level, respectively.

Panel A: Amihud							
ES5%-based strategy							
		EW			VW		
		Amih level					
		L	M	H	L	M	H
ATT	L	-1.56[a]	-2.16[a]	-1.9[a]	-1.15[b]	-1.95[a]	-1.41[a]
	M	-0.43[c]	-1.14[a]	-1.6[a]	-0.20	-1.0[a]	-1.37[a]
	H	-0.15	-.53[b]	-1.34[a]	-0.33	-0.68[b]	-1.35[a]
Diff		-1.41[a]	-1.64[a]	-0.58[b]	-0.95[b]	-1.27[a]	-0.06
α^{FF}		-1.55[a]	-1.71[a]	-0.42[c]	-1.22[a]	-1.27[a]	-0.06
α^{Carh}		-0.77[a]	-0.84[b]	-0.35	-0.46[c]	-0.3	-0.03
IVOL-based strategy							
		Amih level					
		L	M	H	L	M	H
ATT	L	-1.48[a]	-2.12[a]	-2.11[a]	-1.15[b]	-1.80[a]	-1.78[a]
	M	-0.33	-1.16[a]	-1.6[a]	-0.18	-1.04[a]	-1.56[a]
	H	-0.11	-0.52[c]	-1.2[a]	-0.12	-0.75[b]	-1.22[a]
Diff		-1.37[a]	-1.60[a]	-0.93[a]	-1.03[a]	-1.05[a]	-0.56[c]
α^{FF}		-1.52[a]	-1.67[a]	-0.72[c]	-1.38[a]	-1.12[a]	-0.43
α^{Carh}		-0.8[a]	-0.9[a]	-0.7[b]	-0.85[b]	-0.34	-0.46
Panel B: Orthogonalised Amihud							
ES5%-based strategy							
		EW			VW		
		$Amih_{Orth}$ level					
		L	M	H	L	M	H
ATT	L	-2.17[a]	-2.0[a]	-2.86[a]	-1.8[a]	-1.74[a]	-1.4[a]
	M	-1.7[a]	-0.83[a]	-0.54[b]	-1.6[a]	-0.94[a]	-0.21
	H	-1.14[a]	-0.44[b]	-0.05	-1.1[a]	-0.42	-0.2
Diff		-1.03[a]	-1.57[a]	-2.8[a]	-.71[c]	-1.3[a]	-1.2[a]
α^{FF}		-0.80[b]	-1.6[a]	-2.73[a]	-0.5	-1.2[a]	-1.3[a]
α^{Carh}		-0.42	-0.81[a]	-2.3[a]	0.11	-0.48	-0.92[a]
IVOL-based strategy							
		$Amih_{Orth}$ level					
		L	M	H	L	M	H
ATT	L	-2.2[a]	-1.7[a]	-2.9[a]	-1.8[a]	-1.35[a]	-2.0[a]

	M	-1.7[a]	-0.79[a]	-0.46[b]	-1.61[a]	-0.79[a]	-0.10
	H	-1.06[a]	-0.35	0.06	-1.14[a]	-0.44	-0.14
Diff		-1.15[a]	-1.36[a]	-2.97[a]	-0.67[c]	-0.91[b]	-1.85[a]
α^{FF}		-0.99[a]	-1.42[a]	-2.85[a]	-0.60	-0.88[b]	-1.85[a]
α^{Carh}		-0.68[b]	-0.74[b]	-2.46[a]	-0.11	-0.35	-1.44[a]

stocks and -0.43% for the high Amihud stocks. Unsurprisingly, adding the momentum factor to the F-F three factors highly attenuates the explanatory power of the underreaction-driven behaviour. To clarify this point, consider the stocks with low Amihud measure and the value-weighted ES5% strategy, adjusting the value-weighted left-tail momentum to the Carhart four-factor model, the difference between the extreme levels of attention drop from -0.95% to -0.46%.

The observations in Panel B of Table 3.9 confirm that the information risk has a significant effect on the liquidity-return relationship. However, the inference regarding the ability of the attention level to determine the examined anomalies does not change.

Therefore, the results in Table 3.9 reconfirm the previous result that the underreaction-related behaviour produces stronger continuation behaviour for the stocks with longer left-tail risk and higher idiosyncratic risk. In other words, there is evidence that the documented left-tail momentum and the IVOL puzzle are partially driven by the underreaction behaviour. Moreover, controlling for the suggested information uncertainty channel, this underreaction-related anomalous behaviour is independent of the illiquidity effect.

3.4.6. Fama and Macbeth Cross-sectional Regression Results.

In the double and triple sort procedures, it is difficult to control for more than two variables at a time. To control for other potential return predictors in a multivariate set, Fama and Macbeth's cross-sectional regression is performed. For more details about the Fama and Macbeth cross-section procedures and the included set of controlling variables, refer to the methodology section. To examine how the predictive ability of the IVOL and ES5% interact with the attention features and the other underreaction channels, their effect is included as interaction terms with the ES5% and IVOL in the Fama-Macbeth regression. To address any potential nonlinearity in their effect and to ease the explanation of their economic significance, the attention index and the other underreaction mechanisms are ranked into vintiles based on their values within each month and then scaled to range from 0 to 1.

Including the attention effect with other potential underreaction causes, i.e., information risk and illiquidity (Amihud) helps us to disentangle their effects and to gauge their relative importance. The regressions are estimated for the whole sample from January 1996 to December 2017.

Table 3.10 represents the Fama-Macbeth regressions. In Panel A of Table 3.10, the six-month ahead excess returns are regressed against the ES5%, the underreaction channels, the interaction between these channels and the ES5%, and a set of control variables. The reported results highlight some worth mentioning observations. Firstly, confirming the portfolio analysis, the left-tail risk inversely predicts the returns over the next six months. In Panel A of Table 3.10, without controlling for any other effect, the average slopes coefficients for the ES5% is -0.37 with a newey-west t-statistic of -7.15. Secondly, controlling for the effect of the attention index considerably attenuates the ability of the ES5% to predict the next six-month excess returns. For example, the attention effect reduces the magnitude of the average slope coefficients for the ES5% from -.37 to -0.23, however, it remains significant with a newey-west t-statistic of -6.20.

Thirdly, the interaction between attention and ES5% (ATT*ES5%) is positive and significant, both statistically and economically. In Panel A of Table 3.10, column 3 shows that, with no control for any other effect, the average slope coefficients on (ATT*ES5%) is 0.17 and significant with a newey-west t-statistic of 2.79. Even after controlling for other underreaction mechanisms, the attention interaction remains significant. Column 11 of Panel A shows that the average slope coefficients on (ATT*ES5%) is 0.09 and marginally significant (t-statistic = 1.7). These results imply that the attention-driven slow price discovery and considerably contributes to the left-tail momentum anomaly. The ES5%-related price continuation (the left-tail momentum) is stronger for low-attention stocks, even after controlling for other price impediments, especially the information uncertainty.

Also, besides the attention effect, Panel A of Table 3.10 reports an important rule for the information uncertainty in generating the left-tail momentum. In regressions, with attention index or without attention index, the interaction between ES5% and the information uncertainty (Inf*ES5%) is negative and significant. Controlling for the attention level along with all other controlling variables, column 11 in Panel A of Table 3.10 shows that the average slope coefficient on (Inf*ES5%) is -0.14 with a newey-west t-statistic of -2.10. In general, both attention and information uncertainty appear to play key role in explaining the left-tail momentum anomaly. To clarify this point, consider column 6, introducing the attention and the information uncertainty channels substantially reduces the left-tail predictive power of the future returns, the average slope coefficients on the ES5% is only -0.12 and marginally significant (newey-west t-statistic is -1.68).

In contrast to the attention effect and the information uncertainty channel, illiquidity shows an insignificant contribution to the left-tail momentum anomaly. Panel A of Table 3.10 reports an insignificant coefficient on (Amih*ES5%) for all models.

Panel B of Table 3.10 reports the results for Fama-Macbeth regressions, but with the idiosyncratic volatility (IVOL) instead of the left tail risk (ES5%). Therefore, through these sets of regressions, we examine the merit of the underreaction-related mechanisms in explaining the IVOL puzzle. Regarding the attention mechanism, the reported results in Panel B show are similar to those shown in Panel A. Unsurprisingly, attention level shows a similar effect on the IVOL puzzle to that on the left-tail momentum. The average slope coefficients on the interaction term (ATT*IVOL) are significant statistically and economically for all cases. Column 11 of Panel B in Table 3.10 shows that, even after controlling for the information uncertainty, the illiquidity, and all other controlling variables, the average slope coefficients on (ATT*IVOL) is 0.33 with a t-statistic of 3.33. Thus, the IVOL puzzle is stronger for the stocks with a low-attention level. In contrast to the attention channel, the information uncertainty and the illiquidity show no significant effect on the ability of IVOL to predict the next six-month returns.

The reported failure of the information uncertainty (InfRisk) to affect the IVOL puzzle, may be related to the nature of the IVOL as a major proxy of information uncertainty and arbitrage cost. Pontiff (2006) suggests idiosyncratic volatility as a primary cost faced by arbitrageurs.

In general, these results line up with the previous empirical results in Hong et al. (2000), Doukas et al. (2005), and Hou et al. (2009), among others about the importance of the investors' attention in fuelling efficient price discovery processes. Also, these findings confirm the results in Atilgan et al. (2020) who attributed the poor performance of the high left-tail risk stocks to the underreaction behaviour by the investors due to their inattentive action and to the costlier arbitrage position they have to take.

Overall, the results in Table 3.10 suggest that both inattention and information uncertainty contribute to the mid-term return predictability of ES5% and IVOL. The results imply that the mid-term return continuation associated with the left-tail risk and the idiosyncratic risk is partly due to the inattentive reaction by the investors. The poor performance of the ES5%-based and the IVOL-based strategies is stronger when the investors are inattentive.

Table 3.10 Fama and MacBeth cross-sectional regressions.

This table shows the Fama-MacBeth regressions. Each column represents the average coefficients of monthly cross-sectional that regress the six-month ahead excess returns over the ES5% or IVOL, attention index, other potential underreaction mechanisms, interaction terms between ES5%, or IVOL and any of the underreaction mechanisms, and a set of control variables. t-stat is the newey and west t-statistic adjusted for six-lag. The analysis spans the period of January 1996 to December 2017.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Panel A						ES5%					
ES5%	-0.37	-0.23	-0.27	-0.19	-0.16	-0.12	-0.09	-0.26	-0.20	-0.12	-0.10
t-stat	(-7.15)	(-6.20)	(-8.28)	(-7.38)	(-2.12)	(-1.68)	(-1.65)	(-3.53)	(-3.61)	(-1.70)	(-1.89)
ATT		2.27	1.62	1.07		1.71	1.26		1.69	1.78	1.29
t-stat		(5.89)	(3.50)	(2.79)		(4.56)	(3.86)		(4.40)	(4.77)	(4.05)
ATT*ES5%			0.17	0.13		0.12	0.09		0.14	0.11	0.09
t-stat			(2.79)	(2.37)		(2.01)	(1.65)		(2.63)	(1.93)	(1.7)
InfRisk					-0.68	0.02	0.35			-0.21	0.33
t-stat					(-1.16)	(0.05)	(0.35)			(-0.42)	(0.92)
Inf*ES5%					-0.15	-0.16	-0.11			-0.15	-0.14
t-stat					(-2.01)	(-2.13)	(-1.84)			(-2.13)	(-2.10)
Amih								-0.51	0.11	0.34	0.03
t-stat								(-1.01)	(0.26)	(1.29)	(0.14)
Amih*ES5%								-0.07	-0.08	0.00	0.04
t-stat								(-1.13)	(-1.47)	(-0.09)	(1.04)
Control	no	no	no	yes	no	no	yes	no	no	no	yes
Rsq	0.03	0.05	0.10	0.16	0.11	0.16	0.17	0.08	0.11	0.12	0.18
Panel B						IVOL					
IVOL	-0.71	-0.48	-0.66	-0.43	-0.42	-0.54	-0.27	-0.65	-0.68	-0.57	-0.32
t-stat	(-7.54)	(-5.96)	(-7.98)	(-7.11)	(-2.24)	(-3.04)	(-2.24)	(-3.90)	(-4.74)	(-3.22)	(-2.65)
ATT		2.42	1.40	0.97		1.35	1.12		1.35	1.38	1.12
t-stat		(6.02)	(2.95)	(2.43)		(3.53)	(3.52)		(3.28)	(3.52)	(3.60)
ATT*IVOL			0.55	0.38		0.55	0.32		0.56	0.54	0.33
t-stat			(4.96)	(3.23)		(5.17)	(3.26)		(5.68)	(5.30)	(3.33)
InfRisk					-0.85	-0.33	0.15			-0.44	0.34
t-stat					(-1.38)	(-0.57)	(0.37)			(-0.85)	(0.90)
Inf*IVOL					-0.20	-0.09	-0.16			-0.12	-0.31
t-stat					(-1.10)	(-0.50)	(-1.11)			(-0.65)	(-1.83)
Amih								-0.73	-0.22	0.13	-0.26
t-stat								(-1.39)	(-0.48)	(0.45)	(-0.93)
Amih*IVOL								0.00	0.04	0.06	0.21
t-stat								(0.02)	(0.28)	(0.65)	(2.03)
Control	no	no	no	yes	no	no	yes	no	no	no	yes
Rsq	0.07	0.09	0.10	0.16	0.08	0.11	0.17	0.08	0.11	0.12	0.18

3.5. Robustness Checks.

In this section, the main results reported above in this work will be tested against the different specifications of the variables and sub-samples. Also, the long-term behaviour of the reported anomalies will be analysed.

3.5.1. Alternative Specifications of the IVOL, ES, and the Limited Attention Proxies.

This subsection checks whether the empirical results are robust to changes in the measurement of the main variables. To this end, the IVOL and the ES5% are measured over the past 250 days rather than the short period of the past 66 days. Moreover, except for the 52-week high ratio, the underreaction proxies are measured using the different specifications. The abnormal volume is measured by the difference between the average trading volume over the past three months and the same average over the past 12 months. The delay measure of Hou and Moskowitz (2005) is measured by weekly returns over the past year, and the continuous information index is measured by the daily data over the past 6 months.

3.5.1.1. IVOL and ES5% Measured Over the Past 250 Days.

In Table 3.11, the single-sort analysis based on the IVOL or ES5% is repeated with the changes mentioned above. The results reconfirm the anomalous underperformance of the stocks with high IVOL and long left-tail (high ES5%). The one-year measure of the IVOL and ES5% produce similar results to that of the 66-day measure. Whatever the performance measure, over the next midterm horizon, on average, the returns are strikingly diminishing with the risk. Again, the results contradict the standard assumption of the risk-return trade-off.

Table 3.12 outlays the double-sort analysis on IVOL and ES5%. Again, the empirical results are consistent with the ones represented in the main body of this work. There is a close link between the two pricing anomalies.

In Panel A of Table 3.12, controlling for the ES5%, the IVOL-based strategy generates a marginally significant positive return over the subsequent month (skipping the first month). For example, considering the stocks with the lowest ES5% levels, the average value-weighted returns of the IVOL-based strategy is 0.41% and significant with a newey-west t-statistic is 1.88. The corresponding Carhart’s alpha is also insignificant. Moving to the highest tercile of

ES5%, the IVOL effect is highly significant, both in economic and statistical terms. The IVOL based strategy, within the highest ES5% level, generates a substantial loss that ranges from -1.76% to -2.49%. Again, these results indicate that the documented IVOL effect within the UK market may be part of the continuation in returns associated with left-tail risk.

Table 3.11 Future returns analysis with IVOL and ES5% measured over the past 250 days.

This table represents the performance of the decile portfolios based on ES5% and IVOL. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. Each month, the stocks are sorted into 10 groups based on the ES5% or IVOL levels, then the performance of these portfolios is measured by the next month returns (skipping the first month after the formation period) and the average of monthly returns over the next 2-7 months. The performance is weighted by the market value (VW) and equally (EW). P10-P1 (P9-P2) is the differential raw returns between the highest (second highest) and the lowest (second lowest) decile and α^{carh} is the corresponding alpha of the Carhart four-factor model. The t-stat is the newey-west t-statistic. The sample covers the period from January 1996 to December 2017.

Panel A	Sorting on IVOL												
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	α^{carh}	P9-P2	α^{carh}
EWR_{T+2}	0.60	0.62	0.53	0.52	0.24	0.12	-0.49	-0.97	-1.91	-2.98	-3.58	-3.84	-2.53	-2.76
t-stat											-5.44	-7.53	-4.44	-5.92
VWR_{T+2}	0.52	0.69	0.54	0.55	0.15	0.13	-0.15	-0.77	-1.75	-2.99	-3.51	-4.19	-2.44	-3.03
t-stat											-3.66	-5.37	-3.49	-4.84
EWR_{T+2-7}	0.59	0.49	0.43	0.50	0.19	-0.09	-0.55	-1.32	-2.16	-2.96	-3.55	-3.94	-2.65	-2.73
t-stat											-6.13	-8.82	-5.04	-6.57
VWR_{T+2-7}	0.56	0.57	0.44	0.55	0.13	0.03	-0.30	-0.99	-2.14	-3.04	-3.60	-4.46	-2.70	-2.79
t-stat											-4.30	-6.01	-4.27	-5.80
Panel B	Sorting on ES5%													
	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	P10-P1	α^{carh}	P9-P2	α^{carh}
EWR_{T+2}	0.95	0.67	0.72	0.53	0.35	0.01	-0.58	-1.22	-1.90	-3.27	-4.22	-4.33	-2.57	-2.71
t-stat											-6.56	-9.80	-4.22	-5.86
VWR_{T+2}	0.75	0.45	0.59	0.29	0.31	0.02	-0.29	-0.86	-1.40	-2.92	-3.67	-4.06	-1.85	-1.88
t-stat											-3.66	-4.90	-2.31	-3.23
EWR_{T+2-7}	0.81	0.59	0.60	0.40	0.20	-0.19	-0.71	-1.32	-2.00	-3.25	-4.06	-4.30	-2.58	-2.68
t-stat											-6.97	-10.15	-4.82	-7.33
VWR_{T+2-7}	0.70	0.51	0.57	0.25	-0.04	0.07	-0.45	-0.74	-1.46	-3.25	-3.95	-4.51	-1.97	-2.06
t-stat											-4.12	-5.54	-2.99	-4.27

In Panel B, the ES5%-based strategy is built while controlling for the level of IVOL. The ES5%-based strategy payoffs are concentrated within the highest level of IVOL. Although it is concentrated in the highest IVOL tercile, the ES5% effect is significant within all levels of IVOL.

3.5.1.2. Alternative Specifications of the Limited Attention Proxies.

Table 3.13 represents the double-sort analysis on the attention proxies and the IVOL- or ES5%-based strategy. The stocks are sorted on one of the attention proxies and then on the

IVOL or ES5% levels. This analysis is analogous to the one shown in Table 3.5, but this time with the new specifications.

Table 3.12 Interaction of the IVOL puzzle and the left-tail momentum.

This table represents the double-sort analysis on the IVOL and ES5%. In Panel A (B), the stocks are sorted into tercile based on the ES5% (IVOL) levels, then within each ES5%-group (IVOL-group), the stocks are resorted into another three groups based on the IVOL (ES5%) levels. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. EW (VW) is the equally (value) weighted returns. H-L is the difference between the highest and lowest group, vertically, and α^{carh} is the corresponding alpha of the Carhart four-factor model. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017.

Panel A	ES5% then IVOL											
	EW						VW					
Holding	T+2			T+2 to T+7			T+2			T+2 to T+7		
	ES5% Level			ES5% Level			ES5% Level			ES5% Level		
Level	Low	M	High	Low	M	High	Low	M	High	Low	M	High
Low IVOL	0.63	0.14	-1.18	0.59	0.13	-1.09	0.42	0.38	-0.56	0.48	0.19	-0.54
M IVOL	0.76	0.10	-1.81	0.63	-0.03	-2.11	0.68	0.05	-1.69	0.70	-0.08	-1.88
High IVOL	0.90	0.05	-2.94	0.69	-0.27	-2.94	0.82	-0.11	-2.94	0.70	-0.24	-3.03
H-L	0.26	-0.09	-1.76	0.09	-0.40	-1.86	0.41	-0.49	-2.37	0.22	-0.43	-2.49
t-stat	1.48	-0.39	-5.33	0.60	-2.30	-6.66	1.88	-1.70	-3.97	1.31	-1.96	-5.16
α^{carh}	-0.13	-0.55	-2.10	-0.34	-0.81	-2.30	-0.09	-0.98	-2.87	-0.39	-0.79	-3.04
t-stat	-0.78	-2.43	-6.96	-1.65	-4.80	-9.05	-0.45	-3.23	-5.68	-1.70	-3.07	-6.68
Panel B	IVOL then ES5%											
	EW						VW					
Holding	T+2			T+2 to T+7			T+2			T+2 to T+7		
	IVOL Level			IVOL Level			IVOL Level			IVOL Level		
Level	Low	M	High	Low	M	High	Low	M	High	Low	M	High
Low ES5%	0.89	0.76	-0.51	0.78	0.63	-0.92	0.74	0.56	-0.69	0.67	0.48	-1.01
M ES5%	0.63	0.29	-1.85	0.55	0.08	-1.93	0.59	0.23	-1.24	0.54	0.14	-1.42
High ES5%	0.20	-0.64	-3.13	0.18	-0.62	-3.15	0.37	-0.37	-2.68	0.34	-0.27	-3.11
H-L	-0.69	-1.40	-2.62	-0.60	-1.25	-2.23	-0.37	-0.94	-1.99	-0.33	-0.75	-2.10
t-stat	-3.49	-5.23	-8.67	-3.42	-5.05	-8.68	-1.42	-2.79	-3.26	-1.46	-2.30	-3.36
α^{carh}	-0.99	-1.46	-2.62	-1.00	-1.28	-2.37	-0.77	-0.98	-1.93	-0.89	-0.74	-2.28
t-stat	-7.72	-7.53	-11.87	-9.05	-7.77	-13.13	-2.81	-3.66	-3.36	-3.76	-2.74	-4.11

The results are closely similar to those shown in the main body of this work. The poor performance subsequent of the high IVOL and ES5% is stronger if the stocks belong to the low attention group. Regardless of the attention proxy, the difference in the raw returns between the highest and the lowest tercile of IVOL or ES5% strategy is significantly lower for the stocks with lower attention by the investors. By construction, the attention index summarises the common component of these proxies. Considering the highest tercile of this index, over the next 6 months, the zero-cost strategy based on IVOL (ES5%) generates statistically insignificant returns of -0.39% (-0.28%). The difference in the zero-cost strategy of IVOL (ES5%) between the lowest and the highest tercile of the attention-based rank is -2.74% (-2.3%) over the subsequent month and -2.65% (-2.2%) over the next 6 months. all these differences are significant at 1% confidence level. Adjusting the raw returns to the risk structure assumed under the Carhart four-factor pricing model subsumes part of these differences, but it remains statistically significant.

Table 3.13 Double-sort analysis with the alternative specifications of the underreaction-related proxies, the IVOL, and the ES5%.

This table represents the double-sort analysis on the attention proxies and IVOL or ES5%. Firstly, the stocks are sorted into terciles based on one of the attention proxies, then, within each attention-tercile, the stocks are resorted (dependently) into another terciles based on IVOL or ES5%. Panel A reports the results for the IVOL-based strategy while Panel B reports the same analysis for the ES5%-strategy. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. AbnVol is the abnormal trading volume which is defined as the standardised difference between the average of dollar trading volume over the past 3 months and the same average over the past 12 months. Delay is the Hou and Moskowitz (2005) delay response measure calculated using weekly returns over the past 52 weeks. ID is the information discreteness index calculated from daily returns over the past 6 months. PH52 is the ratio of the current price to the 52-week high price. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. H-L is a zero-cost strategy based on IVOL or ES5%, αFF3 is the corresponding the Fama-French three-factor alpha, and αCarh4 is the corresponding alpha of the Carhart four-factor model. The return is value-weighted. L-H is the difference between the low attention group and the high attention group. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017. a, b, and c indicate significance at the 1%, 5%, and 10% percent level, respectively.

Panel A		IVOL											
		T_{+2}						$T_{+2\ to\ +7}$					
		L	M	H	H-L	α_{FF3}	α_{Carh4}	L	M	H	H-L	α_{FF3}	α_{Carh4}
AbnVol	L	0.47	-0.01	-2.12	-2.60[a]	-3.29[a]	-2.75[a]	0.56	-0.25	-1.92	-2.49[a]	-3.26[a]	-2.43[a]
	M	0.52	0.5	-0.84	-1.36[b]	-1.95[a]	-1.66[a]	0.49	0.48	-0.9	-1.39[a]	-2.07[a]	-1.47[a]
	H	0.71	0.22	-0.59	-1.31[b]	-1.87[a]	-1.77[b]	0.54	0.12	-1.05	-1.59[a]	-2.38[a]	-2.37[a]
L-H					-1.29[b]	-1.42[a]	-0.98[c]				-0.9[c]	-0.9[b]	-0.54
Delay	L	0.2	-0.06	-1.82	-2.02[a]	-2.64[a]	-2.84[a]	0.23	-0.07	-2.17	-2.39[a]	-3.06[a]	-2.93[a]
	M	0.66	0.31	-1.22	-1.88[a]	-2.52[a]	-2.37[a]	0.55	0.24	-1.4	-1.94[a]	-2.63[a]	-2.3[a]
	H	0.5	0.01	-0.64	-1.14[c]	-1.86[a]	-1.64a	0.48	-0.03	-0.78	-1.27[b]	-2.13[a]	-1.66[a]
L-H					-0.89	-0.78	-1.2[a]				-1.13[c]	-1.09[b]	-1.32[b]
ID	L	0.32	-0.62	-2.39	-2.71[a]	-3.43[a]	-2.9[a]	0.34	-0.49	-2.72	-3.06[a]	-3.95[a]	-3.36[a]
	M	0.59	0.3	-0.96	-1.54[a]	-2.25[a]	-2.17[a]	0.55	0.25	-1.03	-1.58[a]	-2.41[a]	-2.21[a]
	H	0.56	0.82	0.32	-0.24	-0.79[b]	-1.05[b]	0.55	0.65	0.03	-0.52	-1.19[a]	-1.21[a]
L-H					-2.47[a]	-2.63[a]	-1.85[a]				-2.53[a]	-2.75[a]	-2.14[a]
PH	L	-0.25	-1.16	-3.39	-3.14[a]	-3.66[a]	-3.86[a]	-0.33	-1.27	-3.42	-3.09[a]	-3.64[a]	-3.47[a]
	M	0.54	0.29	-0.47	-1.01[b]	-1.59[a]	-2[a]	0.52	0.39	-0.48	-1[a]	-1.68[a]	-1.89[a]
	H	0.63	0.79	0.44	-0.19	-0.65[c]	-1.05[b]	0.62	0.65	0.22	-0.4	-1.01[a]	-1.41[a]
L-H					-2.96a	-3.01[a]	-2.81[a]				-2.69[a]	-2.62[a]	-2.06[a]
ATT	L	-0.15	-0.99	-3.21	-3.06[a]	-3.69[a]	-3.62[a]	-0.28	-1.02	-3.32	-3.04[a]	-3.73[a]	-3.3[a]
	M	0.59	0.21	-0.75	-1.34[a]	-1.87[a]	-2.09[a]	0.47	0.41	-0.7	-1.18[a]	-1.82[a]	-1.85[a]
	H	0.66	0.69	0.34	-0.32	-0.87[b]	-1.24[a]	0.61	0.5	0.22	-0.39	-1.03[a]	-1.26[a]
L-H					-2.74[a]	-2.81[a]	-2.38[a]				-2.65[a]	-2.7[a]	-2.04[a]

Continued

Panel B		Underreaction with ES5%											
		T_{+2}						$T_{+2\ to\ +7}$					
		L	M	H	H-L	α_{FF3}	α_{Carh4}	L	M	H	H-L	α_{FF3}	α_{Carh4}
AbnVol	L	0.64	-0.07	-2.03	-2.68[a]	-3.44[a]	-2.6[a]	0.6	-0.24	-1.73	-2.32[a]	-3.14[a]	-2.13[a]
	M	0.6	0.27	-0.31	-0.9[c]	-1.59[a]	-1.22[a]	0.63	0.13	-0.28	-0.91[c]	-1.6[a]	-0.96[b]
	H	0.81	0.21	-0.88	-1.69[a]	-2.38[a]	-2.26[a]	0.66	0.05	-1.03	-1.69[a]	-2.57[a]	-2.62[a]
L-H					-1[c]	-1.1[c]	-0.3				-0.6	-0.6	-0.2
Delay	L	0.38	-0.22	-2.04	-2.42[a]	-3.1[a]	-2.96[a]	0.36	-0.35	-2.06	-2.41[a]	-3.17[a]	-2.98[a]
	M	0.7	0.16	-1.08	-1.77[a]	-2.46[a]	-2.03[a]	0.59	0.17	-1.14	-1.74[a]	-2.47[a]	-1.9[a]
	H	0.63	-0.12	-0.44	-1.08[c]	-1.82[a]	-1.59[a]	0.58	-0.17	-0.5	-1.09[c]	-1.9[a]	-1.46[a]
L-H					-1.34[b]	-1.28[b]	-1.4[a]				-1.32[b]	-1.35[b]	-1.5[a]
ID	L	0.45	-0.62	-2.27	-2.71[a]	-3.52[a]	-2.6[a]	0.4	-0.64	-2.2	-2.6[a]	-3.53[a]	-2.67[a]
	M	0.59	0.19	-0.82	-1.41[b]	-1.67[a]	-2.02[a]	0.66	0.13	-0.73	-1.38[a]	-2.22[a]	-1.96[a]
	H	0.64	0.59	0.38	-0.26	-0.83[b]	-1.07[b]	0.65	0.43	0.32	-0.33	-1[a]	-1.14[a]
L-H					-2.5[a]	-2.7[a]	-1.5[a]				-2.3[a]	-2.5[a]	-1.5[a]
PH	L	-0.24	-1.39	-2.54	-2.29[a]	-2.77[a]	-2.55[a]	-0.42	-1.1	-2.82	-2.4[a]	-2.97[a]	-2.65[a]
	M	0.65	0.18	-0.17	-0.83[c]	-1.38[a]	-1.76[a]	0.67	0.07	-0.18	-0.85[b]	-1.53[a]	-1.63[a]
	H	0.71	0.56	0.59	-0.12	-0.61[c]	-1.04[a]	0.68	0.62	0.41	-0.27	-0.88[b]	-1.3[a]
L-H					-2.2[a]	-2.2[a]	-1.5[a]				-2.1[a]	-2.1[a]	-1.4[a]
ATT	L	-0.12	-1.14	-2.39	-2.28[a]	-2.92[a]	-2.46[a]	-0.3	-1.02	-2.8	-2.5[a]	-3.24[a]	-2.45[a]
	M	0.58	0.09	-0.47	-1.05[b]	-1.63[a]	-1.51[a]	0.6	0.07	-0.34	-0.94[b]	-1.62[a]	-1.37[a]
	H	0.59	0.39	0.59	0	-0.54	-0.98[b]	0.65	0.31	0.37	-0.28	-0.91[b]	-1.33[a]
L-H					-2.3[a]	-2.4[a]	1.48[b]				-2.2[a]	-2.3[a]	-1.1[b]

Therefore, the results in Table 3.13 reconfirm the general findings in this study regarding the significant effect that the underreaction behaviour holds over the anomalous pricing behaviour that is associated with the IVOL- and the ES5%-based strategy.

Table 3.14 exhibits the empirical results of the Fama and MacBeth cross-sectional regression. Again, similar to the analysis in Table 10, the individual stocks return over the next six months are regressed against the IVOL or the ES5%, the attention index, the interaction term between the attention index and one of the IVOL or ES5%, and the set of control variables we define in Table 3.10 The findings indicate that the inference reached by the main analysis holds. The IVOL and the ES5% inversely predict the returns over the next 6 months across the stocks in the sample. The average slope coefficients of the IVOL and ES5% are -0.7 and -0.44 with a newey-west t-statistic of -13.12 and -15.35, respectively. Moreover, this predictability is weakened with the attention level. The average slope coefficients on the interaction term between the IVOL (ES5%) and the attention index is 0.428 (0.189) and highly statistically significant with a newey-west t-statistic of -3.46 (-2.57). This result indicates that the higher the attention level, the weaker the net predictive power of the IVOL and the ES5% on the future returns and vice versa.

3.5.2. Long-term Performance.

Analysing the long-term performance of the pricing anomalies would reveal important information regarding the origin of these pricing irregularities. Therefore, under this subsection, the performance of the IVOL- and ES5%-based strategy is examined over the next two years (24 months). This task aims to uncover the trend in the payoffs of these strategies beyond the first 6 months. Consistent with the main goal in this study, the performance conditioned on the limited attention index. Analysing the long-term performance of these anomalies while controlling for the underreaction level can give a better understanding of their nature.

Table 3.14 Fama and MacBeth cross-sectional regression with alternative specifications of the underreaction-related proxies, the IVOL, and the ES5%.

represents the cross-sectional regression of Fama and MacBeth (1973). The stock returns over the next 6 months are regressed on one of the IVOL or the ES5%, the attention index, the interaction term between one of the IVOL of the ES5% and the attention index, and the set of control variables. V represents the IVOL or ES5%. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017. Control indicates whether the control set is accounted for or not. ***, **, * indicate significance at the 1%, 5%, and 10% percent level, respectively.

	IVOL			ES5%		
Variables	M1	M2	M3	M4	M5	M6
V	-0.70***	-0.651***	-0.408***	-0.44***	-0.387***	-0.238***
t-stat	-13.12	-6.837	-4.975	-15.35	-7.157	-5.298
ATT		1.729***	0.850**		1.192**	0.711*
t-stat		-3.40	-2.30		-2.46	-1.79
ATT*V		0.428***	0.286**		0.189**	0.153**
t-stat		-3.46	-2.17		-2.572	-2.06
Constant	1.35***	-0.24	-2.792***	1.98***	0.56	-2.283***
t-stat	9.64	-0.456	-5.363	13.94	-1.145	-4.700
control	no	no	yes	no	no	yes
R-squared	0.06	0.09	0.15	0.07	0.09	0.15

Interestingly, Table 3.15 displays a distinguished behaviour for the ES5%- and IVOL-based strategies conditioning on the attention level. The difference between the low attention stocks and the high attention stocks is the strongest in the first three months after the portfolio formation. Mainly, the underperformance reported for the IVOL- and the ES5%-based strategies is attributed to the continuous performance of the loser stocks that are likely to dominate the low attention group. Within the high attention group, the ES5%-based zero-cost strategy generates zero returns in the first two months after the formation period. Then, from the third month onwards, the positive returns generated by this portfolio over the past 12 months are reversed to losses. These losses persist up to the next 2 years.

Table 3.15 Long-term performance of the IVOL puzzle and left-tail momentum conditional on the attention level.

This table represents the long-term performance of the zero-cost payoffs of the IVOL- and ES5%-based strategy with Low and high attention levels. Firstly, the stocks are sorted into three equal groups based on the attention index and then on IVOL or ES5%. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. The sample covers the period from January 1996 to December 2017.

	IVOL effect		ES5% effect	
Horizon	Low ATT	High ATT	Low ATT	High ATT
T-12 to T	-17.735	25.828	-37.066	11.115
T-6 to T	-7.666	20.387	-16.692	9.849
T+1	-3.674	-0.140	-2.962	-0.001
T+2	-3.057	-0.316	-2.275	0.000
T+3	-2.799	-0.169	-2.428	-0.131
T+4	-2.602	-0.389	-2.294	-0.372
T+5	-2.487	-0.532	-2.153	-0.354
T+6	-2.977	-0.634	-2.440	-0.429
T+7	-2.948	-0.559	-2.189	-0.542
T+8	-2.142	-0.405	-1.939	-0.443
T+9	-1.931	-0.275	-2.104	-0.397
T+10	-2.321	-0.273	-2.074	-0.197
T+11	-1.954	-0.456	-1.623	-0.357
T+12	-1.763	-0.478	-1.707	-0.211
T+13	-1.696	-0.713	-1.289	-0.670
T+14	-1.874	-0.506	-1.560	-0.678
T+15	-2.028	-0.422	-1.766	-0.527
T+16	-1.929	-0.504	-1.770	-0.546
T+17	-2.132	-0.616	-2.161	-0.632
T+18	-2.150	-0.588	-1.917	-0.650
T+19	-1.755	-0.386	-1.683	-0.496
T+20	-2.024	-0.826	-1.928	-0.430
T+21	-1.783	-0.983	-1.659	-0.528
T+22	-1.735	-0.642	-1.624	-0.462
T+23	-1.493	-0.529	-1.593	-0.662
T+24	-2.034	-0.840	-1.873	-0.893

By its nature, the pattern of attractive stocks is consistent with overreaction behaviour. Such behaviour may be explained by the difference of opinions and short-selling restriction hypothesis in Miller (1977); under this model, the investors have heterogeneous beliefs. The high arbitrage cost drives the pessimistic traders to set aside and leave the market to the optimistic party. Consequently, the momentum and the reversal patterns appear in the prices. Moreover, this result is in line with Hur and Singh (2016) who find that both underreaction and overreaction behaviour contribute to price momentum.

In general, although the results suggest that a large part of the anomalous underperformance associated with the high IVOL and ES5% stocks is attributed to the underreaction behaviour, the investors' overreaction also generates a part of this future negative returns, especially in the long-term.

3.5.3. Subperiod Analysis.

This section provides a subsamples analysis by dividing the full sample into two subsamples: January 1996-December 2008 and January 2009-December 2017.

Table 3.16 Subperiod analysis: 1996-2008 and 2009-2017.

This table represents the double sort analysis on the attention proxies and IVOL or ES5% during different subsamples. Firstly, the stocks are sorted based on one of the attention proxies and then on IVOL or ES5%. Panel A reports the results for the IVOL-based strategy while Panel B reports the same analysis for the ES5%-strategy. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. H-L is a zero-cost strategy based on IVOL or ES5%, and αCarh4 is the corresponding alpha of the Carhart four-factor model. The return is value-weighted. L-H is the difference between the low attention group and the high attention group. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017.

	1996-2008								2009-2017							
	T+2				T+2-T+7				T+2				T+2-T+7			
Panel A	IVOL effect															
ATT levels	H-L	t-stat	α_{Carh4}	t-stat	H-L	t-stat	α_{Carh4}	t-stat	H-L	t-stat	α_{Carh4}	t-stat	H-L	t-stat	α_{Carh4}	t-stat
L	-3.47	-3.86	-3.95	-5.42	-3.37	-3.95	-3.05	-5.24	-2.46	-3.38	-3.03	-3.98	-2.56	-5.37	-2.48	-4.95
M	-1.96	-2.80	-2.57	-4.38	-1.71	-2.88	-1.92	-3.75	-0.44	-0.72	-0.54	-0.83	-0.40	-1.19	-1.12	-2.78
H	-0.63	-1.00	-1.55	-2.35	-0.65	-1.38	-1.37	-2.68	0.14	0.25	-0.25	-0.47	-0.01	-0.02	-0.44	-0.83
L-H	-2.84		-2.40		-2.72		-1.69		-2.60		-2.78		-2.55		-2.04	
t-stat	-3.60		-3.43		-3.70		-3.09		-4.43		-3.25		-5.24		-3.41	
Panel B	ES5% effect															
ATT levels	H-L	t-stat	Alpha	t-stat	H-L	t-stat	Alpha	t-stat	H-L	t-stat	Alpha	t-stat	H-L	t-stat	Alpha	t-stat
L	-3.11	-3.56	-3.16	-5.08	-3.27	-3.45	-2.70	-4.61	-1.07	-1.01	-0.99	-1.02	-1.38	-2.59	-1.13	-1.72
M	-1.61	-2.49	-1.82	-3.66	-1.45	-2.48	-1.34	-3.01	-0.22	-0.29	-0.27	-0.33	-0.21	-0.52	-1.24	-3.17
H	0.02	0.04	-0.99	-1.44	-0.30	-0.56	-1.22	-2.19	-0.03	-0.06	-0.92	-1.58	-0.25	-0.74	-0.88	-1.98
L-H	-3.14		-2.17		-2.97		-1.48		-1.03		-0.07		-1.13		-0.25	
t-stat	-3.82		-2.52		-3.78		-2.62		-1.02		-0.08		-2.04		-0.39	

Table 3.16 shows different behaviour for the performance of the IVOL-based strategy and the ES5%-based strategy during the analysed two sub-periods. The difference between the predictability of return by the IVOL and the ES5% between the low attention stocks and the high attention stocks is significant during the two sub-periods. Over the next midterm horizon, this difference in the payoffs of the IVOL-based zero-cost strategy is -2.72% (newey-west t-statistic =-3.7) during the 1996-2008 period and -2.55% (newey-west t-statistic =-5.24) during the 2009-2017 period. Whereas, the reported underperformance of the ES5%-based zero-cost strategy is substantially stronger in the first period of 1996-2008. For instance, over the next month, the differential raw returns between the high ES5% and low ES5% groups of stocks are highly significant of -3.14% during the period from 1996-2008 while it is insignificant of -1.03% through the period of 2009-2017. Nevertheless, the effect of attention level on the ES5%-based strategy is apparent and significant in both sub-periods. The empirical findings in Panel B of Table 3.16 indicate that, over the next midterm horizon, this difference in the payoffs of the ES5%-based zero-cost strategy is -2.92% (newey-west t-statistic =-3.78) during the 1996-2008 period and -1.13% (newey-west t-statistic =-2.04) during the 2009-2017 period.

Therefore, the reported relationship between the attention level and the behaviour of the IVOL effect and the left-tail momentum is confirmed in both sub-periods (1996-2008 and 2009-2017) and thus it is not a temporary phenomenon in a specific period.

3.5.4. Sentiment and Market State.

Investors' behaviour in the financial market has been found to be state-dependent. In particular, the anomalous continuation trend in the returns of stocks has been found to be significantly stronger after the period of positive market returns or an optimistic state (Cooper et al. 2004, and Baker and Wurgler 2006). These states are a fertile environment for the growth of overconfidence among investors. Therefore, this variation could be taken as a supportive evidence of the irrational pricing that has been widely observed in the financial market.

To separate between the Up and the Down states of the general market, the returns over the past 36 months are employed. Simply, the market is in Upstate if the return over the past 36 months is positive and in Downstate otherwise. To proxy the market returns, the FTSE all-share index is used.

Table 3.17 Analysis of the different market state

This table represents the double sort analysis on the attention proxies and IVOL or ES5% after two different market states, the UP state, and the Down State. In the UP (Down) state is a dummy variable that takes 1 if the FTSE all-share index return over the past 36 months is positive and 0 otherwise. Firstly, the stocks are sorted based on one of the attention proxies and then on IVOL or ES5%. Panel A reports the results for the IVOL-based strategy while Panel B reports the same analysis for the ES5%-strategy. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. H-L is a zero-cost strategy based on IVOL or ES5%, and αCarh4 is the corresponding alpha of the Carhart four-factor model. The return is value-weighted. L-H is the difference between the low attention group and the high attention group. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017.

Panel A	IVOL							
	T+2				T+2-T+7			
	Raw Return							
	Up		Down		Up		Down	
	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat
H	-3.39	-5.13	-1.88	-1.49	-3.15	-4.94	-2.65	-2.13
M	-1.74	-3.03	0.07	0.07	-1.52	-3.12	0.05	0.08
L	-0.60	-1.21	0.68	1.05	-0.57	-1.40	0.27	0.50
L-H	-2.79		-2.56		-2.58		-2.93	
t-stat	-4.64		-2.71		-4.38		-3.12	
	Carhart Alpha							
	Up		Down		Up		Down	
	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat
L ATT	-3.80	-6.08	-2.97	-3.55	-3.31	-6.23	-3.25	-4.19
M	-2.49	-4.97	-0.64	-0.81	-2.13	-5.17	-0.83	-2.06
H ATT	-1.47	-3.08	-0.40	-0.64	-1.29	-3.01	-1.16	-2.31
L-H	-2.33		-2.57		-2.02		-2.10	
t-stat	-3.87		-2.91		-3.84		-2.58	
Panel B	ES5%							
	T+2				T+2-T+7			
	Raw Return							
	Up		Down		Up		Down	
	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat
L ATT	-2.56	-3.69	-1.25	-0.70	-2.64	-3.78	-1.99	-1.22
M	-1.43	-2.64	0.30	0.33	-1.33	-2.71	0.42	0.51
H ATT	-0.06	-0.13	0.23	0.33	-0.39	-0.88	0.14	0.29
L-H	-2.50		-1.48		-2.25		-2.13	
t-stat	-3.41		-1.09		-3.47		-1.68	
	Carhart Alpha							
	Up		Down		Up		Down	
	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat
L ATT	-2.60	-3.62	-1.93	-1.71	-2.46	-4.31	-2.39	-2.95
M	-1.87	-4.17	-0.22	-0.27	-1.68	-4.30	-0.26	-0.52
H ATT	-1.03	-2.14	-0.80	-1.22	-1.35	-3.00	-1.26	-2.38
L-H	-1.57		-1.13		-1.11		-1.13	
t-stat	-1.95		-1.27		-1.99		-1.65	

Table 3.17 represents the market state analysis. Under this analysis the relationship between the attention level and the performance of the trading strategies that are based on IVOL or ES5% is examined separately after the Up and Down-market state. The revealed patterns show that the reported effect of the attention level on the payoffs of the examined trading strategies is constant and evident after both the Up and the Downstate.

In comparison to the high attention group, Over the next midterm period, the IVOL-based zero-cost strategy within the low attention group generates lower payoffs by -2.58% (newey-west t-statistic =-4.38) and -2.93% (newey-west t-statistic =-3.12) after the Up and Down market, respectively. The corresponding differences for the ES5%-based strategy is -2.25% (newey-west t-statistic =-3.47) and -2.13% (newey-west t-statistic =-1.68) respectively.

Defining the investors' sentiment is a more complex task. To simplify this task, a strand of the prior literature employed a well-established survey that measures consumer satisfaction and expectation regarding the general economy (see, for example, Lemmon and Portniaguina 2006). Following this strand of studies, this study employs the Economic Sentiment Indicator, published monthly by the European Commission, as a proxy for the total sentiment. To extract the irrational component, this indicator is regressed against four economic variables, the change in the industrial production, the unemployment rate, the change in the consumer price index, and the difference between the yields of the 10-year government bonds and the three-month Treasury rate (e.g. term premium). The residual of this regression is the proxy for irrational sentiment. Extracting the irrational sentiment index, the whole period is classified into three states, optimistic, middle, and pessimistic. Under the optimistic (pessimistic) state, the average of the sentiment index over the past three months belongs in the top (bottom) 30% of the 3-month rolling average sentiment time series. The analysis spans the period of January 1996 to December 2017.

In Table 3.18 the effect of the attention behaviour on the IVOL- and the ES5%-based strategy is analysed after three different sentiment states (Pessimistic, Mild, and Optimistic). In the case of the IVOL effect, the influence of the attention level is stronger after the optimistic period than the pessimistic period; however, this effect is significant after all three different sentiment states. Over the next month, the difference in the payoffs of the IVOL-based zero-cost strategy between the low attention and high attention groups is -3.15% (newey-west t-statistic = -2.96) and -1.94% (newey-west t-statistic = -2.62) after the Optimistic and Pessimistic state respectively.

Table 3.18 Analysis of the investor sentiment.

This table represents the double-sort analysis on the attention proxies and IVOL or ES5% after two different sentimental states, the Optimistic, Mild, and Pessimistic. Firstly, the stocks are sorted based on one of the attention proxies and then on IVOL or ES5%. Panel A reports the results for the IVOL-based strategy while Panel B reports the same analysis for the ES5%-strategy. ES5% denotes the expected-shortfall that corresponds to -1 times the average of return observations under the 5th percentile of daily returns in the past 12 months. IVOL is the standard deviation of error terms of the Carhart four-factor model over the past 250 days. ATT is the attention index, measured by the first component of the principal component analysis of the four individual attention proxies. H-L is a zero-cost strategy based on IVOL or ES5%, and αCarh4 is the corresponding alpha of the Carhart four-factor model. The return is value-weighted. L-H is the difference between the low attention group and the high attention group. The t-stat is the newey west t-statistic. The sample covers the period from January 1996 to December 2017.

Panel A	IVOL											
	T+2						T+2-T+7					
Raw return												
State	Optimistic		Mild		Pessimistic		Optimistic		Mild		Pessimistic	
	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat
L	-3.67	-4.11	-3.21	-4.28	-2.25	-1.74	-3.26	-3.93	-3.58	-4.66	-2.11	-2.4
M	-1.52	-2.43	-1.79	-2.43	-0.58	-0.71	-1.84	-3.94	-1.51	-2.6	-0.08	-0.13
H	-0.52	-0.82	-0.17	-0.36	-0.31	-0.27	-0.89	-2.23	-0.13	-0.38	-0.22	-0.31
L-H	-3.15		-3.04		-1.94		-2.36		-3.45		-1.9	
t-stat	-2.96		-4.01		-2.62		-2.67		-5.08		-3.89	
Carhart Alpha												
State	Optimistic		Mild		Pessimistic		Optimistic		Mild		Pessimistic	
	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat
L	-3.41	-3.98	-3.96	-5.32	-3.42	-3.48	-3.24	-3.46	-3.35	-6.61	-3.3	-4.11
M	-1.66	-3.67	-2.68	-3.88	-1.79	-2.55	-1.94	-3.65	-2.02	-4.29	-1.56	-3.31
H	-0.77	-1.18	-1.35	-3.39	-1.58	-1.64	-0.96	-1.78	-1.01	-2.72	-1.82	-2.73
L-H	-2.65		-2.61		-1.83		-2.27		-2.34		-1.47	
t-stat	-2.59		-3.11		-2.34		-2.58		-4.28		-2.44	
Panel B	ES5%											
Raw return												
State	Optimistic		Mild		Pessimistic		Optimistic		Mild		Pessimistic	
	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat	H-L	t-stat
L	-2.64	-2.64	-3.33	-3.64	-0.52	-0.49	-2.95	-3.95	-3.32	-3.49	-0.97	-1.01
M	-1.59	-2.32	-1.48	-2.24	0.07	0.07	-1.56	-3.27	-1.39	-2.2	0.24	0.38
H	0.31	0.76	-0.29	-0.43	0.07	0.07	-0.48	-1.07	-0.06	-0.14	-0.35	-0.51
L-H	-2.95		-3.05		-0.59		-2.46		-3.25		-0.62	
t-stat	-2.64		-3.42		-0.63		-2.95		-3.95		-0.96	
Carhart Alpha												
State	Optimistic		Mild		Pessimistic		Optimistic		Mild		Pessimistic	
	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat	αCarh4	t-stat
L	-2.06	-2	-3.48	-3.96	-1.6	-2.24	-2.52	-2.84	-2.62	-4.06	-2.19	-3.06
M	-1.49	-2.84	-1.86	-2.98	-1.11	-1.37	-1.67	-3.11	-1.45	-3.28	-0.98	-1.97
H	-0.16	-0.28	-1.47	-2.57	-1.2	-1.44	-0.9	-1.59	-1.15	-2.67	-1.96	-2.8
L-H	-1.9		-2.01		-0.4		-1.62		-1.48		-0.22	

This difference between the Optimistic and the Pessimistic states is more evident in the case of the ES5%-based strategy. The difference in the payoffs of the zero-cost strategy is not significant after the pessimistic state. For example, over the next month, the difference in the payoffs of the IVOL-based zero-cost strategy between the low attention and high attention groups is -0.59% (newey-west t-statistic = -0.63). While after the Optimistic period, this difference is highly significant of -2.95% (newey-west t-statistic = -2.64). This result is in line with the evidence in Bi and Zhu (2020). The stronger effect after the optimistic period confirms the behavioural explanation of underperformance associated with the high-risk stocks.

In sum, the above evidence reconfirms the significant relation between the underreaction-related behaviour and the anomalous pricing of the idiosyncratic risk and left-tail risk in the UK market.

3.6. Summary and Concluding Remarks.

Standard asset pricing theory assumes that the market is informationally efficient, and the representative investors are rational and risk-averse. Consequently, the asset prices fully reflect all of the available risk-related information immediately and returns are thus unpredictable. However, the empirical findings have posited many challenges to this rational theoretical setting. Empirical studies find an inverse relationship between risk and future returns in the stock market. Recently, studies by Ang et al. (2006) and Atilgan et al. (2020) find that idiosyncratic volatility and left-tail risk inversely predict the future returns across the stocks in the US market.

This work examines whether the left-tail risk and the idiosyncratic volatility have a predictive power of the future returns across the stocks in the UK market. Also, a behavioural explanation of these anomalies, if they exist, is examined. Specifically, the study examines whether the reported predictive power of the idiosyncratic volatility (IVOL) and the left-tail risk (proxied by the expected shortfall, ES5%) is generated by the underreaction-related behaviour (i.e. the investors' attention). Four different proxies of investors' attention are employed, and an index of attention is built from the principal component analysis (PCA) of these proxies. The analysis covers the period of 1996 to 2017.

Consistent with the evidence from the U.S. market, the empirical findings report a strong negative relation between the future returns and idiosyncratic volatility and the left-tail risk. Contradicting the market efficiency hypothesis and the risk-averse behaviour, the stocks with high ES5% and high IVOL, on average, underperforms the stocks with low ES5% and IVOL. This puzzling relationship persists over the next midterm horizon and unexplained by the risk factors in the asset pricing model of Carhart (1997). Moreover, the bivariate stocks sorting analysis and the multivariate cross-sectional analysis show that underreaction-related behaviour is a significant determinant of these pricing anomalies. The return predictability by the IVOL and the ES5% is stronger when the investors are likely to pay less attention to the news, especially the bad news. In particular, past loser stocks with low attention levels largely contribute to the underperformance reported to the stocks with high IVOL or ES5%. These results are robust to subsamples analysis, different sentiment and market states, and controlling for other potential stock return predictors.

Besides the persistent losers with High IVOL and ES5%, the stocks with high attention levels and high IVOL and ES5% are associated with past gains that reverse to losses in the subsequent months. These patterns suggest that, besides the underreaction, part of the returns predictability shown through this study is explained by the overreaction and the subsequent reversal anomaly. Arena et al. (2008) report a similar pattern for the IVOL.

Therefore, these results imply that the UK market is inefficient and the investors' behaviour inconsistent with rational risk-averse models. The Inattentive behaviour toward the loser stocks may lead the investors to overvalue these stocks. Combining this underreaction-related mispricing of the past losers with the high arbitraging costs that attributed to the high IVOL and ES5% may explain the persistent underperformance of these stocks. Whereas, the reversal of the winners with the attractive features and high IVOL or high ES5% is consistent with the model of Miller (1977). Under this model, high uncertainty forces the pessimistic investors (i.e. short sellers) to set aside and leave the market to the optimistic participants which lead to momentum in the prices and subsequent reversal.

These results suggest many interesting implications. Employing the standard rational paradigm (e.g. the CAPM) in the financial decisions making process would lead to erroneous applications. Interestingly, employing the information embedded in the past return’s distributions (i.e. the idiosyncratic volatility and the left-tail shape) could help to predict the future returns of the socks in the UK market, thus creating a lucrative trading strategy.

Considering these risk-related characteristics may also help the investors in the UK market to build a more stable momentum strategy. For instance, concentrating on the losers with high IVOL and screening out the winners with high IVOL could generate a more stable and profitable momentum strategy.

Also, the results highlight some interesting directions for future research. The results encourage future studies to investigate the ability of the underreaction-related behaviour associated with high arbitrage cost (e.g. high idiosyncratic volatility) to explain some of the pricing anomalies reported by the prior studies in the UK market. For example, Foran et al. (2015) find that illiquid stocks underperform liquid stocks in the UK market. Also, investors in the UK market have been found to misprice the persistence of accounting fundamentals (see, for example, Soares and Stark 2009; Jiang et al. 2016; and Papanastasopoulos 2020). Considering the patterns reported in this study may help explain such anomalous pricing behaviour. The empirical results also show that part of the predictability of the returns by the idiosyncratic volatility and left-tail risk is staying unexplained by the mechanisms tested here in this study. Therefore, considering another potential channel may have an incremental explanatory power of these highly persistent pricing anomalies. An interesting channel is the expected profitability and the investors' response to the expectations regarding firms' fundamentals.

CHAPTER FOUR

Expected Profitability, Anchoring Bias, and the Idiosyncratic Volatility Puzzle.

Abstract

This work investigates the joint ability of fundamental-based news and market-based news to explain the anomalous underperformance of stocks with high idiosyncratic volatility (high IVOL). An out-of-sample prediction of future profitability is adopted as a proxy for the fundamental–based news while the market-based news is represented by the 52-week high ratio. A sample of stocks from the UK market during the period January 1996 to December 2017 is analysed. The empirical results indicate that both the fundamental-based projected profitability along with the 52-week high ratio is important in explaining the IVOL anomaly in the UK market. This relationship is more pronounced following a period of high sentiment and Bull Market. The results suggest that the investors in the UK market underreact to the news embedded in the firm fundamentals and the price. Interestingly, this delayed response by the investors contributed largely to the IVOL puzzle. However, the IVOL puzzle is more complex and the overreaction behaviour such as the lottery preference plays a substantial role.

Keywords: Returns Predictability; Market-efficiency; Idiosyncratic Volatility; Anchoring Bias; Expected Profitability.

4.1. Introduction.

In a seminal paper, Ang et al. (2006) document a puzzling cross-sectional negative association between the idiosyncratic volatility and the future realised return (hereafter IVOL puzzle). Since the first time observed, an increasing amount of empirical evidence has been reported from different markets on the existence of the IVOL puzzle. Surprisingly, this negative risk-return predictability contradicts the widely accepted standard theories of asset pricing in the financial market. Neither the single-index model, such as the CAPM that assumes no relationship nor the multi-index model such as ICAPM, which assumes a positive relationship, provided a rationale for such behaviour.

The possible force behind this puzzling inverse risk-return relationship is still controversial. Explaining this nonstandard pricing behaviour, asset pricing literature has debated various channels that could plausibly drive the IVOL puzzle. Most of these explanations are attributed to irrational behaviour. For example, gambling-like behaviour (see, for example, Bali et al. 2011) and sentimental-driven mispricing (see, for example, Stambaugh et al. 2015).

To a lesser degree, some suggest microstructure biases as an explanation for this anomalous pricing behaviour (see, Huang et al. 2010, and Han & Lesmond 2011). Also, failure of the widely known risk factor models (e.g., the CAPM) does not completely rule out the risk-based explanations (see, for example, Barinov 2009).

For many reasons, expectations regarding the firm's fundamentals seem to express useful information about the idiosyncratic risk anomaly. Firstly, the payoffs associated with idiosyncratic risk anomalies are found to be highly persistent. Literature from the U.S. market reports a persistent returns predictability by the IVOL over the next 12 months (see, for example, Ange et al., 2006). It could be argued that this persistent pattern is less likely to be explained by the overreaction and underreaction to the current market news, and the investors' slow response to the news regarding the future profitability could be a key player in shaping this behaviour. Secondly, some recent studies have linked the IVOL-related anomalies to the expected profits and growth in the asset. For example, both Liu & Zhang (2017) and George et al. (2018) link the continuation anomalies to future profit and growth. Also, Liu & Zhang (2017) argue that there is a link between momentum and expected growth in investment. While George et al. (2018) demonstrate that the ability of the 52-week high ratio to predict the stocks' future returns could be driven by its ability to project future profit and investment growth. Thirdly, behavioural theories attribute the pricing anomalies to the investors' overreaction or/and underreaction. Generally, the informationally inefficient response by the investors is supposed to be triggered by the investors' biased expectations and responses to both the firms' fundamentals and the market-based news. One prominent example is the unified theory established in Hong & Stein (1999). This theory assumes that momentum and subsequent reversal in stock prices can be generated by the interaction between two different types of traders. These groups of traders are heterogeneous in their ability to process the available information. Furthermore, this heterogeneity in the information processing ability requires considering both the projected fundamental-based information and the market-based information. Fourthly, recent theoretical and empirical evidence suggests the expected profit and growth in the asset as an additional pricing factor. Using different estimation procedures, Clubb & Naffi (2007), Lin & Lin (2019), and Detzel et al. (2019) show that expected profitability contributes significantly to the prediction of future returns and possesses useful information beyond that embedded in the past observation. Hou et al. (2020) support this pricing role in the case of the expected growth in firm investment. Therefore, this non-redundant rule of the expected fundamentals requires their inclusion in the pricing equation.

However, prior attempts to explain the IVOL puzzle widely ignore the investor’s response to information relevant to future earnings. In light of the above points, it could be that the slow investor response to the expected fundamental (e.g. cash flow news) is the reason behind the persistent IVOL puzzle. For example, if the investor underreacts to the expected cash flows, he would be surprised by the realised information, and subsequently, a continuous trend will be shown in the returns. Riedl et al. (2020) show that mispricing of the information embedded in the expected profit is conditional on the investors' sentimental behaviour. In the period of high sentiment, the investors understate the loss persistence and overstate the profit persistence and vice versa. Moreover, they find this effect to be asymmetric and stronger for the loss firms.

All of the aforementioned points suggest that expected profitability could be informative about the IVOL puzzle. Nevertheless, this is still an open question and under-researched by the literature. Thus, this work aims to fill this gap and contributes to the literature by investigating the ability of the expected profit to explain the IVOL effect. In addition to the information measured from market prices (e.g., the 52-week high ratio), the IVOL puzzle will be conditioned on the expected profit of the UK firms. In addition to the cross-section test, we will contribute to the literature by testing an augmented version of the asset pricing model. Specifically, employing the well-known Fama & French (1993) stocks grouping procedure. Two factors are built to mimic the market payoffs for the expected profit and 52-week high ratio. The conjecture is that these two additional factors are informative about the IVOL effect.

Although these pricing behaviours are consistent with both irrational and rational pricing alike, the behavioural explanation appears to be more reasonable as will be shown in the empirical analysis.

To measure the expected profit, the work employs procedures similar to the one used in Fama & French (2006) and Hou & van Dijk (2019). Each month, we employ a cross-sectional regression to fit the firm’s profitability to a set of selected variables that are widely accepted in the past literature. Despite its parsimony, the model explains a good part of the next period's profitability. We require all the fitting information to be available at the time of forecasting (i.e. data for the last accounting year), hence, the expected profitability is computed for the next year using out of sample observations. Therefore, this work assumes that this fitted value is a reliable proxy of future profitability.

As will be shown in the results section, indeed, the expected profitability (EROA) and the 52-week high ratio (PH52) are both independently useful in predicting the realised future returns over the next 12 months, across the stocks in the UK market. Creating a zero-cost portfolio that goes long on the highest decile of EROA (PH52) and short on the lowest decile of the EROA rank generates, value-weighted, differential returns of 3.5% (2.55%) with a newey-west t-statistic of 6.2 (3.96).

Consistent with the main conjecture in this study, the expected profitability and the IVOL are negatively associated. This strong negative association helps the EROA to absorb a substantial part of the IVOL effect. In the value-weighted return, the difference between the IVOL effect within the lowest group of EROA and the lowest group of EROA is -2.2% with a newey-west t-statistic of -5.24. Thus, as expected the IVOL effect is largely generated by the stocks with expected poor profitability.

Interestingly, the triple-sort analysis reveals that the EROA and the PH52 are incrementally informative regarding the IVOL effect. The IVOL effect is completely absent in the group of stocks with high EROA and PH52. The value-weighted IVOL hedge strategy, within the high EROA and high PH52 group, is undistinguished from zero of -.07% (newey-west t-statistic = -0.29). Moreover, in a multivariate setting, the results from the Fama-MacBeth cross-sectional regression confirm the ability of the EROA and the PH52 to predict the future returns and subsume the IVOL effect across the stocks in the UK market. Controlling for the effect of EROA and the PH52, the average slope coefficients on the IVOL are not significant over the next 3 months and marginally significant for the returns over the next 12 months. Accounting for a set of competent returns predictors, the EROA and the PH52 preserve their ability to predict the future returns and the IVOL-return relationship.

Analysis of the interaction between the EROA, the PH52, and the IVOL shows that, in addition to the evident continuation pattern, the reversal pattern is also possible with the high IVOL. Specifically, after controlling for the continuation pattern that PH52, EROA, and IVOL determine cooperatively, the stocks with high IVOL and extreme levels of PH52 or EROA experience negative returns in the subsequent months. The further analysis shows that the overreaction behaviour induced by the firm investments and the lottery-like effect offers a complementary explanation, in addition to the underreaction mechanism, for the IVOL effect.

In the time-series analysis, two factors are built to mimic the time-variation in payoffs of the EROA and PH52 trading strategy. The evidence re-emphasises the ability of EROA and PH52 to predict the IVOL effect. In particular, the pricing model that incorporates the EROA and the PH52 related factors, in addition to the market factor and size factor, outperforms the Carhart (1997) pricing model.

These findings are robust for alternative proxies of profitability, the empirical results are very similar to those reported for the EROA. Analysing different states of the market and investors' sentiment, the IVOL effect is significantly stronger following up market state (i.e. positive return over the past 36 months) and high investors' sentiment, especially for the stocks with bad news. Thus, the IVOL effect is more likely to be driven by the investors' mis-valuation of the available news. It appears that a large part of this anomalous pricing behaviour arose from the investors' underreaction to the persistent poor performance.

The rest of the chapter is organised as follows. Section 2 will present the previous literature and the motivation behind the empirical works. Section 3 describes the data, the construction of the expected profitability and growth variables, and the econometrics methods that will be used to test the hypothesised relations. Section 4 represents the empirical results. Finally, section 5 provides concluding remarks.

4.2. Related Literature.

Through this section, the related literature is reviewed and the motivations behind the main predictions in this work are shown. We will begin by having a glance at the prior works related to the earnings expectations and their applications to asset pricing. Then, we will turn to the recent literature that drew our attention to the predicted relationship between the expected fundamentals and the IVOL effect.

4.2.1. Earnings Expectation and their Applications to Finance.

Estimating firms' cash flows is an essential part of many financial decisions. Primary topics such as risk-return relationship, firm valuation, capital budgeting, portfolio allocation, and other central issues all depend on the estimated cash flow in some way or another. In the case of the risk-return relationship and the asset pricing-related issues, the expected earnings play a key role in estimating the expected return.

Prior works have followed different approaches to represent estimated earnings. The vast part of these studies employed the analysts' earnings forecast as a proxy for the cash flow expectations. However, this method is notoriously biased. Firstly, the analysts' data is limited, and that there is a coverage concern. For example, analyst coverage for loss, small, and financially distressed firms is limited (Hong et al. 2000; Hou et al. 2012; and Li & Mohanram 2014). In addition to this limitation, Zhang (2006), Hou et al. (2012), and Hribar & Mclinns (2012) find analysts' forecasts to be biased for uncertain and hard-to-value stocks. Moreover, Richardson et al. (2004) and Bradshaw et al. (2016) point out that besides the forecasting difficulty, analysts have a strategic incentive to overestimate the earnings for some related firms. Last but not least, analyst estimations show little predictive ability for future stock returns (see, for example, Easton and Monahan 2005). Notice that hard-to-value and informationally opaque stocks contribute a large part of the IVOL effect. Therefore, the coverage issue is a big concern for testing the IVOL effect and any associated market anomalies such as the lottery effect.

The above issues led the researchers to follow a different approach that was supposed to address these shortcomings. They estimate the firms' earnings using a set of predictors rather than relying on the analyst forecast. Particularly, they intended to fit the earnings to a wide range of predictors in a time-series or cross-sectional settings and extract the estimated part of earnings. Both methods exhibit reliability in estimating the firms' earnings. However, in comparison to the cross-sectional method, the time series approach suffers one influential drawback.[3] Econometrically, to reach a reliable estimation, the time-series method requires the availability of a long history of earnings data and the selected predictors. This restrictive requirement reduces the sample and creates survivorship bias in the analysis (see, Fama & French 2000).

Using a large cross-section of data helps to tackle the availability restriction and the associated survivorship bias. Under this method, the researchers regress the earnings data to a selected predictors using a large cross-sectional set of firms. This procedure tackles the need for a long history of data, allowing the analysis to cover more units. To illustrate, the forecasting parameters can be estimated by running a cross-sectional regression using only the firms with available required current and lagged data of earnings and predictors. After fitting the available data and estimating the required parameters to forecast future earnings,

[3] Allee (2011) and Clubb & Naffi (2007) are two examples of the studies that estimate earnings employing the time-series methods.

these parameters are generalised to all firms with only available current data to predict the future earnings (or firms' future growth). These procedures allow a more accurate out-of-sample estimate of earnings (Li & Mohanram 2016). This approach can be traced back to the Fama and French (2000, 2006).

Motivated by the powerful predictive ability and the suitability of the cross-sectional approach, an increasing number of researchers have applied this method to predict future earnings for the required rate of return estimation. Examples of these studies are Lee et al. (2011), Patatoukas (2011), Hou et al. (2012), Jones & Tuzel (2012), Ashton & Wang (2013), Li & Mohanram (2014), and Harris & Wang (2019). Regardless they are all employed cross-sectional data sets, they differ in terms of the selected earnings predictors and some technical issues. Take Hou et al. (2012) as an example, they fit the following cross-sectional regression on a yearly basis:

$$E_{t+1} = \alpha_0 + \alpha_1 A_{i,t} + \alpha_2 D_{i,t} + \alpha_3 DD_{i,t} + \alpha_4 E_{i,t} + \alpha_5 NegE_{i,t} + \alpha_6 AC_{i,t} + \varepsilon_{i,t+1}, \qquad (1)$$

where E_{t+1} is the earnings of firm i in year t+1, $A_{i,t}$ is the total assets, $D_{i,t}$ is the dividend payment, $DD_{i,t}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise, $NegE_{i,t}$ is a dummy variable that equals 1for firms with negative earnings and 0 otherwise, and $AC_{i,t}$ is accruals. They estimate the targeted parameters by running the above regression using the previous ten years of data. Then, they used the estimated coefficients and the last available firms' data to predict the next period's earnings. Similar procedures have been used by other studies but with different backgrounds and hence earning predictors.

The aforementioned empirical works link the expected required rate of return to the predicted earnings through the net present value framework (NPV). Practically, this method implicitly assumes an unknown risk-return functional relationship. Employing the NPV context, another strand of studies derives a closed formula that links the stock expected rate of return to the firm investments. Cochrane (1991) and Lin & Zhang (2013) are two important works that exemplify this strand well. They suggest that the expected returns can be represented by the investment approach that optimises the firm value through equating the benefit and the cost of the firm investments. This setting is the basis for the widely-known q-factor theory. Building on this insight, Hou et al. (2015) derived an empirical asset pricing model that links the stock expected rate of return to its expected profitability and the investment level. Practically, their model adds two new pricing factors to the market and size factors that are already the foundation of the well-known Fama and French (1993) pricing model. They added the return on equity (ROE) as a proxy for the profitability factor and the growth in the asset as a proxy for the investment factor. Therefore, their q-factor model will be as follows:

$$E[R_i]-rf= \beta_{i,MKT}\, E[R_{MKT}]+\beta_{i,MEE}\, [R_{ME}]+\beta_{i,I/AE}[R_{I/A}]+\beta_{i,ROE}\, E[R_{ROE}], \qquad (2)$$

where $E[R_i]$ is the stock's required rate of return, R_{MKT} is the general market return, R_{ME} is the expected return premium for the size factor, $R_{I/A}$ is the expected return premium for investment factor, R_{ROE} is the expected risk premium of profitability factor, and $\beta_{i,MKT}$, $\beta_{i,ME}$, $\beta_{i,I/A}$, and $\beta_{i,ROE}$ is their factor loadings, respectively. In addition to the intuitive theoretical argument behind the q-factor theory, they show that their factor model is empirically preferable to the Fama and French model and Carhart models. The addition of the profitability and the investment factors helped explain many of the pricing anomalies. For example, the momentum and growth anomalies are better explained by the q-factor model than other available pricing models.

Recently q-factor theory and the model developed by Hou et al (2015) have received empirical support from the literature. For example, Wu et al. (2010), Fabozzi et al. (2016), Liu & Zhang (2014), Zhang (2017), and Hou et al. (2017, 2019), to name but a few, are all confirmed the preference of the q-factor model over the extant ones.

Overall, to this extent all the evidence that has been mentioned highlights and stresses the importance of the expected profitability in predicting the future stock return. Therefore, in this study we will test the importance of the firm's expected profitability, besides the price-based news, to explain the pervasive IVOL effect.

In the following, we will proceed and discuss the literature and the evidence that motivate us to link the IVOL effect to the expected profitability.

4.2.2. Link to the IVOL Puzzle.

In the past two empirical chapters of this academic work, robust evidence on the existence of the IVOL effect within the UK stocks market has been shown. Furthermore, the empirical analysis indicates the reported IVOL effect is attributed to the behavioural & cognitive biases of the traders in the UK market. Nevertheless, this puzzling underperformance of the stocks with high IVOL is not completely subsumed by the suggested behavioural explanation, namely, the investors' limited attention. But under that investigation, the analysis only controls for the market information and the investor behaviour toward this information.

Under this chapter, the analysis is deepened by shedding some light on the role of the profitability expectations to explain the IVOL effect. The argument here is that the reaction of investors to the expected profitability should explain, at least partly, the reported IVOL effect. In the following, we will briefly cite the premises that led us to this prediction.

Profitability premium is one of the most prominent asset pricing phenomena documented in finance (see, Novy-Marx 2013, Nichol & Dowling 2014, Ball et al. 2015, 2016, Fama & French 2015, 2016, Hou et al. 2015, Wahal 2019, and Hanauer & Huber, 2019). Practically, the q-factor model employs past profitability as a proxy for the future profitability effect. Although the q-theory interpretations of this profitability premia are appealing, a growing body of research has shown the likelihood of behavioural pricing. In particular, most of the empirical studies attribute the profitability premium to the investor mispricing. Min et al. (2018) study the reliability of the q-theory interpretation by conditioning the investment and profitability premia on risk-related reasons. They investigate the variability of these premia in the light of movement in business cycle conditions. In contrast to the investment premia, their analysis indicates that the variation in the profitability premium is negatively related to the business cycle, thus the q-factor interpretation is not supported. Wang & Zhu (2017) directly test the mispricing effect on the validity of the q-theory interpretation. Employing the short-selling activity, they find profitability premia to be attributed to the investor sentimental activities and the absence of arbitrage trading. Moreover, Wang & Yu (2013) link the profitability premium to the investors' under-reaction behaviour attributed to limited attention bias. In particular, they find that the delayed response by the investors is a more plausible driver of the return continuation associated with firm profitability.

In addition to the aforementioned works, recently several studies support the suggested relationship between the IVOL and the expected profitability. These studies find an empirical relationship between the expected profitability and the IVOL-related anomalies. In the previous chapter of this work, the 52-week high ratio is employed as a proxy of the anchoring bias and the investor's underreaction to the price trend. The results indicate that this ratio explains a large part of the reported IVOL effect in the UK stock market. George et al. (2018) suggest 52-week high ratio predictive power is driven by its ability to predict future profitability and growth in the asset. Interestingly, the 52-week high ratio positively predicts the future return, profitability, and growth. Furthermore, they show that the 52-week high ratio contains important information about the expected growth that could improve the q-model pricing ability. Similar to the IVOL effect, Riedl et al. (2020) demonstrate that the investors' mispricing of the information content of expected profit depends on the state of the market sentiment. They show that in a period of high sentiment, the investors' optimistic mood leads them to understate the persistence of the losses and overstate the persistence of the profits. While in the period of low sentiment, they are pessimistic, and therefore, they overstate the losses persistence and understate the profits persistence. More interestingly, they find this effect of sentiment on the investors' expectations is stronger for the loss firms. In light of these observations, the investors' expectation error regarding future profitability could be an important channel that induces the sentiment-driven anomalies.

In light of the above findings, it is arguable that the IVOL predictive power of the stock returns is explained, at least partly, by the expected firm profitability. Stocks with high IVOL are found to be the ones that traded at price further from their 52-week price (Byun et al. 2020). Also, much empirical evidence has pointed out that the IVOL effect is sentimentally driven mispricing behaviour (Stambaugh et al. 2015). Therefore, the IVOL effect is stronger for stock with a low 52-week high ratio and after the period of high sentiment. Furthermore, IVOL is more likely to be higher for the hard-to-value stocks like the loss firms. Thus, the IVOL effect would be a manifestation of the negative returns generated by the stocks with expected losses. If the investors understate the persistence of the firms' losses in a period of high sentiment, the expected return of these firms would persist. Then, the IVOL effect may be part of this return-profit momentum pattern.

Similar to market-based information, a recent strand of papers has documented investors anchoring to the firms' profit-related information. Under this cognitive bias, the investors fixate their expectations of cash flows on the past level and trend in firms' profitability. Giving a great attention to the simple past trend and level of profitability leads them to miss the future profit-relevant news. For example, Cen et al. (2013) employ the industry median as a reference point and find stock analysts anchored to this point when they produce their estimation of future earnings. They argue that the stock analysts are optimistic for the firms with earnings lower than the industry median while they are pessimistic in their prediction for the firms under the industry median. Employing firm-specific records of earnings as a reference point, Jang & Lee (2020) find investors are inattentive to the usual earnings. To illustrate, they found the investors underreact to the earnings news if the firm's earnings are closer to their record. They also demonstrate that this phenomenon is distinguished and independent from that documented in market-based information, namely, the 52-week high ratio. A similar conclusion was reached by the studies of Akbas et al. (2017), Huang et al. (2019), and Avramov et al. (2020).

Generally, the aforementioned discussion supports our conjecture on the importance of testing the relationship between the expected profitability and the IVOL effect. If the investors anchored to the past information and failed to adjust their expectations adequately, they would reach an inaccurate stock valuation. Consequently, when the ignored earnings information is confirmed, and they get recognised this information they start to adjust their valuation for the stocks. Finally, this slow adjustment process will generate momentum in the returns in the direction of future profit.

The above discussion raises another important question. Would combining the market-based information and fundamental-based information produce more superior return-predictive power? Several papers have contributed to answer this question. For example, Battman et al. (2009), Chen et al. (2014), Hong & Wu (2016), and Zhu et al. (2020) stresses the importance of both market-based information and fundamental-based information. The role of fundamental information dominates in the cases of the long horizon and high information uncertainty. Theoretically, these empirical findings are consistent with the behavioural model of Hong and Stein (1999). Under this theoretical model, the market is populated by two kinds of investors, the “news-watchers” and the “momentum traders”. Their heterogeneity is attributed to the types of information they can process. The news-watchers can only process a subset of private information relevant to the prospect of firms’ fundamentals. Whereas, momentum traders can only process the market past information for specific lagged periods. Under this setting, neither the fundamental-based information nor the market-based information gives a complete picture of the future returns. Empirically the importance of market-based information is also highlighted by the ability of the market price to reveal investors’ expectations of future profitability. These expectations are found to be biased and different from the fundamental-based expectations (Keskek, et al. 2020).

The 52-week high ratio is one of the most market-based information that has been documented as a powerful return’s predictor (George & Hwang 2004, Marshall & Cahan 2005, Du 2008, Liu et al. 2011, and Hao et al. 2018). The trading strategy of buying long stocks with prices near to the past 52-week high record and shorting the stocks with spice furthest from the 52-week high record generates abnormal returns that are unexplainable by the available risk factors. In other words, there is an anomalous continuation pattern associated with this ratio. Almost there is a consensus on the behavioural explanation of this continuation pattern. This behavioural story states that the investors anchored to the past 52-week high price, therefore, underreact to the value-relevant information (Li & Yu 2012, Huang et al. 2020). Interestingly, the effect of this reference point (i.e. 52-week high price) goes beyond the individual investors to also affect the professional practitioners. In a similar way to the individual investors, Lin (2017) and Li et al. (2020) show that stock analyst's valuation is affected by the nearness to the 52-week high price. Therefore, this influence on the analysts' expectations would be the channel that gives the 52-week high ratio the power to predict the future returns.

Overall, the above discussion highlights the importance of the profit expectation and the investors' inefficient response to this information in explaining the future stock returns therefore the pricing anomalies. Also, it appears important to include the profit expectations and the market-based information to explain many of the widely documented anomalies. Nevertheless, this area of study is still under-researched and there is a gap that should be filled. Under this work, this work contributes to fill part of this gap. Particularly, we will study the joint effect of the fundamental-based expected profit and the 52-week high ratio on the payoffs of the IVOL anomaly. We will do so in cross-sectional and time-series settings. In the cross-sectional-setting, we will investigate the individual effect of the expected profit and the 52-week ratio on the IVOL effect. To this end, this work employs the stock-sorting analysis and the Fama-Macbeth cross-sectional regression. In the time-series setting, this study will contribute to the literature by testing a modified version of asset pricing that corporate two new factors. Consistent with the general goal of this study, these new factors are built to mimic the effect of the expected profit and the 52-week high effect.

This work is closely related to the studies of Malagon et al. (2015) and George et al. (2018). However, it is distinguished from that of Malagon et al. (2015) in some important matters. First, they used the past profitability while in this work the profitability is proxied by the projected profit using a fundamental-based model. Second, we test the joint effect of the expected profit and the 52-week high ratio. Third, a modified version of the asset pricing model is tested. George et al. (2018) propose a modified version of the q-factor model and demonstrate its ability to outperform the original version of the q-factor model in pricing the accrual and the research and development anomalies. The modified version employed in this work is different in some aspects. First, in their suggested model they modify the original profitability factor to reflect the information contained in the price information. Whereas, in this work, separate factors are adopted to reflect the information contained in the 52-week high ratio in addition to the profitability factor. Second, they employ past profit as a proxy for future profitability.

4.3. Variable definitions, Data, and Methodology

Under this section, the proxies employed to represent the main variables in this study, the data sample, and the methodology are described in brief details.

4.3.1. Variable Definitions.

This section outlines the definitions and the measurement procedures of the variables employed in this study.

4.3.1.1. Idiosyncratic Volatility**.**

Empirically, this measure is designed to represent the unsystematic part of returns variation. The investors are more likely to misvalue stocks with high unsystematic volatility (see, Kumar 2009). The findings in the third chapter demonstrate a close link between the idiosyncratic volatility and the underreaction behaviour. In the financial literature the idiosyncratic volatility serves as a proxy for different features. Some argue that IVOL is a proxy for the lottery-like feature (e.g. Bali et al. 2011), while others link this variable to the arbitrage cost (e.g. Cao and Han, 2016). To measure the idiosyncratic volatility, we follow Ang et al. (2006). In specific, each month we run the following Carhart (1997) pricing model,

$$R_{it} - rf_t = \alpha_i + \beta_m * (R_{mt} - rf_t) + \beta_{smb} * SMB_t + \beta_{hml} * HML_t + \beta_{umd} * UMD_t + \varepsilon_{it}, \quad (3)$$

Where R_{it} is the return of stock i on day t, R_{mt} is the market return on day t, rf_t is the risk-free rate, SMB_t is the small minus big factor, HML_t is the high minus low factor, UMD_t is the winner minus loser factor, and ε_{it} is the unexplained component of the stock i returns. Also, α_i, β_m, β_{smb}, β_{hml}, and β_{umd} are the estimated parameters. After estimating the model, the idiosyncratic volatility is calculated as the standard deviation of the residuals. To mitigate the effect of nonsynchronous trading we require a minimum of 140 observations to be available to estimate Carhart's four-factor model. These procedures are re-estimated monthly. The data for Carhart's four-factor model is obtained from the following link http://business-school.exeter.ac.uk/research/centres/xfi/famafrench/. For more details about the factors construction process, please, refer to Gregory et al. (2013).

4.3.1.2. Price to 52-week high (PH52).

Evidence on the anchoring bias from the financial markets states that the investors pay limited attention to value-relevant news, as they stick to the old reference point in their valuation. George and Hwang (2004) claim that the performance continuation pattern associated with a 52-week high strategy is a manifestation of the anchoring bias. Also, Li and Yu (2012), George et al. (2015), and Hur and Singh, (2019) all suggest the 52-week high ratio as a proxy for the limited investor attention. Following these studies, the 52-week high ratio is used as a proxy for the investor's inattentive behaviour to the market news. This ratio is calculated as a following,

$$PH52 = P_{it} / \text{52-week high price}, \quad (4)$$

where P_{it} is the current closing price for stock i and the denominator is the highest price recorded during the past 52 weeks. According to the anchoring bias and the revealed empirical evidence, the stocks with a closing price far from the past 52-week high price are likely to underperform in the subsequent periods. Therefore, it is expected that the persistent underperformance reported for the IVOL-based zero-cost strategy to be stronger for the stocks with a price far from the past 52-week high.

4.3.1.3. Forecasting Profitability.

Recently, empirical researches in finance and accounting have increasingly applied the cross-sectional approach to fit the next period's earnings (see, for example, Lee et al. 2011, Li & Mohanram 2014, and Harris & Wang 2019, Hou & van Dijk 2019). There is no consensus on the nature and the number of earnings predictors in these studies. However, there are a parsimonious number of these predictors that are commonly used in these studies and show sound predictive power for future earnings. Naturally, the profitability level is known to be highly persistent (see, Fama & French 2006 and the reference therein). Also, the mean reversion in profitability is documented by past studies (Fama and French 2000). Dividend payer firms are expected to be more profitable than non-payers firms (Fama and French, 1999). Hou and Robinson (2006) and Hou and van Dijk (2019) find that Tobin's q strongly predicts future profitability. Richardson et al. (2004) and Papanastasopoulos (2020) show that accruals are strong predictors of future profitability. Dickinson (2011) and Vorst and Yohn (2018) suggest that firm life cycle information is useful in forecasting firms' profitability.

Following this strand of studies, the next year profitability is estimated by running the following model month by month and across the available stocks:

$$ROA_{i,t+1}=\alpha_0+ \alpha_1 ROA_{i,t} + \alpha_2 Neg_{i,t} + \alpha_3 TQ_{i,t} + \alpha_4 DD_{i,t} + \alpha_5 D_{i,t}/B_{i,t} + \alpha_6 PACC_{i,t} + \alpha_7 DCycle_{i,t} + \alpha_8 Rev_{i,t} + \varepsilon_{i,t+1}, \quad (5)$$

where ROA is the return on asset of firm i in year t and defined as the net income scaled by the lagged book assets, $Neg_{i,t}$ is a dummy variable that equals 1 for firms with negative earnings and 0 otherwise, $TQ_{i,t}$ is the traditional Tobin's q and defined as market equity plus total liability scaled by book assets, $D_{i,t}/B_{i,t}$ is the dividend payment scaled by the book value equity, $DD_{i,t}$ is a dummy variable that equals 1 for dividend payers and 0 otherwise, and $PACC_{i,t}$ is the percent accruals and is measured by the change in operating assets scaled by the absolute value of net income (see, Papanastasopoulos 2020), $Rev_{i,t}$ is the difference between the past year ROA and the average ROA over the past five years. $DCycle_{i,t}$ is a dummy variable that equals 1 for firms in the introductory and declining stages and 0 otherwise, see Dickinson (2011) for life cycle classification. In the first step, to estimate equation (5), data should be available at the past accounting year. For example, to find the projected earnings for 1997, data from 1995 is used to estimate the parameters of equation (5).

After estimating the equation (5), the parameters are applied to the last available observations of the selected predictors to forecast the firms' profitability over the next year. By this, the procedures seek to generate a reliable series of out-of-sample ex-ante profitability. To clarify, by estimating the parameters assumed under equation (5), to predict the next period profitability of the individual stock, the availability of the current observations is only needed. To ensure the availability of the information, the accounting observations from the year that ended at least 6 months ago are considered in the estimation process. For example, to estimate the next year's profitability in June 1997, the observations collected at the end of December of 1996 are required.

To test the reliability of our analysis against a variant definition of profitability, in the robustness test at the end of this work, the profitability is also measured by the return on book equity, operating profit to book equity, and cash-based operating profit to book assets. The Cash-based operating profit is calculated as the difference between operating profit and the total accruals. Accruals equal the annual change in current assets (excluding cash) minus current liabilities (excluding short-term debt) minus depreciation.

4.3.1.4. Other Firms Characteristics.

To isolate the potential effect of other return predictors, we control for a set of return predictors that are widely documented in the financial literature. This set of controlling variable is as follows,

1- Unrealised capital gains: following Grinblatt and Han (2005), the unrealised capital gains are measured as follows,

$UCG_t = \frac{P_{-1}-R_{-1}}{P_{-2}}$, (6)

where P_{-1} is the stock price at the end of the last month, and

$R_{-1} = \frac{1}{k}\sum_{n=1}^{750}(V_{-1-n}\prod_{k=1}^{n-1}[1-V_{-1-n-k}])P_{-1-n}$ (7)

where k is constant that makes the weights on past prices sum to one, V_{-j} is the daily turnover at the previous j days from the end of month t. In this work, the UCG is measured using the past three years data.

2- Book-to-market ratio BM: is the ratio of the book equity to the market value of equity.
3- The earnings-to-price ratio (EP): is the ratio of earnings per share to the price per share.
4- Market value (MV): is the market capitalisation of the firm and calculated as the share closing price times by the number of shares outstanding.
5- Asset growth: following Copper et al. (2008) and Hou et al. (2015), the growth in assets is measured using the year-on-year percentage change in total assets.
6- Market Beta: traditionally measured by regressing the stock's risk premium (R_i-r_f) on the market risk premium (R_m). To mitigate the impact of nonsynchronous trading, we follow Lewellen and Nagel (2006) and Cederburg and O'Doherty (2016) by adding four lags of the market premium to the regression, as a following,

$$Rp_{i,t} = \alpha_i + \beta_{i,t} * Rp_{m,t} + \sum_{n=1}^{4}\beta_{i,t-n} * Rp_{m,t-n} + \varepsilon_{i,t},$$

$$\beta_i = \beta_{i,t} + \sum_{n=1}^{4}\beta_{i,t-n} \qquad (8)$$

Where Rp_i and Rp_m is the weekly risk premium for the stocks i and the market portfolio, respectively, and βi is the estimated beta. The beta will be re-estimated monthly using the weekly returns over the past 12 months.

7- Downside Beta (Dbeta): is a systematic left-tail risk proxy, measured in a similar way to the market beta, however, the stock returns are regressed on the negative market returns rather than the total market returns series.

8- Med-term Momentum (Mom): following Jegadeesh & Titman (1993), med-term momentum is defined as the cumulative return over the past 6 months after skipping a month between the portfolio formation period and the holding period.

9- Short-term reversal (Rev): following Jegadeesh (1990), this variable is measured using the stock return over the past month.

10- Maximum return: following Bali et al (2011) the maximum returns are employed as a proxy for the lottery-likeness and defined as the average of 5 maximum daily returns over the past 3 months.

11- Continuous overreaction index (CO): this variable is developed by Byun et al. (2016) to capture the trend in the investors' overconfidence. They define this measure as following,

$$CO_{i,t}=\frac{sum\ (w_j \times SV_{i,t-j},\ldots\ldots\ldots\ldots,w_1 \times SV_{i,t-1})}{mean\ (VOL_{i,t-j},\ldots\ldots\ldots\ldots,VOL_{i,t-1})} \quad (9)$$

where $SV_{i,t}$ is the signed volume for stock *i* in month *t*,

$$SV_t = \begin{cases} VOL_t & if \quad r_t > 0, \\ 0 & if \quad r_t = 0, \\ -VOL_t & if \quad r_t < 0, \end{cases} \quad (10)$$

where VOL_t is the dollar volume in month t and r_t is the stock return in month t, J is the length of the formation period, and w_j is a weight that takes a value of J-j +1 in month t-j (i.e., w_j=1 and w_1=J). In this work, the continuous overreaction (CO) is measured using a 12-month formation period.

12- Investment-capital ratio (I/K): is a proxy of firm investment and defined as follows,

$$I/K = \frac{I_{t-1}}{K_{t-2}} \quad (11)$$

where I is the sum of capital expenditure and research and development expense, and K is net property, plant, and equipment.

13- Price impact ratio: following Amihud (2002) and Florackis et al (2009), this liquidity measure is defined as,

$$RtoTR_{i,t} = \Sigma\ \{|R_{i,d}| / TR_{i,d}\}, \quad (12)$$

Where $R_{i,t}$ is the return of stock i in day d, and $TR_{i,d}$ is the daily trading turnover for the stock i in day d.

14- Zero-return days: this liquidity proxy is measured over the past 12 months as the number of days with zero returns to the total number of trading days.

15- Delay response measure: is the price delay measure of Hou and Moskowitz (2005), which defined as,

$$Delay_i = 1 - \frac{R^2_{unrestriscted}}{R^2_{restricted}}, \quad (13)$$

where $R^2_{unrestriscted}$ is the fraction of stock return explained by the market model with 4 lag terms, and $R^2_{restricted}$ is the fraction of returns explained by the traditional market model (i.e. CAPM). The higher value of Delay indicates a higher predictive ability for the past information, therefore a more delayed response to this available information in the market.

16- Shock to the volume: Low abnormal trading volume signals low visibility of stocks (Gervais et al., 2001). Specifically, the abnormal volume of stock i in month t is

$$ABnV_i = (Volume_{it} - \sum_{n=1}^{12} \text{Volume}_{it-n}) / \text{Std}(\text{Volume}_i) \quad (14)$$

where Volume is the pound trading volume in month t, Std is the standard deviation of the volume over the past 12 months. Equation (6) allows us to define the degree of drop and rise in the trading activity of a particular stock. According to this equation, if the investors pay little attention to stocks i, they should trade this stock less frequently.

17- Information risk Index: It is more likely for individual investors to pay less attention to complex and difficult-to-process information (Hirshleifer et al. 2017). Zhu et al. (2019) found that both limited attention and information asymmetry are important in explaining the documented fundamental-based anomaly. We employ 5 different proxies of information uncertainty. These proxies are firm size, firm age, and turnover volatility, return synchronicity, and the bid-ask spread. To summarise the common component of these uncertainty proxies we employ the PCA to extract the first common component of these proxies which will be used as the index of information uncertainty.

(i) Firm size: the firm size is represented by the market value of the firm which is the number of shares outstanding multiplied by the closing price.

(ii) Age: In this study, the Firm's age is the number of months since the firm's initial appearance in the DataStream database.

(iii) Turnover volatility: George and Hwang (2010) demonstrate that stocks with high turnover volatility are more likely to be overvalued due to high information uncertainty. To evaluate the turnover uncertainty, we measure the standard deviation of the daily turnover over the past 12 months.

(iv) Bid-Ask spread: The daily bid-ask spread is the difference between the closing bid and ask prices divided by their average. We take the average of daily bid-ask spread over the past year.

(v) Return Synchronicity: In their categorical learning model, Peng and Xiong (2006) link the return co-movement to the limited attention capacity by the investors. Following Chue et al (2019), return synchronicity Defined as,

$$\text{Synch} = \text{Log}\left(\frac{R^2}{1-R^2}\right), \qquad (15)$$

where R^2 is the coefficient of determination of the standard Market model (CAPM).

4.3.2. Data.

The sample includes all common stocks traded at the main market in the London stock exchange and have available data at the Worldscope database, covering the period from January 1996 through December 2017. The whole sample includes 5414 shares. To avoid survivorship bias, the currently listed and the unlisted firms are included in the sample. Following the past literature, financial firms are excluded. Stocks with prices less than 3 pounds or traded for less than 150 days over the last year (the formation period) are excluded. Also, any stocks with no available earnings data or negative book equity are dropped out of the sample. The number of stocks included in the analysis varies from month to month, the lowest is 227 stocks in the March of 1996 and highest is 657 in the June of 2006. These numbers are enough to conduct a reliable stock sorting analysis and Fama and MacBeth (1973) cross-sectional regressions. The market prices-related data are from the Datastream database. To illustrate, 227 shares are enough to build decile portfolios with approximately 23 shares in each. Accounting variables are obtained from the Worldscope database available in Datastream. The pricing factors and the risk-free rate data are obtained from Gregory et al (2103).

4.3.3. Analysis Procedures.

4.3.3.1. Cross-sectional Methods.

This section describes the procedures performed to examine the behaviour of the left-tail momentum and the IVOL puzzle in the UK stock market. Firstly, we will have a look at the performance of the investing strategies based on the expected profitability (EROA) and the 52-week high (PH52). To this end, the single-sort approach is employed. Each month, the stocks in the sample are sorted in ascending order into deciles according to the EROA or the PH52. Then, the performance of these decile portfolios is evaluated by measuring their raw returns over the next 3 and 12 months. Besides the raw returns, the risk-adjusted performance is evaluated by the alpha of the 4-factor model of Carhart (1997).

Moving forward, the performance of the IVOL effect is evaluated conditional on the EROA and PH52. Particularly, a triple-sort approach is performed to analyse the performance of the IVOL-based strategy based on the joint level of EROA and PH52. Each month, the stocks are sorted into 2 portfolios based on the EROA or PH52. Then, 4 portfolios are built by intersecting the 2 EROA-based portfolios with the 2 PH52-based portfolios. Lastly, within each one of these 4 portfolios, the stocks are resorted into 3 portfolios according to the IVOL levels. A zero-cost strategy that goes long on the high IVOL portfolio and shorts the low IVOL portfolio is built within each level of EROA and PH52. Similar to the single sort analysis, the performance of these portfolios is evaluated by the raw returns and the alpha of the 4-factor model of Carhart (1997).

Lastly, The Fama and Macbeth cross-sectional regression is performed to analyse the association between these three trading strategies in a multivariate setting.

4.3.3.2. Time-series Method.

In addition to the cross-sectional analysis, the relationship between the EROA, PH52, and the IVOL effect is investigated in a time series setting. For this task, two pricing factors are built to mimic the movement of the payoffs of the investing strategy based on the EROA and PH52.

To accomplish this task, procedures similar to the one used in Fama and French (1993) are applied. Independently, each June, the stocks are sorted into 3 groups based on EROA and PH52 using breakpoints for the bottom 30% (low), middle 40%, and upper 30% (high). Also, based on the market capitalisation (size), the stocks are sorted into a big group (upper 30%) and a small group (bottom 70%). Then, to measure the EROA factor, 6 portfolios are generated by intersecting the EROA-based groups with the two size groups. The EROA factor is calculated as the difference between the average returns of the two high EROA portfolios and the two low EROA portfolios. To build the PH52 factor, 18 portfolios are built by intersecting the three PH52 groups with the three EROA groups and the two size groups. The PH52 factor is defined as the difference between the average returns of the 6 high PH52 portfolios and the 6 low Ph52 portfolios. By this, the PH52 is neutralised to the information given by the size and the EROA. The size factor is defined as the difference between the average returns of the 9 small-size portfolios and the 9 big-size portfolios. Following Fama and French (1993), the size factor is rebalanced on an annual basis.

4.4. Empirical Results.

In this section, a set of analyses is conducted to test the hypothesised relationships between the main variables in this study. Firstly, the general description of the study variables and the cross-sectional predictive regression of the firms' profitability (ROA_{t+1}) are presented. Secondly, the stocks sorting approach is performed to analyse the performance of the portfolios generated based on the fitted ROA (EROA), 52-week high ratio (PH52), and the joint trading strategy that is built on both characteristics. Thirdly, the individual and the joint effect of these two return-predictive signals (i.e., EROA and PH52) on the performance of the IVOL effect. Lastly, the portfolio analysis is supplemented by the Fama-MacBeth cross-sectional regression.

4.4.1. Descriptive Statistics, Correlation, and Profitability Prediction.

Panel B of Table 4.1 shows the average coefficients for the profitability fitting regression as well as their time-series t-statistics. This Panel outlines three models with different variables settings hence complexity. In the first and second models, the profitability is fitted only to the past profitability information. While the third model adds the rest of the predictors to show their incremental explanatory power. Evidently, a large part of the next year's profitability is attributed to the profit level persistence–the model that includes only the past profitability level explains 48% of the next year's profitability. However, adding a set of other predictors substantially improves this predictive power. To illustrate, Model3 of Table 4.1 shows that adding other predictors to the past profitability substantially improves the R2 of profitability-regression from 48% to 55%. Accordingly, these results support the selection of model 3 to predict future profitability.

The estimated results in panel 2 of Table 4.1 are similar to those found in the US market by studies of Fama & French (2000), Hou & Robinson (2006), and Hou & van Dijk (2020). This similarity is in both the explanatory power and the estimated relationship between the future profitability and the employed predictors. According to the reported figures, unsurprisingly, the firms' profitability is highly persistent, the average slope coefficients on the lagged profitability is 0.56 and highly statistically significant (t-statistic = 49.1). Profitability is mean reverting, higher than past average profitability is negatively related to the future level of profitability. The average of slope coefficients on the Rev is negative with a value of -0.19 (t-statistic = -24.3). These findings for the UK sample confirm those found for the US market (see, Fama & French, 2000, 2006). Aspects of dividend policy significantly predict future profitability. The level of dividend paid by the UK firms is positively predicted future profitability. The average slope coefficients on the dividend to equity rate is 0.133 and highly significant with a t-statistic equals to 22.75. Intuitively, this indicates that paying a higher dividend by the firms may signal higher future profitability in the next period. In line with this result, the dummy variable that takes 1 for dividend non-payers firms and zero otherwise is negatively related to the future profitability which means nonpayers are more likely to underperform dividend payers in terms of future profitability. In contrast to theory and the traditional findings, Panel B of Table 4.1 shows that Tobin's Q proxy is negatively related to future profitability, the average slope coefficients on this variable is -0.005 (t-statistic = -6.92). Papanastasopoulos (2020) reports that percent accruals are negatively predicted the future profitability of the UK firms and refer that to the widely documented accruals reversibility. These results confirm this predictable pattern, on average, the slope coefficients on the percent accruals are negative and significant. Accordingly, firms with higher accruals tend to be less profitable in the year. Moreover, the results indicate that, on average, firms in the introduction and decline stages are significantly less profitable by 0.061 percent than the ones in the other stages (t-statistic = -35.95). Firms in the introduction and decline stages have been found to generate persistence losses over the subsequent years (Dickinson, 2011).

Table 4.1 Descriptive statistics and the results of profitability predictive cross-sectional regressions.

The table represents the descriptive statistics (in panel A) and the cross-sectional predictive regression of profitability (in panel B). IVOL is the idiosyncratic volatility measured over the past 12 months, ROAt, EROA, and ROAt+1 are the last year return on asset, the fitted value of return on asset, and the next year realised return on asset respectively, PH52 is the 52-week high ratio, Max is the average of 5 maximum daily returns over the three months, MOM is the return over the past 6 months, Last is the return over the last month, MV is the market value in millions of pound, GA is the growth in assets, Amih is logarithmic value of the Amihud price impact ratio, Zdays is the zero returns days, Beta is the market beta measured through the last 52 weeks, Dbeta is the down beta measured through the last 52 weeks, BM is the ratio of book equity to market value, EP id the earnings to price ratio, Delay is Hou and Moskowitz delay index, I/K is the ratio of capital expenditure plus research and development to capital, CO12 is the continuous overreaction measure of Byun et al. (2016), and UCG is unrealised capital gains. Also, in panel B, Neg is a dummy variable equal 1 if the firm has negative profitability and zero otherwise, Rev is the difference between the ROA in the last year and the average of ROA over the past 3 years, PACC is the percent accruals, T is Tobin's q, DD is a dummy variable equal 1 if the firm does not pay a dividend in the last year and zero otherwise, D/B id the ratio of dividend to book equity, and DLife is a dummy variable equal 1 if the firm is in the introduction or decline or the growth stage (Dickinson, 2011). R^2 is the coefficient of determination. a, b, and c indicate significance at 1%, 5%, and 10% respectively. The sample covers the period from January 1996 to December 2017.

Var	Mean	p50	sd	p25	p75	Var	mean	p50	sd	p25	p75
IVOL	2.68	2.15	1.73	1.51	3.28	Amih	2.35	2.14	1.1	1.6	2.94
ROA_t	-0.01	0.05	0.25	-0.02	0.1	Zdays	0.16	0.1	0.14	0.03	0.28
EROA	-0.004	0.06	0.19	-0.03	0.09	Beta	1.21	1.06	1.31	0.44	1.81
ROA_{t+1}	-0.01	0.05	0.23	-0.02	0.1	Dbeta	1.33	1.11	1.99	0.27	2.18
PH52	0.76	0.83	0.22	0.64	0.94	BM	0.63	0.39	0.88	0.2	0.72
MAX	5.83	4.6	4.13	3.18	7.06	EP	-0.01	0.04	0.24	-0.01	0.07
MOM%	1.94	5.16	39.4	-15	22.41	Delay	0.51	0.49	0.31	0.23	0.8
Last%	-0.1	0.37	13.7	-6.5	6.88	I/K	1.22	0.27	3.85	0.15	0.62
MV	1614.4	262.8	4213.8	71.2	1033.8	CO12	11.46	9.22	31.78	-11.89	32.27
GA	0.28	0.08	0.87	-0.02	0.27	UCG	0.012	0.057	0.379	-0.14	0.228
Panel B:	Profitability predictive regression										
		ROA_t	Neg	Rev	PACC	TQ	DD	D/B	DLife	Cons	R^2
Model1	Coeff	0.67^{a}								0.0017^{*}	0.48
	t-stat	70.44								1.63	
Model2	Coeff	0.67^{a}	-0.05^{a}		-0.28^{a}					0.016^{a}	0.52
	t-stat	51.44	-15.3		-30.89					12.62	
Model3	Coeff	0.56^{a}	-0.02^{a}	-0.19^{a}	-0.0006^{a}	-0.005^{a}	0.13^{a}	-0.018^{a}	-0.06^{a}	0.032^{a}	0.55
	t-stat	49.1	-8.011	-24.29	-4.307	-6.923	22.75	-10.12	-35.95	20.6	

Generally, the empirical observations laid in Panel B of Table 4.1 confirm most of the predicted relationships between the future profitability and the selected set of predictors. Furthermore, if we combine these observations with substantial explanatory power, the fitted value of model 3 would represent a powerful and meaningful proxy for future profitability. Therefore, following Hou and Dijk (2020) and the references therein, we will apply the parameters estimated by fitting this model to the currently available observations of the selected predictors to generate an out-of-sample prediction of future profitability.

Table 4.2 Correlation analysis

The table represents the cross-sectional correlation between the variables. Ret12 is the average of monthly returns over the subsequent year, IVOL is the idiosyncratic volatility measured over the past 12 months, ROA_0, EROA, and ROA are the last year return on asset, the fitted value of return on asset, and the next year realised return on asset respectively, PH52 is the 52-week high ratio, Max is the average of 5 maximum daily returns over the three months, MOM is the return over the past 6 months, Last is the return over the last month, logv is the logarithm of market value in millions of pound, GA is the growth in assets, Amih is logarithmic value of the Amihud price impact ratio, Zdays is the zero returns days, Beta is the market beta measured through the last 52 weeks, BM is the ratio of book equity to market value, EP id the earnings to price ratio, ATT id the indention index , INF is the information uncertainty index, I/K is the ratio of capital expenditure plus research and development to capital, CO12 is the continuous overreaction measure of Byun et al. (2016), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017.

Var	Ret_{t+1}	IVOL	EROA	PH52	ATT	ES5%	MAX	INF	Amih	ZDays	Mom12	CG	logV	PACC	TQ	D/B	LCycle
Ret_{t+1}	1																
IVOL	-0.19	1															
EROA	0.22	-0.51	1														
PH52	0.19	-0.58	0.32	1													
ATT	0.16	-0.42	0.32	0.55	1												
ES5%	-0.18	0.9	-0.45	-0.74	-0.42	1											
MAX	-0.18	0.96	-0.5	-0.47	-0.37	0.82	1										
INFUn	-0.17	0.65	-0.47	-0.42	-0.54	0.57	0.62	1									
Amih	-0.02	0.42	-0.22	-0.22	-0.21	0.4	0.42	0.39	1								
Zdays	-0.07	0.23	-0.23	-0.17	-0.35	0.18	0.26	0.61	0.23	1							
Mom12	0.08	-0.23	0.09	0.77	0.46	-0.47	-0.1	-0.15	-0.13	-0.06	1						
CG	0.11	-0.35	0.21	0.8	0.5	-0.52	-0.25	-0.25	-0.25	-0.11	0.82	1					
logV	0.15	-0.59	0.42	0.45	0.52	-0.55	-0.56	-0.86	-0.41	-0.63	0.22	0.32	1				
PACC	-0.05	0.06	0	-0.1	-0.05	0.09	0.04	0.04	-0.01	0.03	-0.08	-0.07	-0.03	1			
TQ	-0.17	0.13	-0.33	-0.13	-0.05	0.13	0.13	0.11	-0.05	0.01	0.02	0.02	-0.01	-0.02	1		
D/B	0.1	-0.28	0.35	0.17	0.19	-0.26	-0.27	-0.31	-0.13	-0.18	0.03	0.08	0.32	-0.08	0.01	1	
LCycle	-0.2	0.47	-0.73	-0.31	-0.31	0.42	0.47	0.47	0.21	0.24	-0.1	-0.2	-0.43	0.09	0.19	-0.28	1
INV	-0.07	0.19	-0.32	-0.12	-0.14	0.17	0.19	0.2	0.08	0.09	-0.03	-0.06	-0.18	0.04	0.15	-0.13	0.29

Table 4.2 displays the cross-sectional correlation coefficients between the variables. The observations reveal that the projected profitability (EROA) is highly correlated with the IVOL and the PH52. As expected, the 52-week high ratio (PH52) and the projected profitability (EROA) are positively correlated with a coefficient of 0.32. This indicates that in general the trend in the market is consistent with the trend in the firms' fundamentals. While the IVOL is negatively correlated with both the PH52 ratio and the EROA, the correlation coefficients are 0.58 and 0.51, respectively. Therefore, stocks with high IVOL are more likely to receive negative news signalled either by the market-related information or by the fundamental-related information. In light of this negative IVOL-EROA relationship, the reported negative correlation between the average monthly returns over the next year and the IVOL (the so-called IVOL effect) is expected. This triangle relationship between, the expected profitability, the IVOL, and the stock returns is reasonable in light of irrational behaviour story (e.g., the underreaction behaviour) combined with arbitrage frictions. Consistent with the underreaction story, the IVOL and the EROA are highly correlated, but with opposite signs, with the investors' attention level (i.e. Delay measure). The correlation coefficients between the ATT and the IVOL and The EROA are -0.42 and -0.32, respectively.

Combined with the observed low PH52, it seems that the investors in the UK market are more likely to pay little attention and therefore underreact to the stocks with low expected profitability. If this pattern is proven, we should expect a stronger continuation pattern in the returns of the loss firms with high IVOL. In addition to these important observations, similar to the stocks with high IVOL, stocks with low profitability are less liquid and more uncertain in terms of information. For example, the correlation coefficients between the EROA on the one hand and the Amihud illiquidity measure (Amih) and the information uncertainty index (INFUn) on the other hand are -0.22 and -0.47, respectively. Information uncertainty could lead to a higher difficulty in the profitability estimation (see, Bradshaw et al. 2016).

The above discussion gives a preliminary picture of the assumed relationship between the IVOL effect and the expected profitability. In the following sections, we will proceed to analyse the payoffs to the trading strategy based on the EROA and the PH52 ratio in addition to their individual and joint effect on the IVOL-based strategy payoffs.

4.4.2. Portfolio Analysis.

Prior researches report positive payoffs for the zero-cost trading strategy that goes long on high profitability stocks and goes short on low profitability stocks (for example see, Novy-

Marx 2013, Fama & French 2015, and Ball et al. 2016). Nichol & Dowling (2014) confirm the existence of the profitability premium within the 350 biggest stocks in the UK market. In these works, profitability was measured by past observations. However, Kyosev et al. (2020) demonstrate that the premium associated with past accounting-based measures such as profitability is driven through their ability to project the future growth in profitability and nothing else. Under this section, having a proxy for the expected profitability, a further step will be taken to analyse the payoff for the same trading strategy but employing the projected profitability (EROA) instead of the realised observations (ROA_t). Similarly, the performance of the PH52-based portfolios is shown. Then, a further step is taken to achieve the main goal in this study by analysing the impact of these two trading strategies on the IVOL effect.

4.4.2.1. Sorting on the EROA and PH52.

We will begin by analysing the performance of portfolios based on EROA and PH52. To this end, each month, 10 portfolios are built based on the expected profitability (EROA) and the PH52, separately. To illustrate, each month, the stocks are sorted based on their EROA into deciles to generate 10 portfolios, portfolio 10 contains stocks with the highest EROA while portfolio 1 contains stocks with the lowest EROA. After forming these decile portfolios, their performance will be measured by average monthly returns over the next 3 and 12 months, skipping the first month after formation. The portfolio returns are calculated by weighting, equally or by market value, the returns of the included stocks. The analysis spans the period from January 1996 to December 2017.

Table 4.3 shows the performance analysis of the portfolios generated based on EROA or PH52. The figures represent the portfolio returns over the next 3 and 12 months and the difference in returns of highest and lowest decile portfolios. The differential performance is tested by the raw returns and the risk-adjusted alphas. The Carhart 4-factor model is considered to adjust the raw returns for risk. Also, some important characteristics are shown through this table.

Panel A of Table 4.3 outlines the performance analysis of the EROA-based portfolios. The observed patterns are clear, the return is an increasing function of the expected profitability (EROA). Considering different time horizons and weighting schemes, the returns dramatically increase from the lowest to the highest decile of the EROA. For example, over the next 12 months, if we value the returns by the market capitalisation, on average, the stocks that make up the lowest decile of EROA will lose -2.8%, while the stocks that make up the highest decile of the EROA-rank will gain 0.69%. The 3.49% of differential returns is statistically significant at 1% level (newey-west t-statistic = 6.2). This premium in raw return persists adjusting for the risk factors suggested by Carhart (1997). For instance, adjusting the mentioned 3.49% of differential returns almost changes nothing and generates an alpha of 3.38% that is statistically significant at 1% (newey-west t-statistic = 6.27). To make sure these patterns are not a special case of the extreme deciles, a more conservative strategy that goes long on the second-highest decile of EROA and goes short on the second-lowest decile of EROA is tested. Although with lower magnitude, implementing this conservative strategy generates a significant Carhart's alpha of 1.45% (newey-west t-statistic = 4.24).

To a large part, this abnormal premium associated with the expected profitability is attributed to the three smallest deciles. To illustrate, moving up from the 4th decile to the highest decile, generate a noticeably small premium in returns. For example, considering the equally weighted returns over the next 3 (EW_{2-4}), panel A of Table 3 shows that the difference in raw returns between the lowest and the 5th deciles is 2.9% (0.25%+2.65%) whereas moving up from the 5th decile to the highest decile of EROA generates only -0.09% (0.16-0.25). This confirms the general conclusion reached by the previous studies that the short-leg dominates many of the widely documented anomalies (see, Stambaugh et al. 2012).

The general implication of this pattern is that, if the investors can trade based on EROA, they should generate attractive gains by shorting the stocks with the lowest decile of the expected profitability and buying long the ones in the highest decile of the expected profitability. The annualised differential return ranges from 32.76% to 41.88%. Indeed, it is a lucrative strategy if investors can do so. According to the market efficiency, such a remarkable profit should not exist in the market if the investors are rational and able to arbitrage any predictable pattern in the stock returns. Although many works have attributed this return predictability by the fundamental profitability to rational motives, the irrational explanations combined with the arbitrage frictions could be more plausible according to the patterns in Table 4.3.

Apparently, Panel A of Table 4.3 indicates that the reported $EROA_{t+1}$ premium is concentrated in the lowest four deciles of the rank. Stambaugh et al. (2012) attribute this pattern to the over-pricing behaviour of the investors due to sentimental motives. Moreover, Panel A of Table 4.3 displays an interesting pattern in the idiosyncratic volatility (IVOL) and information uncertainty (INFUn) through the EROA deciles, strikingly, the IVOL and the

INFUn barely change within the highest 6 deciles (5^{th} decile to highest) then they start to increase continuously from the 5^{th} decile to lowest. These observable patterns support the prediction adopted in this work that the IVOL effect is strongly related to the information content of the projected profitability and the investors' response to this information.

Table 4.3. Single-sort analysis on the EROA and the PH52.

The table represents the single sort analysis for the EROA and PH52. Each month, the stocks are sorted into 10 deciles according to the value of EROA or PH52. Then, the returns of these decile portfolios are measured as the value- or equal-weighted returns of the stocks included in the decile over the next 3 or 12 months skipping the first month after the portfolio formation. EW_{2-12} (EW_{2-4}) is the equally-weighted average monthly return over the next 12 (3) months, and VW_{2-12} (VW_{2-4}) is the value-weighted average monthly return over the next 12 (3) months, H-L is the differential return between the highest decile and the lowest decile, 4Fα is the alpha with respect to the Carhart (1997) four-factor model, and P9-P2α is the Carhart-alpha of hedge strategy that goes long on the second-highest decile and short on the second-lowest decile. The t-stat is the newey-west t-statistic. IVOL, PH52, INFUn, Delay, and Mom represent the average value of idiosyncratic volatility, 52-week high ratio, information uncertainty index, Delay index, and past 12-month return, respectively, for each decile portfolio. The analysis covers the period from January 1996 to December 2017.

Panel A:	Sort on EROA											
	Low	P2	3	4	5	6	7	8	P9	High	H-L	4Fα	P9-P2α
EW_{2-12}	-2.64	-1.91	-0.94	-0.3	0.11	0.23	0.29	0.3	0.39	0.08	2.73	2.37	1.92
t-stats											6.87	5.66	5.71
VW_{2-12}	-2.8	-1.38	-0.36	0.14	0.45	0.52	0.36	0.35	0.51	0.69	3.49	3.38	1.45
t-stats											6.2	6.27	4.24
EW_{2-4}	-2.65	-1.87	-1.02	-0.25	0.25	0.3	0.37	0.36	0.5	0.16	2.81	2.52	2.1
t-stats											6.07	6.72	5.86
VW_{2-4}	-2.54	-1.52	-0.29	0.18	0.43	0.41	0.57	0.3	0.48	0.78	3.32	3.37	1.89
t-stats											5.1	5.66	5.54
IVOL	4.63	4.02	3.12	2.53	2.21	2.03	1.95	1.92	1.99	2.1			
PH52	0.6	0.65	0.71	0.77	0.8	0.82	0.82	0.82	0.82	0.8			
INFUn	1.83	1.11	0.34	-0.13	-0.47	-0.63	-0.67	-0.72	-0.57	-0.30			
Delay	0.64	0.61	0.56	0.51	0.48	0.47	0.47	0.46	0.46	0.47			
Mom	-7.57	-5.8	-1.85	4.76	8.57	8.41	8.16	8.72	9.59	8.97			
Panel B:	Sort on PH52												
	Low	2	3	4	5	6	7	8	9	High	H-L	4Fα	P9-P2α
EW_{2-12}	-2.71	-1.94	-1.25	-0.73	-0.19	0.04	0.25	0.42	0.51	0.5	3.22	2.24	1.54
t-stats											7.03	5.43	4.41
VW_{2-12}	-1.98	-1.26	-0.42	-0.2	0.22	0.36	0.45	0.48	0.53	0.54	2.55	1.76	0.67
t-stats											3.96	3.57	1.8
EW_{2-4}	-3.13	-2.24	-1.32	-0.67	-0.18	0.14	0.45	0.66	0.76	0.79	3.92	2.96	2.19
t-stats											5.96	8.19	7.45
VW_{2-4}	-2.36	-1.47	-0.48	-0.12	0.22	0.43	0.55	0.58	0.53	0.62	2.99	1.81	0.87
t-stats											3.79	3.63	2.11
IVOL	4.97	3.74	3.11	2.67	2.39	2.22	2.08	1.99	1.92	2.06			
EROA	-0.13	-0.08	-0.04	0.00	0.02	0.03	0.04	0.05	0.05	0.05			
INFUn	1.61	0.76	0.33	-0.02	-0.24	-0.42	-0.54	-0.62	-0.65	-0.49			
Delay	0.63	0.57	0.54	0.51	0.49	0.47	0.47	0.46	0.47	0.50			
Mom	-89.55	-29.72	-8.75	3.25	11.89	19.48	25.44	30.14	35.50	43.87			

Moreover, many studies demonstrate that the past profitability premium is a manifestation of investors' erroneous expectations regarding the future cash flows and the associated irrational pricing behaviour (for example, see, Wang & Yu 2013, Min et al. 2018, Lam et l. 2020).

To a large degree, the results displayed in Panel B of Table 3 are similar to the one shown in Panel A of Table 4.3. Generally, Investing based on the 52-week high ratio (PH52) generates premiums similar to that found for the EROA. Particularly, the observations shown in Panel B of Table 4.3 outlines an increasing pattern in the returns associated with the rising of the PH52 ratio. Considering the value-weighted return over the next 12 months, moving from the lowest decile to the highest decile of the PH52, on average, the returns rise from -1.98% to 0.54%. Thus, trading strategy that goes long on the highest PH52-decile and goes short on the lowest PH52-decile generates an economically and statistically positive premium of 2.55% (newey-west t-stats = 3.96). Adjusting this premium to Carhart’s model does not change the general conclusion, the adjusted alpha is 1.76% and significant at 1% level (newey-west t-statistic = 3.57).

Moreover, considering the more conservative case of this strategy reduces the magnitude and the significance of the premium to 0.67% (newey-west t-statistic =1.8). Probably, a large part of this reduction in the magnitude of this premium is due to the inclusion of the momentum factor in Carhart’s model. These empirical results can be generalised to other cases of the PH52 strategy. This pattern confirms the prior findings in the US and other international markets (George & Hwang 2004, Liu et al. 2011). Also, Liu et al. (2011) investigate the UK market within an international sample of 20 stock markets, they report a significant positive premium for the PH52 strategy in the UK market.

Besides, Table 4.3 shows that the PH52 strategy and the EROA strategy are similar in the concentration of the premium in the first four deciles (from the lowest decile to 4th decile). For instance, moving from the lowest decile to the 5^{th} decile, the difference in the equally-weighted return over the next 3 month (EW_{2-4}) is 2.95% (-0.18% + 3.13%) while moving from the 5^{th} decile to the highest decile generates a substantially lower difference of 0.97%. This pattern in returns of the PH52-based strategy is associated with a similar trend in the EROA. On average, the lowest four deciles contain loss stocks at the same time the deciles from the 5^{th} to the high contain profit stocks. Almost, the trend in the EROA mimics the pattern in the returns over the first four deciles of the PH52-rank. All these observations highlight and confirm the expected resemblance in the behaviour of the EROA-based and

PH52-based strategies. This resemblance in the two strategies confirms the results in George et al. (2018), which suggest that the PH52 predictive power for the future realised returns is driven by the ability of the PH52 ratio to project the future profitability and growth in investments.

However, George et al (2018) suggest the q-theory as a rationale for the documented link between PH52 and future profitability and their predictive power for the future returns, this work adopts the irrational behaviour as a plausible explanation for this relationship. This speculation on the behavioural origin is supported by the empirical results displayed in Table 4.3. Specifically, Table 4.3 shows that the anomalous low returns associated with the first four deciles of the EROA and PH52 are accompanied by lower attention from the investors (delay) and higher information uncertainty (INFUn & IVOL) hence higher transaction cost. These observations imply that the investors are more likely to miss out on the value-relevant news for the stocks with low expected profitability (EROA) and prices far from their 52-week high (PH52). Therefore, the investors underreact and miss-value these stocks which leads to a continuation pattern in their returns. Furthermore, the higher information uncertainty amplifies the consequences of this behaviour via limiting the arbitrage activities hence leads to more persistent momentum in these stocks returns (see, Shleifer & Vishny 1997, Jiang et al. 2005, and Zhang 2006).

These results are consistent with many prior studies on the underreaction of the investors to the value-relevant information (Abarbanell & Bushee 1998, Wang 2013, Akbas et al. 2017, Avramov et al. 2020, and Riedl et al. 2020).

Overall, the above discussion of the empirical results reported in Table 4.3 demonstrates the ability to predict the stock return based on the information content of the expected profitability (EROA) and the past market information (PH52) in the UK market. In specific, on average, the stocks' returns over the 12 months are positively related to the ex-ante (expected) future profitability (EROA) and the proximity of the current price to the past 52-week high price. As well, adjusting this predictive power to the risk in the context of Carhart's four-factor model reproduces the same inference. Although the results imply that the investors in the UK market could be able to generate substantial gains by applying a simple short-long hedging strategy based on these two returns predictive signals, the associated high transaction costs (e.g. information uncertainty) seem to inhibit such profitable trading strategies. Thus, cast doubt on the efficiency of the UK market.

Now we will turn to analyse the relationship between reported payoffs for the EROA and PH52 strategy on the IVOL effect.

4.4.2.2. $EROA_{t+1}$ and PH52 return-predictive power and the IVOL effect.

In the previous section, we saw how sorting stocks based on the EROA and the PH52 could generate a significant return premium. To illustrate, on average, stocks with the highest EROA decile are past winners and continue to outperform other stocks in other deciles with lower EROA over the next 12 months. Also, a similar pattern is associated with the PH52 ratio. In this section, the impact of the EROA and PH52 on the IVOL effect is analysed. The empirical results of the double-sort analysis (firstly, sort on the EROA or PH52, and then on the IVOL) and the triple-sort analysis (firstly, sort, independently, on the EROA and PH52, and then on the IVOL) are displayed.

Motivated by the reasons cited in the literature review and the empirical results reported in Table 4.3, we conjecture that the IVOL effect will be concentrated in the lowest 4 deciles of the EROA and PH52. In other words, the IVOL effect is a manifestation of the continuous poor performance of the stocks with low expected profitability and past returns. If the investors anchored to the past reference points on both the fundamentals and the market performance, they would miss out on the information related to future performance. These cognitively erroneous expectations are stronger for the firms with prior bad news (Abarbanell & Bushee 1998, Riedl et al. 2020).

The performance of the IVOL effect will be analysed on the level of the EROA and PH52, separately and jointly. To this end, each month, the stocks will be allocated equally into 3 portfolios according to the EROA or PH52, then, within each group, the stocks resorted into another 3 portfolios according to the IVOL. Consequently, 9 different portfolios will be created. The objective of this process is to test the magnitude of the IVOL effect within a different level of EROA or PH52. In addition to the separate effect, we will test the joint of EROA and PH52 on the IVOL effect. For this purpose, each month, the stocks will be allocated into two equal groups (Low & high) based on the EROA or PH52. Then, 4 intersection portfolios will be created from these Low and High portfolios of EROA and PH52. To clarify, the stocks with Low EROA and Low PH52 will be in one portfolio and so on. Next, within each one of these 4 portfolios of EROA and PH52, the stocks will be reallocated into 3 portfolios according to the IVOL value. By that, we can analyse the IVOL effect based on the EROA and PH52 jointly. After formation, the performance of these portfolios will be checked by their average returns over the next 12 months. The conditional IVOL effect will be represented in raw returns and by Carhart’s adjusted alpha. Moreover, the significance of this differential performance will be measured by newey-west t-statistics.

Table 4.4 Effect of the EROA and PH52 on the performance of the IVOL puzzle.

This table represents the analysis of the IVOL effect conditional on the level of EROA or/and PH52. Panels A & B show the double-sort analysis of the IVOL effect within the different levels of the EROA or PH52. Firstly, each month, the stocks are sorted into tercile based on the EROA or PH52, then, within each tercile, the stocks are resorted into another three portfolios based on the IVOL. The performance of the IVOL effect is evaluated at the level of EROA or PH52. In Panel C, independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value- and equal-weighted differential returns between the highest and the lowest IVOL-based portfolio. The analysis spans the period from January 1996 to December 2017. t-stats is the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

Panel A		EROA then IVOL													
		EW							VW						
		IVOL Level							IVOL Level						
EROA		Low	M	High	H-L	t-stats	4Fα	t-stats	Low	M	High	H-L	t-stats	4Fα	t-stats
Low		-0.65	-1.81	-2.51	-1.86	-4.39	-1.86	-5.66	0.00	-1.76	-2.79	-2.79	-4.85	-2.88	-6.23
M		0.51	0.40	-0.46	-0.97	-3.65	-1.08	-5.27	0.56	0.46	-0.09	-0.65	-2.22	-0.71	-3.18
High		0.48	0.54	-0.27	-0.76	-3.14	-1.11	-5.16	0.50	0.52	-0.09	-0.59	-1.86	-1.16	-3.33
Diff					-1.10		-0.75					-2.20		-1.73	
t-stats					-4.06		-4.09					-5.24		-4.48	
Panel B		PH52 then IVOL													
		EW							VW						
PH52		Low	M	High	H-L	t-stats	4Fα	t-stats	Low	M	High	H-L	t-stats	4Fα	t-stats
Low		-0.88	-1.89	-2.83	-1.96	-5.70	-2.13	-6.88	-0.24	-1.28	-2.96	-2.72	-5.89	-2.88	-8.00
M		0.33	0.17	-0.90	-1.23	-3.69	-1.53	-5.84	0.44	0.31	-0.69	-1.14	-3.08	-1.72	-4.89
High		0.63	0.64	0.09	-0.53	-2.18	-1.22	-5.44	0.55	0.56	0.07	-0.48	-1.84	-1.41	-4.53
Diff					-1.42		-1.16					-2.24		-1.72	
t-stats					-5.89		-5.23					-5.58		-4.22	
Panel C		Joint effect of EROA and PH52 on the IVOL													
		EW							VW						
PH52	EROA	L	M	H	H-L	t-stats	4Fα	t-stats	L	M	H	H-L	t-stats	4Fα	t-stats
Low	Low	-0.82	-1.92	-2.67	-1.85	-5.15	-1.99	-5.91	-0.17	-1.58	-2.87	-2.70	-5.56	-2.92	-7.28
	High	0.04	-0.09	-1.00	-1.04	-3.99	-1.25	-5.58	0.23	0.07	-0.81	-1.04	-2.76	-1.10	-5.12
High	Low	0.56	0.26	-0.60	-1.16	-3.70	-1.64	-5.64	0.49	0.31	-0.84	-1.33	-3.99	-2.05	-5.86
	High	0.60	0.69	0.56	-0.04	-0.24	-0.65	-3.29	0.56	0.67	0.49	-0.07	-0.29	-1.00	-3.40

Table 4.4 displays the empirical analysis of the EROA and PH52 impact on the IVOL effect. Panel A of this table represents the double-sort analysis to test the separate effect of EROA and PH52 on the IVOL-based strategy’s payoffs while in Panel B the triple-sort analysis is represented to test how the EROA and PH52 jointly influence the anomalous returns generated by the IVOL-based strategy. Many interesting observations deserve highlighting.

The general pattern in Panel A of Table 4.4 reveals that the so-called IVOL effect is diminishing in the expected profitability (EROA). Specifically, moving from the tercile of stocks with the lowest EROA to the tercile of stocks with the highest EROA, the economic and statistical significance of the difference between the high IVOL group and the low IVOL group weakens markedly. For example, the magnitude of the value-weighted IVOL effect diminishes from -2.79% (newey–west t-stats = -4.85) within the high EROA group to -0.59% (newey–west t-stats = -1.86) within the lowest EROA group. The difference between the IVOL effect in low and the high EROA groups is -2.20% and statistically significant at 1% level (newey–west t-stats = -5.24). Strikingly, adjusting these raw differences (i.e. the IVOL effect) to the risk factors suggested by Carhart's model does not reduce the IVOL effect, rather produces a stronger one especially for the high EROA tercile. For instance, again considering the value-weighted scheme, the Carhart's risk-adjusted alpha of the IVOL-based strategy is -1.16% (newey-west t-stats = -3.33); which is stronger, economically and statistically, than the raw differential returns of -0.59% (newey–west t-stats = -1.86). Nevertheless, the risk-adjusted IVOL effect in the low EROA group is still considerably stronger than the counterpart in the high EROA group, the difference is -1.73% (newey–west t-stats = -4.48). This interesting observation highlights the role of the employed asset pricing model, as a benchmark, in generating part of the anomalous IVOL effect and other pricing anomalies. This in turn indicates the necessity of amending these models in the direction that enhances their explanatory power for these anomalies. Later, we will return to this point in more detail.

In this sense, the empirical evidence in Panel A of Table 4.4 confirms this study's prediction regarding the concentration of the so-called IVOL effect within the group of stocks with poor expected profitability – more than half of the IVOL effect is attributed to the group of stocks with low EROA. The observations displayed previously in Table 4.3 reveal that the stocks with low expected profitability (lowest 4 deciles) are more likely to have high IVOL, low attention index, and notably performed poorly in the past 12 months. Panel A of Table 4 reveals the poor performance of the low EROA group persists in the next 12 months especially for the stocks with high IVOL levels. Collectively, these observations support the underreaction behaviour as a credible explanation for these anomalous payoffs generated by the low EROA and high IVOL stocks. Specifically, if the investors are inattentive to news related to future profitability, they would underreact to the predictably persistent poor fundamental profitability. In general, this conclusion is consistent with the prior evidence on the investors' misevaluation of the information relevant to the firms' future profitability in the UK market (see, Setiono and Strong 1998, Jiang et al. 2016, and Papanastasopoulos 2020). Interestingly, Jiang et al. (2016) investigate the investor's pricing behaviour of the loss firms in the UK market and demonstrate the failure of investors to fully incorporate information relevant to the persistent losses within these firms. A similar conclusion has been reached by Papanastasopoulos (2020).

Another observation that deserves highlighting is the performance of the stocks in the high EROA and high IVOL groups. On average, the performance of these stocks appears to exhibit a reversal behaviour. To illustrate, in contrast to other groups in the high EROA tercile, the stocks with high IVOL show a relatively poor performance rather than continuing the record of past gains in a similar way to other subgroups in this tercile. For instance, Panel A of Table 4.4 displays that, within the high EROA tercile, the group of the socks with high IVOL generate, on average, negative returns of -0.27% (for the EW case) and -0.09% (for the VW case) over the next 12 months.

Panel B of Table 4.4 represents the double-sort analysis of the PH52 and the IVOL. Similar to Panel A of this table, the portfolios are constructed by sorting the stocks first on the PH52 and then, dependently, on the IVOL. The variation of the IVOL effect on the PH52 levels is similar to that shown in Panel A of Table 4.4 for the EROA levels. On average, the farther the stocks from their 52-week high value the stronger the IVOL effect. For example, the value-weighted spread, in the raw returns, between the high IVOL stocks and the low IVOL stocks is -2.72% (newey-west t-stats = -5.89) for the low PH52 tercile but weakens to only -0.48% (newey-west t-stats = -1.84) for the high tercile of PH52. The difference of -2.20% between these IVOL zero-cost strategies within the extreme levels of PH52 is significant at the 1% level (newey-west t-stats = -5.58). Again, adjusting these raw spreads to the Carhart (1997) model produces a significant difference of -173% (newey-west t-stats = -4.22).

These results confirm the concentration of the IVOL effect within the stocks with a low PH52 ratio. Prior studies refer to this PH52 predictability of returns to the anchoring bias by the investors (George & Hwang 2004, and Li & Yu 2011). George and Wang (2004) argue that the stocks with low PH52 are more likely to receive bad news and the investors intend to miss this news as they anchored to the past 52-week high point. Therefore, consistent with the results for EROA, the investors are more likely to underreact for the news relevant to the value of stocks with bad prior market performance (low PH52). As shown in Table 3, these stocks are associated with higher information uncertainty (INFUn) which prohibits the arbitrage activity and thus leads to more persistent poor performance for these stocks. This explanation is in line with the study of Burghof & Prothmann (2011), who study the UK market and find that the 52-week high momentum strategy is stronger for stocks with high information uncertainty.

However, the IVOL effect is stronger for the stocks with low expected profitability (EROA) and current price distant from its 52-week high, this anomalous behaviour persists in other groups of stocks even in the highest tercile of EROA and PH52. Panel C of Table 4.4 reports the results of the triple sort on the EROA, PH52, and IVOL. As mentioned before, this analysis aims to analyse the joint impact that both EROA and PH52 impose on the IVOL effect. The results reveal the absence of the IVOL effect in the stocks with good news (i.e., high EROA and high PH52).

Either weighted by market value or equally, the average monthly returns over the next 12 months are almost stable over the three IVOL-based portfolios generated within the group of stocks with high EROA and high PH52. To illustrate, the equal-weighted spread between the high IVOL portfolio and the low IVOL portfolio is indistinguishable from zero with a value of -0.04% (newey-west t-stats = -0.24). The same result holds for the value-weighted case. Nonetheless, this absence of the IVOL effect in the raw term does not hold out against adjusting for the risk factors in Carhart (1997) model. To clarify, within the high-EROA and high-PH52 group of stocks, the risk-adjusted alpha of the IVOL-hedge strategy is -0.65 (newey-west t-stats = -3.29) for the equal-weighted scheme and -1% (newey-west t-stats = -3.4) for the value-weighted scheme.

These findings state that the market-based information, proxied by the PH52, and the fundamental-based information, proxied by the EROA, jointly explain the IVOL effect. In other words, in the absence of the negative news about the market and the fundamentals, the reported anomalous negative differential return of the high IVOL stock disappears completely. Moreover, regarding the significant alpha of the IVOL-hedge strategy within the group of stocks with positive news, we can refer this to the misspecification of the employed version of the Carhart model. This version is constructed by Gregory et al. (2013). They conclude that despite its superiority over the single factor model of CAPM, their version of the Carhart model is still misspecified. Moreover, they suggest that adding other factors such as the profitability factor might mitigate this insufficiency. We will deal with this issue later in this work.

Overall, the results reported in Table 4.4 confirm the main conjecture here and suggest that to a large extent the IVOL effect is a manifestation of the investor's underreaction to flowing negative news and the simultaneous high information uncertainty. Further, the results imply that both market-based information and fundamental-based information regarding the prospect is important to explain the IVOL effect in particular, and the pricing anomalies in general.

In the next section, the above stocks sorting technique will be supplemented by the Fama-MacBeth cross-sectional regression.

4.4.3. Fama and MacBeth Cross-sectional Regression.

Under this section, the analysis is extended by performing the multivariate Fama and MacBeth (1973) cross-sectional regression. In the sorting technique, it is difficult to control for a large set of variables, even sorting on only two variables leaves the constructed portfolio with a low number of stocks. Besides that, grouping the stocks ignores the relationship between the tested variables within the created layers. To address these issues, the widely used Fama-Macbeth cross-sectional regression is employed. In this two-stage approach, the association between the future returns and the IVOL, the EROA, and the PH52 can be analysed while simultaneously controlling for a large set of other well-known returns predictors. Specifically, in the first stage, a variant of the following full set regression is fitted on monthly basis,

$$R_{it+12} = \alpha_t + B_{1t}\, IVOL_{it} + B_{2t}\, PH52_{it} + B_{3t}\, EROA_{it} + \sum_{j=1}^{J} \gamma_j Z_{jit} \qquad (16)$$

Where R_{t+i} denotes the average monthly return over the next 3 or 12 months on stock i, $IVOL_{it}$ is the idiosyncratic volatility of stock i at month t, $PH52_{it}$ is the 52-week high of stock i at month t, $EROA_{it}$ is the expected profitability of stock i at month t, and Z_{jit} is a vector of control variables for stock i at month t. This selected set of control variables includes maximum returns (lottery-effect proxy), past month return, midterm price momentum (return over the past six months), stock market beta, downside beta, growth in assets, market value, book-market ratio, earning-price ratio, information uncertainty index, unrealised capital gains (over the past three years), zero-days ratio, price impact liquidity measure. All these controlling variables are measured at the end of the past month. For more details about these controlling variables, please, refer to the variables' definitions in the methodology section. For the purpose of comparison, Equation 16 is estimated with a different set of variables. In the second stage of the analysis, a monthly time-series of the coefficients estimated in the first step is generated. Then, these time-series of the estimated coefficients will be tested by the newey-west t-statistic against the null hypothesis of being undistinguished from zero. The Fama-MacBeth regression spans the period from January 1996 to December 2017.

Table 4.5 displays the time-series averages of the slope coefficients from the Fama-MacBeth (1973) cross-sectional. The t-statistics are computed with newey-west standard errors and shown beneath each corresponding coefficient. Generally, the analysis is performed using the average monthly returns over the next 3 months or 12 months, skipping the first month after the variable measurement date. The results for the control variables are suppressed to save space.

The results outlined in Table 4.5 reconfirm the previously reported confusing negative relationship between the idiosyncratic volatility and the future realised returns, namely, the so-called IVOL effect. In particular, columns 1 and 2 (C1 & C2) of Table 4.5 show that the average slope coefficients of regressing the subsequent stocks return over 3 and 12 months on the current IVOL are -0.72 and -0.66, the newey-west t-statistics are -4.95 and -5.49 respectively. In the first chapter of this academic work a similar, in sign and magnitude, the relationship between the subsequent month returns and the IVOL had been reported for the UK market. Intuitively, this observation suggests that the IVOL effect is more than a transient short-term phenomenon.

The results under columns C3 and C4 in Table 4.5 confirm the results reported in Table 4.3 regarding the positive EROA-return predictive relationship. The average slope coefficients of the EROA is 3.13 (newey-west t-stats = 5.11) and 3.46 (newey-west t-stats = 6.1) for the 3- and 12-months horizon respectively. Interestingly, the results under columns 3 and 4 are consistent with the trend uncovered by the sorting approach which affirms the importance of the information content of the ex-ante profitability (EROA) with respect to the reported IVOL effect. The inclusion of the EROA to IVOL in the cross-sectional regression reduces the magnitude of the coefficient on the IVOL. In particular, C4 shows that after the inclusion of the EROA the average slope coefficients on the IVOL, almost, shrank by a third from -

0.66 to -0.47. However, the IVOL effect keeps its high statistical significance. This result suggests that a significant part of the IVOL effect is related to future profitability.

Table 4.5 Fama and MacBeth Cross-sectional regression results.

This table represents the Fama-MacBeth cross-sectional regression. The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stocks are regressed on IVOL, EROA, PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), the logarithmic value of the Amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017. *, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

	C1	C2	C3	C4	C5	C6	C7	C8
VARIABLES	R3M	R12M	R3M	R12M	R3M	R12M	R3M	R12M
IVOL	-0.72***	-0.66***	-0.53***	-0.47***	-0.28**	-0.32***	-0.12	-0.15*
t-stats	(-4.95)	(-5.49)	(-4.32)	(-4.53)	(-2.59)	(-3.33)	(-1.34)	(-1.84)
EROA			3.13***	3.46***			2.760***	3.22***
t-stats			5.11	6.1			4.96	5.99
PH52					4.98***	3.71***	4.84***	3.57***
t-stats					7.9	7.17	7.92	7.02
Constant	1.47***	1.29***	0.99***	0.78***	-3.56***	-2.48***	-3.85***	-2.82***
t-stats	4.71	4.63	3.24	2.74	(-5.09)	(-4.07)	(-5.43)	(-4.55)
Control	no	no	no	no	no	no	no	no
Observations	133779	133779	133779	133779	133779	133779	133779	133779
R-squared	0.055	0.083	0.066	0.101	0.083	0.115	0.093	0.131

	C9	C10	C11	C12	C13	C14
VARIABLES	R3M	R12M	R3M	R12M	R3M	R12M
IVOL	-0.07	-0.11	-0.18	-0.12	0.05	0.0858
t-stats	(-0.75)	(-1.39)	(-0.919)	(-0.78)	0.31	0.62
PH52	3.09***	2.59***	5.2***	4.85***	3.76***	3.76***
t-stats	4.94	4.29	4.08	4.76	3.80	5.096
EROA	1.84***	2.4***	4.12***	4.13***	3.69***	3.77***
t-stats	2.89	4.15	3.17	4.23	3.24	4.73
PH52*EROA			-5.72***	-5.47***	-4.78***	-4.58***
t-stats			(-3.65)	(-4.45)	(-3.7)	(-4.72)
EROA*IVOL			-0.52	-0.513*	-0.61**	-0.63***
t-stats			(-1.6)	(-1.953)	(-2.12)	(-2.6)
PH52*IVOL			-0.32	-0.47**	-0.56***	-0.68***
t-stats			(-1.1)	(-1.98)	(-2.63)	(-4.12)
EROA*PH52 *IVOL			1.41***	1.34***	1.37***	1.32***
t-stats			3.10	3.50	3.63	3.84
Constant	-2.49***	-2.38***	-3.06***	-2.92***	-2.61**	-2.9***
	(-2.78)	(-3.033)	(-2.68)	(-3.3)	(-2.49)	(-4.08)
Control	yes	yes	no	no	yes	yes
Observations	130869	130869	133779	133779	130869	130869
R-squared	0.16	0.20	0.10	0.14	0.17	0.212

Similarly, the PH52-momentum pattern revealed in Table 4.3 above is confirmed by the results shown under columns C6 and C7 in Table 4.5. The 52-week high ratio (PH52) positively predicts the stock returns over the next 12 months. Column C6 shows that the average slope coefficients of PH52 is 3.71 and it is not only significant in the economical term but also highly statistically significant with a newey-west t-statistic of 7.17. Also, similar to the EROA, the information content of the PH52 seems to be highly related to the IVOL effect. In other words, the inclusion of the PH52 information to regression with IVOL absorbs a good part of its predictability power of the future returns. For instance, considering the effect over the next 12 months, the average slope coefficients on the IVOL is halved -0.32, however, it remains statistically significant with a newey-west t-statistic of -3.33.

The above results highlight the importance of the information contained in EROA and PH52 in explaining the IVOL effect but only partially. Regardless of the relative importance, neither the EROA nor the PH52 on its own can absorb the total effect of IVOL on future returns.

In light of this, is the information contained in the expected profitability (EROA) and past price information (PH52) non-redundant and hold an incremental explanatory power for the IVOL effect? To answer this question, under columns C7 and C8, the Fama-MacBeth cross-sectional regression is performed while including IVOL, EROA, and PH52 on the right-hand side of equation 16.

The empirical results listed under columns C7 and C8 validate the main conjecture under this work that the fundamental-based expected profitability (EROA) and the past price-based signal (PH52) are both important in explaining the IVOL effect, and they can jointly explain a substantial part of this anomalous pricing behaviour. Indeed, the results reveal that, parsimoniously, controlling for the EROA and PH52 can fully explain the negative association between the IVOL and the subsequent returns. For instance, column C8 shows that controlling for the EROA and PH52, the average slope coefficients for the IVOL is only -0.12 and statistically insignificant with a newey-west t-statistic of -1.34. For the returns over the next 12 months, the IVOL effect is significant but only at a 10% level. A possible explanation for this remaining, marginally significant, IVOL effect is the reversal in returns that the main variables considered in this study (i.e. EROA and PH52) left behind. For instance, in the first empirical chapter (i.e., chapter 2) the IVOL effect is treated as part of the lottery-like effect, i.e., the investors' preference for the stocks with the extreme observations of returns in the recent past period. By its nature, the lottery effect is likely to explain the short-term reversal in the lottery-like stock prices (e.g., the high-IVOL stocks).

Despite controlling for the competing return predictors, the same inference about the explanatory power of the EROA and PH52 is holding. Columns C9 and C10 display the results for the cross-sectional regression that adds a full set of control variables to the EROA, PH52, and IVOL. Under this multivariate regression, the EROA and PH52 maintain their economical and statistical significance. Considering the predictability over the next 12 months, the average slope coefficients of the EROA and PH52 is 2.4 (newey-west t-statistic is 4.15) and 2.59 (newey-west t-statistic is 4.29) respectively. The IVOL is completely insignificant under this multivariate setting.

Columns C11-C12 represent the cross-sectional regression with interaction terms between the primary variables in this study, namely, the IVOL, the EROA, and PH52. In specific, the returns over the next 12 or 3 months are regressed against the IVOL, the EROA, the PH52, and the interaction between these three variables. It should be noted that under this analysis the EROA and PH52 are replaced by their rank rather than the original continuous version. To illustrate, each month, the stocks are sorted into 10 equal groups (from 1 to 10) according to their levels and then divide this rank index by 10. The main purpose of this regression is to test the movement of the IVOL effect over the different levels of the EROA and PH52 in a multivariate set.

The results confirm the determinant effect that the EROA and PH52 impose on the IVOL effect. Except for the independent IVOL term, the other averages slope coefficients are economically and statistically significant. Notably, the main effect of the EROA and PH52 stay positive and significant with an average slope of 4.13 (newey-west t-statistic is 4.23) and 4.85 (newey-west t-statistic is 4.76) respectively. Controlling for the continuation trend associated with these important returns' predictive signals, the interaction term of EROA*PH52*IVOL is positive of 1.34 and highly statistically significant with newey-west t-statistic of 3.5. This positive slope of the EROA*PH52*IVOL indicates that, at a given level of the EROA and the PH52, the return-continuation trend predicated by the EROA and PH52 is amplified by the higher value of IVOL. Moreover, this result is consistent with the reported arbitrage-friction role of the high idiosyncratic volatility (see, Pontiff 2006, and Au et al. 2009).

The results displayed in Table 4.4 and 4.5 suggest that a large part of the IVOL effect is attributed to the price momentum associated with the investors' underreaction to the trends in the stocks' prices and profitability. However, the results also indicate that the IVOL effect, however with a weaker power, goes beyond the continuation effect and predicts reversibility in the returns of some stocks. To illustrate, the average slope coefficients of the interaction terms of IVOL*EROA and IVOL*PH52 are -0.513 and -0.47 respectively. Interestingly, these two terms are significant only with the next 12 months horizon while insignificant for the 3-month horizon. Controlling for the continuation behaviour, this could be an indication of reversal in the returns of some stocks over the next 12 months. The sorting analysis displayed in Table 4.4 could give some directions on the nature of these stocks. Particularly, Panel C of Table 4.4 shows that for the stocks falling in the high EROA and high PH52 group, the higher value of the IVOL dictates poor performance in the next 12 months. Also, the results show that the stocks with inconsistent profitability signals (e.g. Low EROA and high PH52 or the reverse) and high value of the IVOL generate, on average, a negative return over the next 12 months. It seems that the investors allocate their limited cognitive ability to process one of these information alternatives (i.e. fundamental Vs market) and neglect the information content of the other sources (see, Peng and Xiong 2006). Consequently, the investors overshot the prices of these informationally uncertain stocks. All in all, the higher IVOL is always a signal of poor performance in the next midterm horizon.

All the above discussion suggests that the IVOL effect is largely a manifestation of the investors' inattentive response to the news revealed by the price-based news and the fundamentals regarding the stock's prospects. This pattern may be explained by the documented evidence on the investors' exposure to the anchoring bias. Under this cognitive error, the investor forms his/her expectations about the future cash flow depending on an irrelevant past reference point. For instance, Hwang and George (2004) argue that the investors believe there is no more room for the movement in the direction of the past price-trend when the current stock price is near or farther from its past 52-week high. Consequently, they conclude that the investors erroneously underestimate the likelihood of further going up (down) when the price is close to (far from) the past 52-week high. Ultimately, they underreact to the continuous trend and the well-documented price-momentum in the stock returns emerge (also see, Hao et al 2018). Moreover, the prior evidence demonstrates that the practitioners, both the individuals and the professionals, fail to respond promptly to the news related to future profitability when this news is close to the record (Loh and Warachka 2012, Akbas et al 2017, Avramov et al 2020, and Jang et al 2020). Therefore, the expected profitability (e.g. EROA) predicts the subsequent stock returns and generates momentum in the price. Notice that the results in Table 4.1 show that most of the fitted profitability value (the EROA) is generated by the persistent part of lagged profitability.

Collectively, the results shown in Tables 4.4 and 4.5 confirm the conjecture that the IVOL effect is a manifestation of the returns predictability by the expected profitability and the 52-week high ratio. Investors' underreaction to the poor performance of the stocks seems to generate most of this anomalous negative performance of the stocks with high IVOL. To a lesser degree, the IVOL effect is also found to be an indication of the overvaluation and the subsequent reversal in the prices of the stocks in the UK market.

4.5. Further Issues and the Robustness Checks.

In this section, further analysis of the main relationships tested above in this study is shown. Also, a battery of robustness tests is performed, including (i) time series analysis and alternative risk models, (ii) alternatives proxy of the expected profitability, (iii) subsamples analysis, (iv) alternative explanation.

4.5.1. Time-series Analysis: EROA and PH52 Factors Vs Currently Used Models.

In the following, a model with pricing factors that mimic the reported cross-sectional premium for the strategies based on the EROA and PH52. The purpose of this step is to check whether the explanatory power of the EROA and PH52 is held in the time-series setting as in the cross-sectional setting. Specifically, the subsection checks whether the monthly excess returns generated by the EROA and the PH52 mimicking portfolios could explain the IVOL effect in a better way than the widely employed risk factors (e.g. the Fama and French three-factor model).

To this end, a methodology similar to the traditional factor-construction method originally inspired by Fama and French (1993) is employed. As well known, most of the widely used models of asset pricing are built following this nonparametric method of factor construction. Practically, for the specific return's predictors, the pricing factor is generated by grouping the stocks sample into portfolios that mimic the different levels of this priced characteristic. Then, the value-weighted excess returns of these groups are measured over a suitable time interval. Commonly, these factor-mimicking excess returns are weighted by market capitalisation over a monthly basis. Usually, the sorting step is based on a multi characteristics to account for the observed high correlation between these characteristics. For example, the small-minus-big (SMB) factor in the Fama and French (1993) is built by sorting the stocks into size-based groups with different levels of the book-to-Market ratio.

The suggested model here is motivated by the so far reported empirical results. In addition to the market, the size, and the investment factors in the q-factor model of Hou et al. (2015), two additional factors will be constructed to mimic the EROA and the PH52 return predictive power. To this end, monthly, the stocks are sorted according to the EROA and PH52. Specifically, the stocks will be sorted into three groups on the sample breakpoints for the bottom 30%, middle 40%, and upper 30%. Also, the stocks are sorted according to the investment-to-assets (asset growth) in the same way. Two size groups are created using 70% of the ranked values as a breakpoint. The EROA and the PH52 factors are rebalanced monthly, while the size and the investment factors are rebalanced annually, each June.

To build the EROA factor and the PH52 factor, each month, the stocks are sorted, independently, into two market value groups, three EROA groups, three PH52 groups, and three investment groups. Creating 18 portfolios by intersecting these groups (2×3×3), the PH52 factor is defined as the difference between the average returns of the six high PH52 portfolios and the six low PH52 portfolios. The EROA factor is neutralised to the size effect and the investment effect, by intersecting the three EROA groups with the two size groups and three investment groups. Then, the EROA is calculated as the difference between the average returns of the six high EROA portfolios and the six low EROA portfolios. The size factor is calculated as the difference between the average returns of the nine small-size portfolios and the nine big-size portfolios. Similarly, the investment factor is the difference between the six low investment portfolios and the six high investment portfolios. Perhaps using a triple sort technique helps, to some extent, in neutralising the overlapped components between these four pricing factors.

For the sake of comparison, two widely applied models of Carhart (1997) and Hou et al. (2015) are constructed using the same sample of stocks used in this study.

Table 4.6 represents the IVOL effect after controlling the suggested pricing characteristics. Panel A of Table 4.6 shows that adding the EROA and the PH52 factors to the market and size factors reduce the alpha of IVOL based strategy considerably. The adjusted alpha of the

IVOL effect is reduced from the highly significant of -2.71 (newey-west t-statistic is -3.6) to the marginally significant of -1.39 (newey-west t-statistic is -1.9). This sizable reduction in the IVOL effect is a clear indication of the significant impact of the EROA and the PH52 exert on the reported IVOL effect. Moreover, adding the investment factor does not remarkably influence the IVOL effect. The results reveal that adding the investment factor (Q5F) to the equation reduces the IVOL strategy alpha slightly to -1.34 (newey-west t-statistic is -1.92). The comparison with Hou (2015) 4-factor model shows that both models (Q5F vs Q4F) produce similar explanatory power for the IVOL effect. Perhaps in terms of simplicity and parsimony, the Q 4-factor of Hou et al. (2015) is preferable.

Table 4.6 Pricing performance of the EROA and PH52 factors.

the table represents the single sort analysis for the IVOL. Each month, the stocks are sorted into 10 deciles according to the value of IVOL. Then, the returns of these decile portfolios are measured as the value-weighted returns of the stocks included in the decile over the next 1 or 12 months skipping the first month after the portfolio formation. H-L is the differential return between the highest decile and the lowest decile, Car4F is the alpha with respect to the Carhart (1997) four-factor model, 4FEroe&PH is the alpha of the model that includes the market, the size, the ph52, and the EROA factors, Q5F is the alpha of model that includes the market, the size, the ph52, the EROA factors, and the investment factors, and Q4F is the alpha with of the Hou et al. (2014) Q-factor model. The t-stat is the newey-west t-statistic. The analysis covers the period from January 1996 to December 2017.

Panel A	IVOL effect Next 1-month									
Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	H-L
RP	0.22	0.29	0.3	0.46	-0.07	-0.13	-0.42	-0.97	-2.07	-3.82	-4.04
Car4F	-0.22	-0.03	-0.1	0.2	-0.28	-0.25	-0.39	-0.6	-1.43	-2.68	-2.71
t-stats	-1.56	-0.23	-0.64	0.94	0.27	-0.94	-1.05	-1.57	-2.92	-3.76	-3.6
$4F_{Eroe\&PH}$	-0.34	-0.22	-0.23	0.23	-0.25	-0.01	0.13	0.28	-0.49	-1.48	-1.39
t-stats	-2.28	-1.48	-1.26	1.02	-0.88	-0.01	0.42	0.76	-1.03	-2.31	-1.9
Q5F	-0.34	-0.26	-0.24	0.23	-0.24	0.04	0.2	0.2	-0.4	-1.42	-1.34
t-stats	-2.31	-1.73	-1.32	1.03	-0.84	0.14	0.65	0.65	-0.89	-2.17	-1.92
Q4F	-0.31	-0.13	-0.1	0.31	-0.21	-0.03	-0.12	0.05	-0.44	-1.37	-1.32
t-stats	-1.93	-0.87	-0.53	2.66	1.43	0.94	0	0.15	-1.02	-2.07	-1.89
Panel B	Next 12-month										
Variable	P1	P2	P3	P4	P5	P6	P7	P8	P9	P10	H-L
RP	0.24	0.24	0.24	0.23	0.06	-0.08	-0.53	-1.1	-2.35	-2.89	-3.13
Car4F	-0.02	-0.09	-0.2	-0.14	-0.2	-0.48	-1.08	-1.33	-2.37	-1.81	-1.97
t-stats	-0.1	-0.64	-1.68	-1.02	-1.26	-3.09	-3.28	-3.9	-5.01	-2.89	-2.81
$4F_{Eroe\&PH}$	-0.44	-0.52	-0.56	-0.34	-0.42	-0.15	-0.31	0	-0.56	0.08	0.27
t-stats	-2.26	-2.52	-2.38	-1.99	-1.76	-0.78	-1.06	0.01	-0.97	0.18	0.55
Q5F	-0.38	-0.52	-0.53	-0.49	-0.47	-0.17	-0.17	0.1	-0.55	-0.11	0.02
t-stats	-2.25	-2.5	-2.28	-2.47	-1.76	-0.86	-0.57	0.25	-0.85	-0.21	0.04
Q4F	-0.43	-0.4	-0.49	-0.34	-0.38	-0.19	-0.64	-0.46	-1.33	-0.15	-0.02
t-stats	-1.82	-1.71	-2.15	-1.72	-1.45	-0.78	-1.75	-1.01	-2.37	-0.33	-0.04

The results displayed in Panel B of Table 4.6 demonstrate that considering the next 12-month horizon, the sizable IVOL effect, reported previously in the term of raw returns and Carhart

(1997) adjusted-alpha, is completely vanished when the factors related to the EROA and PH52 are included in the pricing equation. The adjusted-alpha of the IVOL hedging strategy over the next 12-month is indistinguishable from zero of 0.27 with a newey-west t-statistic of 0.55. Therefore, consistent with the sorting approach and the Fama-MacBeth cross-sectional regression, the time analysis revealed in Table 4.6 shows that the EROA and PH52 can explain a large part of the IVOL effect in the short-term and completely subsume the persistent inverse returns predictability by the IVOL observed over the midterm horizon.

Table 4.7 represents the Gibbons, Ross, Shanken (1989) joint test of asset pricing performance. The testing assets are the 10 IVOL portfolios. Under this test, the joint explanatory power of a specific pricing model is examined against the null hypothesis that all alphas of the priced trading strategies are zero. The results indicate that, at a 5% significance level, the GRS test is not significant with a value of 1.83 for the 4FEroe&PH model. In comparison with the widely used Carhart 4-factor model, the models that add the EROA and PH52 to the pricing function produce a substantially lower absolute alpha and higher explanatory power.

Table 4.7 Overall performance test (GRS test) of the alternative pricing models.

This table represents the overall pricing performance of the proposed 4FEroe&PH and Q5F models and the Carhart (1997) 4-factor model and the Hou et al. (2014) Q-factor model. The test assets are the excess return of the 10 IVOL-based decile portfolios. The table reports the average alpha (Av), the Gibbons, Ross, Shanken (1989) joint test (GRS), the probability value of the GRS test (p (GRS)), and the average of determination coefficients (Av (Rsq)), the standard error of alpha, the average of absolute alpha (IαI), and the Sharpe ratio of the corresponding alpha (SR (α). The analysis covers the period from January 1996 to 2017.

Model	Av(α)	GRS	p(GRS)	Av(Rsq)	SE(α)	IαI	SR(α)
Car4F	-0.578	3.079	0.001	0.629	0.281	0.617	0.374
$4F_{Eroe\&PH}$	-0.238	1.832	0.056	0.650	0.280	0.366	0.301
Q5F	-0.207	1.798	0.061	0.650	0.282	0.371	0.300
Q4F	-0.222	1.490	0.143	0.640	0.283	0.293	0.270

It is important to notice that the role of the above analysis is not to suggest the EROA and the PH52 as a pricing factor. This goal is out of this study scope and requires more careful investigation. Rather, the goal is simply to support that previous cross-sectional analysis with time-series evidence on the significant association between the IVOL effect and the EROA and the Ph52.

Generally, the above empirical results are in line with Gregory et al. (2013) comment on the misspecification of the Fama and French (1993) and Carhart (1997) pricing factors and the need to modify them by investigating other potential pricing mechanisms such as the profitability channel. However, it is premature to defend the comprehensive ability of the

EROA and the PH52 factors to price the assets in the UK market. We can consider these findings as preliminary results and suggestions for a larger-scale test.

4.5.2. Alternative Measures of Profitability.

Under this section, the main investigation performed in the main body of this study is repeated by replacing the ROA with other alternative measures of accounting profitability. Following Hou et al (2015), the first alternative is the returns on equity (ROE). Secondly, Fama and French (2015) employ the operating profitability (Op) which is measured as the last available operating earnings scaled by lagged book equity. The third alternative is the cash operating profitability which is measured as the operating earnings minus the working accruals all divided by book assets. Ball et al. (2016) demonstrate that cash operating profitability (Cop) is a more powerful returns predictor than the other widely used accounting profitability measures.

Similar to the cross-sectional approach employed to fit the EROA, the expected value of the three alternative profitability measures is estimated by fitting the currently available observations of ROA on a set of lagged earnings predictors. Of course, the predictors set is the same one that was employed in the ROA prediction regressions.

Table 4.8 displays the empirical results for the alternative profitability measures. The shown figures represent the adjusted alpha of the IVOL long/short strategy conditional on the level of the PH52 and one of the expected profitability measures. The revealed patterns are closely comparable to those found for the EROA. The IVOL effect is concentrated in the stocks with low expected profitability and price farther from the 52-week high. The IVOL effect is magnified when the low expected profitability (EROE or ECop or EOp) coincides with low PH52. For example, considering the expected returns on equity, the excess returns for the IVOL-hedge strategy within a group of stocks with low EROE and low PH52 is -2.82% with a newey-west t-statistic of -5.28. In contrast, implementing the IVOL-hedge strategy within the group of stocks with high EROE and high PH52 generates insignificant excess returns of -0.29 (newey-west t-statistic = -1.28). Moreover, adjusting this nonstandard behaviour to the factors in Carhart (1997) model explains only a small part of this effect and reconfirms the significant excess returns for this strategy. Also, the results in Table 4.8 emphasise the importance of the expected profitability premium and the PH52-induced momentum to explain the anomalous performance of the IVOL-hedge strategy. None of these strategies is significant after accounting for the EROA and PH52 factors, in addition to the market and size factors.

The general conclusion is always that the existence of the IVOL effect depends on the existence of the negative news.

Table 4.9 exhibits the Fama-Macbeth cross-sectional regression of the stock returns for each of the profitability alternative measures. The general observation is that, like EROA, the different measures of profitability positively predict the returns over the next 12 months. The average slope coefficients for the expected profitability measures range from 0.764 to 2.708 with a newey-west t-statistic between 6.076 and 4.216. But it should be that the influence of these profitability measures on the IVOL effect seems to be weaker than that shown in Table 4.5 for the EROA, especially for the 12 months horizon. Column M10 shows that even after controlling for the expected operating profitability and the PH52, the average slope coefficients for the IVOL is -0.216 and significant with a newey-west t-statistic of -2.38. However, after accounting for the other return's predictors, the IVOL predictive power of the future returns is completely insignificant. Largely, this is due to the controlling for the past maximum returns which serve as a proxy for the lottery-like effect document by Bali et al. (2011).

Table 4.8. Triple-sort analysis with the alternative profitability measures.

This table represents the analysis of the IVOL effect conditional on the levels of one of the three profitability alternative measures and PH52. We use the return on book equity (EROE), the cash-based profit on the book asset (ECop), and the operating profit on book equity (EOp) as alternatives to ROA. Independently, each month, the stocks are sorted into two groups based on the expected profitability (EROE, ECop, and EOp) and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns (over the next 12 months) between the highest and the lowest IVOL-based portfolio. The table reports the value-weighted performance measures of the IVOL hedge strategy (H-L). The RP is the excess returns, Car4F is the Carhart alpha, and F4$_{\text{Roa\&PH}}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats are the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

			EROE			ECop			EOp		
PH52	Ex		RP	Car4F	F4$_{\text{ERoe\&PH}}$	RP	Car4F	F4$_{\text{ECop\&PH}}$	RP	Car4F	F4$_{\text{EOp\&PH}}$
L	L	H-L	-2.82	-2.05	-0.17	-2.97	-2.03	-0.08	-2.76	-1.75	0.17
		t-stats	-5.28	-3.13	-0.42	-5.51	-3.38	-0.19	-5.03	-2.59	0.41
	H	H-L	-1.32	-1.26	-0.34	-1.55	-1.20	-0.28	-1.34	-1.23	-0.38
		t-stats	-4.08	-2.98	-0.49	-4.96	-3.64	-0.43	-4.05	-2.96	-0.51
H	L	H-L	-1.64	-1.32	-0.43	-1.44	-1.69	-0.73	-1.45	-1.35	-0.47
		t-stats	-3.83	-3.10	-1.03	-3.37	-3.86	-2.12	-3.29	-3.14	-1.17
	H	H-L	-0.29	-0.45	-0.04	-0.34	-0.57	-0.03	-0.29	-0.51	-0.12
		t-stats	-1.28	-1.65	-0.14	-1.43	-1.98	-0.10	-1.24	-1.70	-0.40

Table 4.9 Fama and MacBeth cross-sectional regression with alternative measures of profitability.

This table represents the Fama-MacBeth cross-sectional regression. The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stocks are regressed on the IVOL, one of the alternative measures of the expected profitability (EROE, ECop, and EOp), PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), the logarithmic value of the amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017. *, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

	EROE				ECOP				EOP			
Model	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	M12
VARIABLES	R3M	R12M	R12M	R12M	R3M	R12M	R12M	R12M	R3M	R12M	R12M	R12M
IVOL	-0.167*	-0.193**	-0.101	0.0921	-0.141	-0.173*	-0.098	0.0468	-0.193*	-0.216**	-0.107	0.14
t-stats	(-1.726)	(-2.134)	(-1.268)	0.723	(-1.420)	(-1.896)	(-1.266)	0.348	(-1.930)	(-2.38)	(-1.340)	1.051
PH52	4.873***	3.590***	2.623***	3.688***	4.896***	3.620***	2.697***	3.340***	4.928***	3.636***	2.659***	3.505***
t-stats	-7.82	-7.02	-4.421	4.372	-7.817	-7.086	-4.565	3.953	-7.866	-7.091	-4.501	4.221
Ex	1.130***	1.409***	1.423***	3.195***	2.376***	2.708***	2.389***	3.465***	0.764***	1.014***	1.0***	3.951***
t-stats	4.367	6.076	5.553	4.553	4.283	5.593	4.285	4.209	4.216	6.042	5.527	4.598
PH*IVOL				-0.541***				-0.503**				-0.636***
t-stats				(-3.189)				(-2.317)				(-3.341)
Ex*IVOL				-0.829***				-0.574**				-0.815***
t-stats				(-3.667)				(-2.393)				(-3.276)
Ex*PH52*IVOL				1.134***				1.003**				1.434***
t-stats				3.934				2.562				3.868
Ex*PH52				-3.229***				-3.821***				-4.443***
t-stats				(-3.898)				(-3.415)				(-3.723)
Constant	-3.833***	-2.806***	-2.419***	-3.038***	-4.080***	-3.053***	-2.632***	-2.705***	-3.888***	-2.884***	-2.504***	-2.900***
t-stats	(-5.259)	(-4.380)	(-3.067)	(-4.024)	(-5.557)	(-4.820)	(-3.231)	(-3.587)	(-5.309)	(-4.489)	(-3.189)	(-4.269)
Control	no	no	yes	yes	no	no	yes	yes	no	no	yes	yes
Observations	133762	133762	130865	130865	132690	132690	129891	129891	133687	133687	130804	130804
R-squared	0.09	0.13	0.20	0.21	0.09	0.13	0.20	0.21	0.09	0.12	0.19	0.21

As a speculative trading behaviour, the lottery-like effect had been found to be strongly associated with the IVOL effect (see, for example, Han & Kumar 2013, and Hou and Loh, 2016). The columns M4, M8, M12 outline the regressions with interaction terms where the PH52 and the expected future profitability measures are considered in the deciles from. Again, the revealed results show that the interaction term Ex*PH52*IVOL is positive and economically and statistically significant regardless of the employed profitability proxy. Moreover, controlling for the continuation component of the IVOL effect, the reversal pattern still evident

4.5.3. Subsamples analysis.

In this subsection, we will redo the main analysis in this study under different sampling setups, (i) the microcap stocks will be removed from the sample, (ii) the effect of different sentimental and market states will be shown, (iii) the full sample will be decomposed into two sub-periods.

4.5.3.1. Do Micro-cap Stocks Matter?

Many of the pervasive asset pricing anomalies are found to be concentrated in the stocks with an extremely small market capitalisation (microcap stocks) (see, Fama and French 2008). Therefore, under this subsection, we will check whether the so far revealed empirical evidence in this study is dominated by the microcap stocks. The sorting analysis exhibited in Table 4.6 shows that the underperformance of the IVOL effect is dominated by the performance of the highest deciles. To address this concern, the analysis is re-performed while excluding the stocks with a market capitalisation of less than 25 million pounds. These exempted stocks constitute approximately 10% of the sample. This criterion is arbitrarily selected to balance between the tasks of controlling for the microcaps effect and keeping an acceptable sample size.

In Table 4.10, the performance of IVOL-based portfolios within the levels of EROA and PH52 is reanalysed after screening out the microcap stocks. In comparison with the results in

Table 4.4, the results indicate that, either in magnitude or in statistical significance, the microcaps have little influence on the IVOL effect. The shown figures reveal that the long/short strategy of IVOL is strongest when both the EROA and PH52 are in their low levels, whereas it is weakest and insignificant when they are both at their high levels. For the group of stocks with low EROA and low PH52, the IVOL effect over the next 12 months is -3.17% with a newey-west t-statistic of -4.13. This figure drops down to the insignificant -0.4% for the stocks with high expected profitability and high PH52. Besides, the results show that the EROA and PH52 pricing factors do a good job in explaining this anomalous behaviour of returns.

Table 4.10. Excluding the small size stocks and the stocks sorting analysis.

This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52 excluding the stocks with a market value of less than 25 million pounds, independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

			IVOL with PH and EROA					
Panel A			Next 3 months VW returns					
PH	EROA		L	M	H	RP	Car4F	$F4_{Roa\&PH}$
L	L	ret	-0.14	-1.46	-2.97	-3.07	-2.41	-0.89
		t-stats	-0.39	-2	-3.65	-5.53	-4.19	-1.73
	H	ret	0.24	0.08	-0.81	-1.3	-0.45	-0.03
		t-stats	0.75	0.17	-1.42	-3.05	-1.1	-0.04
H	L	ret	0.49	0.31	-0.87	-1.61	-1.72	-0.73
		t-stats	2.31	1.13	-1.9	-4.69	-4.01	-2.31
	H	ret	0.56	0.67	0.48	-0.32	-0.61	-0.3
		t-stats	3.1	2.51	1.37	-1.28	-4.19	-0.99
Panel B			Next 12 months VW returns					
PH	EROA		L	M	H	RP	Car4F	$F4_{Roa\&PH}$
L	L	ret	-0.16	-1.53	-3.08	-3.17	-1.97	-1.14
		t-stats	-0.37	-1.83	-3.21	-4.31	-2.93	-2.04
	H	ret	0.22	0.25	-0.79	-1.27	-0.55	-0.146
		t-stats	0.57	0.48	-1.27	-2.97	-1.38	-0.38
H	L	ret	0.59	0.37	-0.48	-1.28	-1.05	-0.7
		t-stats	2.37	1.21	-0.85	-3.49	-2.77	-1.91
	H	ret	0.58	0.75	0.43	-0.4	-0.16	-0.08
		t-stats	2.93	2.39	0.98	-1.19	-0.62	-0.26

In Table 4.11, the cross-sectional regression of the stock's future realised returns against the IVOL, PH52, and EROA while excluding the microcap stocks. The results are very similar to that displayed in Table 4.5 for the full sample. That’s it, the IVOL effect significantly depends on the levels of EROA and the PH52.

Table 4.11 Excluding the small size stocks and the Fama-MacBeth cross-sectional regression.

This table represents the Fama-MacBeth cross-sectional regression. The table reports the average slope coefficients and the corresponding newey-west t-statistic. Firms with a value of less than 25 million pounds are excluded. Each month, the stocks are regressed on the IVOL, one of the alternative measures of the expected profitability (EROA), PH52, and a list of control variables. the list of control variable includes Maximum returns(MAX), the return over the past 6 months (MOM), the return over the last month (Last), the logarithm of market value in millions of pound (Logv), the growth in assets (GA), the logarithmic value of the Amihud price impact ratio (Amih), the zero-returns days (Zdays), the market beta (Beta), the down beta (Dbeta), the ratio of book equity to market value (BM), the earnings to price ratio (EP), the information uncertainty index (INF), and UCG is unrealised capital gains. The analysis covers the period from January 1996 to December 2017. *, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

Model	M1	M2	M3	M4	M5	M6
VARIABLES	R3M	R3M	R12M	R12M	R3M	R12M
IVOL	-0.134	-0.0849	-0.17*	-0.1	-0.022	-0.004
	(-1.34)	(-0.78)	(-1.93)	(-1.19)	(-0.117)	(-0.03)
PH52	4.83***	2.96***	3.58***	2.62***	3.87***	3.44***
	7.60	4.77	6.38	4.37	3.31	5.11
EROA	2.95***	2.025***	3.46***	2.59***	3.19***	2.92***
	5.46	3.29	6.52	4.6	2.72	4.39
EROA*IVOL					-0.32	-0.31
					(-1.09)	(-1.41)
PH52*IVOL					-0.58**	-0.61***
					(-2.133)	(-3.810)
PH52*EROA*IVOL					1.074**	1.03***
					2.45	3.08
PH52*EROA					-4.26***	-3.72***
					(-2.94)	(-4.43)
Constant	-3.82***	-2.23**	-2.79***	-2.20**	-2.33**	-2.35***
	(-5.47)	(-2.35)	(-4.32)	(-2.54)	(-2.03)	(-3.12)
control	no	yes	no	yes	yes	yes
Observations	119,705	117,347	119,705	117,347	117,347	117,347
R-squared	0.091	0.167	0.124	0.203	0.178	0.212

4.5.3.2. Effect of Sentiment and Market State.

Prior studies on asset pricing have shown that investors' mispricing behaviour is state-dependent. Baker and Wurgler (2007) and Stambaugh et al. (2015) demonstrate investors are more likely to over priced stocks in a state of euphoria in investors' sentiment. Moreover, the overpricing will be stronger for the stocks with a vague environment (e.g., firms with losses and high volatility). Cooper et al. (2004) show that momentum is only profitably following a period of positive market returns (upstate). They attribute this continuation pattern following the upmarket to an overreaction by the overconfident investors. Therefore, in the following analysis, the behaviour of the IVOL effect is investigated following different emotional and market states.

To perform this task, the investor sentiment is represented by the Economic Sentiment Indicator published by the European Commission for the UK market. To subtract the rational component, this index is orthogonalised to the monthly change in the industrial production, change in the consumer price index, the unemployment rate, the term premium between the three months treasury bills rate, and 10-year treasury bonds rate. To classify the market states, the returns of the market are measured by the change in the total return of the FTSE all-share index over the past 36, 24, and 3 months. The source of these indicators is the DataStream.

In Panel A of Table 4.12, the association between the IVOL effect and the joint levels of EROA and PH52 is analysed following two different sentiment states. The total period is classified into three sub-periods depending on the 3-month rolling average of the sentiment, Pessimistic (bottom 30%), Mild (middle 40%), and optimistic (upper 30%). The figures represent the IVOL long/short strategy. Consistent with the overpricing behaviour, the IVOL effect is significantly stronger after the optimistic state, especially for the stocks with low PH52. For the stocks with prices far from their 52-week high, following the period of high sentiment, the excess returns of the IVOL strategy are -3.58% (newey-west t-statistic = -9.09) and -1.81% (newey-west t-statistic = -9.46) for the low and high EROA groups, respectively. The corresponding figures for the pessimistic period are -1.15% (newey-west t-statistic = -3.94) and 0.03% (newey-west t-statistic = 0.1).

This result is consistent with the cognitive dissonance phenomenon documented by Antoniou et al. (2013), which states that the news that is inconsistent with the current market sentimental state is diffusing slowly. Thus, the continuation in the loser's performance is stronger after the period of high sentiment due to the associated overpricing of these stocks. Also, consistent with findings in Riedl et al. (2020) regarding the investors' tendency to understate the persistence of the firms' losses during periods of high sentiment.

Comparing the stocks with low EROA and low PH52 to the stocks with high EROA and high PH52, the difference in the excess returns of the long/short IVOL strategy is more than doubled from -1.36% to -2.97% in the optimistic period. The difference of -1.61% is significant with a t-statistic of -2.04. However, this differential returns between the optimism and pessimistic periods are fully explained by the EROA and PH52 pricing factors.

Table 4.12 Effect of the Sentiment and market states.

This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52. Panel A reports this analysis conditioning on the sentiment states. ranking the time series of the investor sentiment index, the Pessimistic state is the months in the bottom 30% while the Optimistic state is the months in the upper 30%. Panel B reports the IVOL effect performance conditioning on the market returns over the past 36, 12, and 3 months. Independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Diff is the difference between the IVOL hedge portfolio performance within the low EROA and low PH52 group and the high PH52 and high EROA group, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

			IVOL Effect within PH52 & EROA								
Panel A			Pessimistic			Optimistic			Optim-Pessim		
PH	EROA		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	Ret	-1.15	-1.58	-0.19	-3.58	-2.56	-1.05	-2.43	-0.98	-0.86
		t-stat	-3.94	-3.31	-0.45	-9.09	-2.46	-1.47	-2.8	-1.01	-1.18
	H	Ret	0.03	-0.23	0.29	-1.81	-0.7	-0.23	-1.85	-0.47	-0.52
		t-stat	0.1	-0.4	0.35	-9.46	-1.79	-0.47	-2.95	-0.63	-0.64
H	L	Ret	-0.95	-1.79	-0.93	-1.81	-1.32	-0.37	-0.86	0.47	0.56
		t-stat	-3.91	-3.41	-2.91	-7.18	-8.28	-0.82	-1.47	0.8	1.21
	H	Ret	0.22	-0.56	-0.33	-0.6	-0.52	-0.3	-0.82	0.04	0.03
		t-stat	1.41	-2.06	-1.15	-3.29	-1.2	-0.65	-2.27	0.1	0.13
		Diff	-1.36	-1.02	0.14	-2.97	-2.04	-0.75	-1.61	-1.03	-0.89
		t-stat	-2.95	-2.42	0.31	-4.79	-2.23	-0.94	-2.04	-1.14	-1.23
	Panel B		Upstate - Downstate								
			36 months			12 months			3 months		
PH	EROA		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	Ret	-2.17	-1.13	-0.8	-0.43	-0.68	-0.03	0.52	0.39	-0.43
		t-stat	-2.84	-1.98	-1.64	-0.36	-1.22	-0.05	0.73	0.81	-1.43
	H	Ret	-0.49	0.62	0.69	-0.3	-0.49	-0.1	-0.06	-0.2	0.01
		t-stat	-0.77	1.16	1.11	-0.27	-0.83	-0.14	-0.12	-0.63	0.03
H	L	Ret	-0.79	-0.17	0.07	0.14	-0.28	0.05	-0.32	-0.55	-0.43
		t-stat	-1.51	-0.4	0.19	0.1	-0.56	0.11	-0.71	-1.75	-1.43
	H	Ret	-0.58	-0.3	-0.13	0.15	-0.04	-0.06	0.28	0.22	0.22
		t-stat	-1.22	-1.09	-0.42	0.26	-0.11	-0.13	0.82	0.97	0.81
		Diff	-1.59	-0.83	-0.68	-0.58	-0.64	0.03	-0.24	0.17	0.32
		t-stat	-2.49	-1.56	-1.22	-0.52	-1.17	0.04	-0.33	0.31	0.62

In Panel B of Table 4.12, the analysis is replicated for two different sub-periods of UP and Downmarket states. The shown figures are the difference in the IVOL effect between the Up states (positive returns) and down states (negative returns) of the market. The difference between the up and down states is significant only for the low PH52 and low EROA stocks for the 36-month case.

4.5.3.3. Pre-crisis Vis Post-crisis.

In Table 4.13, the IVOL effect is reanalysed through two different sub-periods of 1996-2008 and 2009-2017. Unsurprisingly, the poor performance associated with the IVOL long/short strategy is stronger in the period span from 1996 to 2008. During this era, the financial markets in the UK and the world had experienced two of the worst financial crises in history, namely the dot-com crash (2000-2002) and the global financial crisis (2007-2008). Despite this, the general conclusion reached previously by this study does not change.

Table 4.13 Joint effect of the PH52 and the EROA on the IVOL puzzle.

This table represents the analysis of the IVOL effect conditional on the levels of EROA and PH52 during two different sub-periods of 1996-20008 and 2009-2107. Independently, each month, the stocks are sorted into two groups based on the EROA and the PH52. Then, 4 portfolios are generated by intersecting these groups. Within each one of these 4 groups, the stocks are re-sorted into three portfolios based on the IVOL. The IVOL effect is evaluated by the value-weighted differential returns between the highest and the lowest IVOL-based portfolio. The RP is the excess returns, Car4F is the Carhart alpha, and $F4_{Roa\&PH}$ is the alpha of the model that includes the EROA and the PH52 factor. The analysis spans the period from January 1996 to December 2017. The t-stats is the newey-west t-statistic and 4Fα is the alpha with respect to the Carhart (1997) four-factor model.

IVOL effect with PH52 and EROA								
			1996-2008			2009-2017		
PH52	EROA		RP	Car4F	$F4_{Roa\&PH}$	RP	Car4F	$F4_{Roa\&PH}$
L	L	Ret	-3.1	-1.5	-0.65	-2.73	-1.68	-1.08
		t-stat	-4.53	-3.53	-1.64	-4.13	-2.18	-0.54
	H	Ret	-1.85	-0.53	-0.04	-0.48	-0.51	-0.65
		t-stat	-3.21	-1.07	-0.06	-1.69	-1.14	-0.74
H	L	Ret	-1.82	-1.34	-0.99	-1.23	-0.46	0.42
		t-stat	-3.84	-3.23	-3.21	-2.82	-0.85	0.6
	H	Ret	-0.59	-0.56	-0.72	0.08	0.81	1.3
		t-stat	-1.55	-2.36	-2.63	0.33	2.19	2.16
		Diff	-2.5	-1.5	0.06	-2.8	-3.4	-2.38
		t-stat	-7.91	-4.56	0.12	-7.38	-4.71	-1.83

4.5.4. Alternative Explanations.

Prior studies have suggested different explanations for the anomalous inverse performance associated with high idiosyncratic volatility. Investor’s overreaction has been considered as a plausible explanation for this underperformance by stocks with high IVOL. For example, the investors may overreact to stocks with lottery-like features. Bali et al. (2011) suggest the maximum daily returns over the past months (MAX) as a proxy for the lottery-likeness. They found that the IVOL effect is fully absorbed by this lottery proxy. Also, Byun et al (2016) point out that the continuous overreaction fuelled by the investors’ overconfidence could be the reason behind the widely documented price momentum. Also, Polk and Sapienza (2009) provide evidence on the catering hypothesis of investment decisions. They find that high capital expenditures signal an overpricing share price in the market. Accordingly, the rise in capital expenditures predicts a reversal in the subsequent stock returns.

Therefore, the task in this subsection is to test whether the results revealed in this study are attributed to overreaction behaviour. For more details regarding the measurement of the tested overreaction proxies, refer to the data measurement section of this study.

In Table 4.14, the overreaction proxies are added to the cross-sectional regression of stock returns over the next 12 months against the IVOL, EROA, PH52, and interaction terms between them. Except for IVOL, all variables are ranked into deciles and then scaled by 10 to range from 0 to 1.

Confirming the general findings in this study, Table 4.14 confirms the ability of the EROA and PH52 to predict the future returns over the next 12 months and to affect the anomalous inverse IVOL-return relationship. The average slope coefficients are positive and highly significant for the EROA, PH52, and PH52*EROA*IVOL. Except for the continuous overreaction (CO12), the suggested overreaction proxies significantly predict the returns across the stocks. Controlling for the effect of the EROA and PH52, the average slope coefficients on the MAX and I/K is -0.49 (newey-west t-statistic = -1.98) and -0.48(newey-west t-statistic = (-2.09) respectively. Interdicting the investment-to capital variable (I/K) substantially affects the interaction term between the IVOL and the PH52 (EROA*IVOL). After controlling for I/K, the average slope coefficients on EROA*IVOL is not significant with a value of -0.39. More interestingly, after including the MAX and I/K, the average slope coefficients on EROA*IVOL and PH52*IVOL are statistically insignificant. This finding supports the adopted interpretation that the significant coefficients on these interaction terms (PH52*IVOL and PH52*EROA) are driven by the reversed side of the IVOL effect. Specifically, these results indicate that the investor’s speculation on the stocks with lottery-like features and/or high investment rates generates a part of the documented IVOL effect. Stocks with high volatility are found to be attractive for individual investors who prefer stocks with lottery-like features (Boyer et al. 2010). Also, Malagon et al. (2015) link the idiosyncratic volatility anomaly to the firm investment and investors’ preference for skewness.

Polk and Sapienza (2000) argue that the firms' managers cater to the investors' overvaluation of the firm's stock price by pumping an abnormal amount of money into the firm capital which leads to inefficient capital allocation, thereby poor performance in the subsequent period.

Table 4.14 Analysis of the alternative explanation–the overreaction behaviour.

This table represents the Fama-MacBeth cross-sectional regression with overreaction proxies. The table reports the average slope coefficients and the corresponding newey-west t-statistic. Each month, the stock returns over the next 12 months are regressed on the IVOL, the expected profitability (EROA), the PH52, the interaction terms between the IVOL, the EROA, and the PH52, and overreaction proxies (MAX, CO12, and I/K). MAX is the average of 5 maximum daily returns over the past 3 months, I/K is the ratio of capital expenditure plus research and development to capital, and CO12 is the continuing overreaction measure of Byun et al. (2016). The analysis covers the period from January 1996 to December 2017. *, **, *** indicate statistical significance at 10%, 5% and 1%, respectively.

	M1	M2	M3	M4	M5	M6	M7	M8
IVOL	-0.123	-0.01	-0.141	-0.15	-0.119	-0.131	-0.175	-0.156
	(-0.78)	(-0.6)	(-0.86)	(-1.0)	(-0.71)	(-0.86)	(-1.11)	(-0.98)
EROA	4.13***	3.860***	4.171***	3.802***	3.876***	3.590***	3.835***	3.593***
	4.23	4.06	4.34	4.07	4.13	3.91	4.143	3.942
PH52	4.85***	4.73***	4.677***	4.44***	4.48***	4.37***	4.26***	4.12***
	4.76	4.88	4.67	4.73	4.71	4.84	4.59	4.62
EROA*IVOL	-0.513*	-0.468*	-0.541**	-0.453*	-0.49*	-0.418	-0.476*	-0.435*
	(-1.953)	(-1.80)	(-2.12)	(-1.72)	(-1.95)	(-1.62)	(-1.86)	(-1.73)
PH52*IVOL	-0.47**	-0.455**	-0.482**	-0.39	-0.50**	-0.38	-0.407*	-0.393*
	(-1.99)	(-1.98)	(-2.05)	(-1.69)	(-2.01)	(-1.68)	(-1.76)	(-1.74)
PH52*EROA*IVOL	1.34***	1.40***	1.39***	1.22***	1.45***	1.28***	1.28***	1.34***
	3.50	3.611	3.73	3.16	3.85	3.27	3.43	3.53
PH52*EROA	-5.47***	-5.44***	-5.51***	-4.93***	-5.47***	-4.94***	-4.99***	-4.98***
	(-4.45)	(-4.5)	(-4.61)	(-4.22)	(-4.64)	(-4.26)	(-4.34)	(-4.38)
MAX		-0.490**			-0.536**	-0.402*		-0.454*
		(-1.982)			(-2.197)	(-1.745)		(-1.959)
CO12			0.205		0.269*		0.228	0.282*
			1.305		1.721		1.54	1.884
I/K				-0.481**		-0.443**	-0.452*	-0.413*
				(-2.09)		(-1.990)	(-1.934)	(-1.815)
Constant	-2.922***	-2.639***	-2.913***	-2.438***	-2.601***	-2.234***	-2.441***	-2.203***
	(-3.302)	(-3.071)	(-3.272)	(-2.945)	(-3.006)	(-2.739)	(-2.900)	(-2.662)
Observations	133,779	133,779	131,633	133,779	131,633	133,779	131,633	131,633
R-squared	0.14	0.142	0.144	0.145	0.149	0.149	0.152	0.156

In light of the above findings, the investors' overreaction to attention-grabbing events such as the extreme returns (i.e., lottery-preference effect) and the firm's excessive investment contributes to the magnitude of the IVOL effect. Therefore, it seems that the inverse relationship between the IVOL and the future realised returns is more complex than being only represented by the underreaction behaviour without considering the overreaction-related mispricing.

4.6. Summary and Concluding Remarks.

This work investigates the joint ability of the fundamental-related news and the market-based news to explain the anomalous underperformance of the stocks with high idiosyncratic volatility (high IVOL). Specifically, the work tests whether this underperformance of the stocks with high IVOL is due to the investors' response to the bad news related to the expected accounting profitability and the nearness of the stock's current price to the past 52-week high price. To this end, an out-of-sample prediction of future profitability is adopted through this work. A sample of stocks from the UK market through the period from January 1996 to 2017 is analysed.

The empirical results from the stocks sorting approach show that the IVOL effect is the strongest when the investors receive consistent bad news from the market, i.e. (low price to 52-week high) and the projected future profitability (i.e. persistent losses). In contrast, the IVOL hedge strategy generates economically and statistically insignificant returns for the subsample of stocks with consistent good news from the market and the profitability expectations. This pattern is stronger following periods of investors' euphoria, i.e. periods of high sentiment or positive market returns during the past 36 months.

Furthermore, the empirical results from the Fama-MacBeth cross-sectional regression reveal that the information content of the expected profitability and the 52-week high ratio subsumes the IVOL effect. The same inference is reached by the time-series relationship analysis. The pricing factors that are based on the expected profitability and the 52-week high predictive power of future returns across the stocks can explain most of the time-variation in the IVOL effect.

However, the empirical results attribute a large part of the reported IVOL effect to the performance continuation, the reversal cases are also possible. Particularly, for the fundamentally unsupported past winners (i.e. stocks with a high 52-week high ratio but low expected profitability), on average, the high IVOL predicts a reversal in the past positive returns of those winners. According to the analysis, it seems that this reversal part of the

IVOL effect is captured by the overreaction to the firm’s investment and the investors' lottery-like trading.

These findings suggest that the puzzling IVOL-return inverse relationship is originally triggered by the investors’ slow response to news related to the firms’ prospects. Possibly, the investors pay little attention to these persistently underperformed stocks. Combining the underreaction with the high information uncertainty (i.e. high IVOL) deters the arbitraging activities hence leads to a slow correction and persistent downward trend in the prices of these stocks. Consequently, the IVOL-returns inverse relationship emerges in the market.

With these findings, this study contributes to the literature by evidence regarding the pricing efficiency in one of the largest stock markets outside the US equity market. The results are consistent with the previous evidence, from the US and the UK samples, regarding the failure of the investors to fully incorporate the information related to the persistent components of cash flow, especially for the loss firms (see, Jiang et al. 2016, Naoum & Papanastasopoulos 2018, and Papanastasopoulos 2020).

Therefore, the empirical results in this work have some important implications for both the practitioners and the academics. The evidence cast doubt on the pricing efficiency with the UK market. This evidence indicates the possible opportunity to build a profitable strategy based on the revealed information. Going long on the stocks with low IVOL and good signals (i.e. high 52-week high ratio and high expected profitability) and shorts the stocks with high idiosyncratic volatility and bad signals (low 52-week high ratio and low expected profitability) would be a lucrative strategy to the investors in the UK market. Generally, screening out the stocks with high IVOL from the winners' stocks could generate a more stable momentum strategy. Moreover, results from the time-series analysis show that considering additional factors (i.e. the profitability and the 52-week high) to the available pricing model (i.e. Carhart 4-factor model) would be useful in different asset pricing applications to the equity in the UK market. For the academic community, the results point out some important directions for future research. The relationships highlighted in this work may explain some of the anomalous pricing behaviour documented in the UK market recently. For example, Lu and Hwang (2007) and Foran et al. (2015) document a counter-intuitive underperformance of illiquid stocks in the UK market. Stocks with poor performance signals and high IVOL are expected to be illiquid. Also, the empirical findings in this work encourage future researchers to extend the pricing characteristics analysis by testing the ability of the factors based on the expected profitability and the 52-week high ratio to explain other pricing anomalies that have been reported in the financial markets.

CHAPTER FIVE

CONCLUSION

This academic work consists of three empirical papers that provide a separate but related topic on the pricing of the idiosyncratic volatility (IVOL) and other related lottery-like features in the UK stock market. This goal is motivated by the prior evidence from the U.S. literature on the puzzling inverse predictive power of these speculative features for the stock returns. Perhaps, this inverse predictability implies an inverse risk-return function. Therefore, this anomalous pricing behaviour should be related to many vital decision-making tasks in finance. Despite the large amount of research efforts that have been done on the behaviour of stocks with high IVOL risk and lottery-like features, the nature of these pricing anomalies is still controversial.

In the three empirical works that make up this dissertation, the analysis reveals an interesting result on the pricing of the IVOL and the other lottery-like features in the UK stock market. These results suggest some important implications regarding the return predictability therefore the investors' behaviour and the informational efficiency of the UK stock market.

The first empirical paper (Chapter Two) tests whether the lottery-like effect exists in the UK stock market and to shed some light on the potential mechanism(s) behind this anomalous pricing behaviour. A comprehensive sample of common stocks during the period from January 1991 to December 2017 is analysed. The analysis includes the stocks sorting method and the Fama and Macbeth cross-sectional regression. Following the prior literature, four speculative characteristics are employed to proxy the lottery-likeness of the stocks in the UK market. These proxies are idiosyncratic volatility (IVOL), past maximum daily returns (MAX), conditional jump, and closing price. For each individual stock, an index of lottery-likeness is built by averaging the rank corresponding to these features.

To examine the existence of the lottery-like effect in UK stocks, the future performance of a trading strategy that built on the employed lottery-like features is evaluated. The stocks are sorted to create decile portfolios and the performance is represented by the subsequent month's return. This single-sort portfolio analysis reveals that the future return is a decreasing function of the IVOL and other lottery-like features (e.g. MAX). The strategy that goes long on the stocks in the highest lottery-like decile portfolio and goes short on the stocks in the lowest lottery-like decile portfolio would generate, on average, an economically and statistically significant negative return in the next month. Applying this strategy to the IVOL and holding this strategy over the next month generates an average excess return of -3.5% over the period from 1991 to 2017. Moreover, this payoff is unexplainable by the risk structure assumed in the Fama and French (1993) three-factor model and Carhart (1997) four-factor model. Consequently, the idiosyncratic volatility inversely predicts a puzzling abnormal return in the next month. A similar pattern holds for other lottery-like proxies.

Furthermore, the bivariate sorting analysis and the multivariate Fama and MacBeth cross-sectional regression confirm the puzzling negative payoffs for the stocks with high lottery-like features. Under this analysis, the performance of the lottery-like stocks is evaluated while controlling for a list of widely known return predictors and patterns such as the size effect, price reversal, price momentum, liquidity level, systematic risk (i.e. Beta), and left-tail risk. Except for the left-tail risk measure (i.e. the minimum past daily returns), none of the considered return predictors can completely explain the reported underperformance of the stocks with high IVOL and other lottery-like features.

The results suggest that the pricing anomalies related to lottery-like trading (i.e. the IVOL puzzle) exist in the UK stocks. Therefore, the findings imply that investors in the UK market are not risk-averse and prefer lottery-like stocks with a high-risk profile (e.g. high IVOL). Moreover, this result casts doubt about the informational efficiency of the UK stock market and the efficacy of the tools induced by the standard finance theory in making the pricing-related decisions in this market. Therefore, the evidence in this study is of interest to various participants in the UK market.

The bivariate sorting analysis indicates that the reported profitability of the lottery-like trading strategy depends on the level of other returns predictors. Most importantly, this profitability is strongly positively associated with market capitalisation and liquidity-related, but negatively related to the past performance. In particular, the lottery-like effect is stronger for the stocks with lower market capitalisation, lower liquidity (e.g. higher Amihud ratio and bid-ask spread), past negative returns. This pattern is consistent with the mispricing story and suggests that the limited arbitrage could, at least partially, explain the negative payoffs for the stocks with high lottery-like features, especially the high IVOL stocks. Therefore, cast doubt on the size of the abnormal profit reported for the unconditional lottery-like effect. However, the lottery-like effect is robust and significant in the stocks with low transaction costs (e.g., big market value, low bid-ask spread, and past winners).

Furthermore, the analysis shows another interesting pattern in support of the overvaluation hypothesis, the underperformance of the lottery-like stocks is more pronounced during the market downturn and following the optimistic state of the market. This finding is consistent with the evidence in Kumar (2009) which demonstrates that the investors, especially individuals, exhibit a stronger tendency to speculate during the bad state of the market. Also, the investors are more likely to overvalue the lottery-like stocks during the optimistic period (see, for example, Fong and Toh (2014) and Stambaugh et al. 2015).

The ability of the left-tail risk (i.e., the past minimum daily returns) to subsume the lottery-related anomalies (e.g. (IVOL puzzle) suggests that the left-tail momentum anomaly exists in the UK stocks market. Atilgan et al. (2020) document a persistent underperformance for stocks with high left-tail risk (e.g., high expected-shortfall). Such behaviour can plausibly be generated by the underreaction behaviour combined with the limited arbitrage environment. The investors may underreact to the past bad news. This result motivates the next task in this academic work.

In the first analysis theme, the IVOL puzzle is considered as part of the lottery-like effect. However, the lottery preference behaviour is one of the many possible explanations suggested in the literature for the nonstandard inverse relationship between the idiosyncratic volatility and the future return (i.e., the IVOL puzzle).

This second empirical chapter (Chapter Three) extends the analysis by examining whether the IVOL puzzle is a persistent phenomenon. Particularly, the ability of the predictive power of the IVOL for the future returns over the next midterm return (i.e., next 6 months). Also, motivated by the aforementioned result, the analysis is extended by adding evidence on the predictive power of the left-tail risk for the next midterm return. Furthermore, one of the plausible but neglected behavioural explanations of these anomalies is suggested. Specifically, the association between the underreaction-related behaviour (i.e., the investors' attention) and the predictive power of the idiosyncratic volatility (IVOL) and the left-tail risk (proxied by the expected shortfall, ES5%) is examined. Four different proxies are employed to represent the investors' attention, and an index of attention is built from the principal component analysis (PCA) of these individual proxies. The analysis covers the period of January 1996 to December 2017.

Consistent with the evidence reported in Chapter three on the one-month-ahead return predictability, the empirical findings report a strong negative relationship between the next 6-month return and idiosyncratic volatility and the left-tail risk across the stocks in the UK. Contradicting the market efficiency hypothesis and the risk-averse behaviour, the stocks with high ES5% and high IVOL, on average, underperform the stocks with low ES5% and IVOL. This puzzling relationship persists over the next midterm horizon and unexplained by the risk factors in the asset pricing model of Carhart (1997). Moreover, the bivariate stocks sorting analysis and the multivariate cross-sectional analysis show that underreaction-related behaviour is a significant determinant of these pricing anomalies. The return predictability by the IVOL and the ES5% is stronger when the investors are likely to pay less attention to the news, especially the bad news. In particular, past loser stocks with low attention levels largely contribute to the underperformance reported to the stocks with high IVOL or ES5%. These results are robust to different subsamples, sentimental periods, market state, and other potential stock return predictors.

However, the continuation behaviour of the neglected stocks is not the only driver of the IVOL puzzle and left-tail momentum, the reversal pattern takes part in the game. The results suggest that the attractive past winners with high IVOL or ES5% tend to reverse in the next midterm future. These patterns are consistent with results reported in Arena et al. (2008). It seems that the high IVOL or ES5% is an indicator of overvaluation with limited arbitrage activities (e.g. short sale activities). This claim is supported by the evidence on the interaction between the information uncertainty and the underreaction-related behaviour. The bivariate analysis reveals that the reported IVOL puzzle and the left-tail momentum are concentrated within the tercile of stocks with the highest information uncertainty or the stocks with low attention levels. The absence of the information uncertainty and the limited attention behaviour could substantially reduce the alphas of the IVOL- and the ES5%-based strategies to an insignificant level, both economically and statistically.

Therefore, these results affirm the reported evidence on the informational inefficiency of the UK stock market and the irrational risk-seeking behaviour followed by the investors and manifested in the pricing of some UK stocks. Inattentive behaviour toward past losers may lead investors to overvalue these stocks. Combining this underreaction-related mispricing of the past losers with the high arbitraging cost attributed to the high IVOL and ES5% may explain the persistent underperformance of these stocks. Whereas, the reversal in the performance of the attention-grabbing winners with high IVOL or high ES5% may be consistent with the model of Miller (1977). In this model, high uncertainty forces the pessimistic investors (i.e. short sellers) to set aside and leave the market to the optimistic participants which in turn leads to momentum in the prices and subsequent reversal.

These results suggest many interesting implications. Employing the standard rational paradigm (e.g. the CAPM) in the financial decisions making process would lead to erroneous applications. Interestingly, employing the information embedded in the moments of return distribution (i.e. the idiosyncratic volatility and the left-tail shape) could help to predict the future returns of the stocks in the UK market, at least over the next 6-month horizon. Moreover, considering these risk-related characteristics may also help the investors in the UK market to build a more stable momentum strategy. For instance, the conditional momentum strategy that goes long on the past winners with low IVOL or ES5% and goes short on the past losers with high IVOL or ES5% would generate more stable performance over the traditional momentum strategy.

Although the suggested underreaction-related behaviour would play a key role in explaining the anomalous pricing of the IVOL and the ES5% in the UK stocks, this behaviour appears to be more complex, which opens the door to consider other possible channels. So far, the variables included in the analysis are market-based (e.g. 52-week high ratio and past returns) while the possible role of the expected fundamentals remains unknown. However, for many reasons discussed in the third empirical chapter (Chapter Four), the biased response by the investors to the information embedded in the fundamentals regarding the future profitability might be a potential channel.

Extending the analysis of the past two chapters, the last work (Chapter Four) investigates the joint ability of the fundamental-based expected profitability and the market-based news to explain the anomalous underperformance of the stocks with high idiosyncratic volatility (high IVOL). Specifically, the work tests whether this underperformance of the stocks with high IVOL is due to the investors’ response to the bad news related to the expected accounting profitability and the nearness of the stock’s current price to the past 52-week high price. To this end, an out-of-sample prediction of future profitability is adopted through this work. Following the extant literature, the future profitability is estimated across the UK stocks on a monthly basis using a list of well-known earnings predictors. A sample of stocks from the UK market through the period from January 1996 to 2017 is analysed.

The main theme of this analysis is to examine whether the investor's biased response to the readily available expected profit would add to the explanatory power that the 52-week high ratio has for the IVOL puzzle. Here, as defined above, the 52-week high ratio represents the investor underreaction to the information embedded in the past performance of stocks (i.e. Anchoring bias).

The predictive regression results show the ability of the selected predictors to fit a large proportion of the variation in the future earnings across the UK stocks. Therefore, the proposed out-of-sample predicted earnings could serve as a reliable proxy of future profitability.

The portfolio analysis supports the evidence in the prior studies regarding the investors' misreaction to the expected component of the future accounting earnings. Constructing a zero-cost portfolio based on the fitted value of future earnings would generate an abnormal risk-adjusted profit over the next year. This result implies that the investors in the UK stock market don't respond properly to the value-relevant information embedded in the expected profitability of the UK companies. Therefore, the stock prices of these companies do not fully reflect the fundamentals. Similarly, investing based on the 52-week high ratio would also provide the investors in the UK market with a lucrative strategy. Consistent with the prior evidence the 52-week high ratio positively predicts the future returns.

Again, such predictable patterns in the stock returns reaffirm the evidence on the informational inefficiency reported so far for the UK market. Therefore, indirectly lead us to infer that the market participants in the UK market, even the institutional investors, are unable to arbitrage such profitable price discrepancies.

Regarding the IVOL puzzle, the empirical findings reveal that the expected profitability provides an incremental explanatory power over that by the 52-week ratio. The stocks sorting approach shows that the IVOL effect is the strongest when the investors receive consistent bad news from the market, i.e. (low price to 52-week high) and the projected future profitability (i.e. persistent losses). In contrast, the IVOL-hedge strategy generates economically and statistically insignificant returns for the subsample of stocks with consistent good news about the market performance and the profitability expectations. This pattern is stronger following periods of high euphoria, i.e. periods of high sentiment or positive market returns during the past 36 months.

Furthermore, the empirical results from the Fama-MacBeth cross-sectional regression reveal that the information content of the expected profitability and the 52-week high ratio subsumes the IVOL effect. The same inference is reached by the time-series analysis. The pricing factors that are based on the expected profitability and the 52-week high predictive power of future returns across the stocks can explain most of the time-variation in the IVOL effect.

However, the empirical results attribute a large part of the reported IVOL effect to the performance continuation, the reversal cases are also possible. Particularly, for the fundamentally unsupported past winners (i.e. stocks with a high 52-week high ratio but low expected profitability), on average, the high IVOL predicts a reversal in the past positive returns of those winners. According to the analysis, it seems that this reversal part of the IVOL effect is captured by the overreaction to the firm's investment and the investors' lottery-like trading.

These findings suggest that the puzzling IVOL-return inverse relationship is originally triggered by the investors' slow response to news related to the firms' prospects. Possibly, the investors pay little attention to these persistently underperformed stocks. Combining the underreaction with the high information uncertainty (i.e. high IVOL) deters the arbitraging activities hence leads to a slow correction and persistent downward trend in the prices of these stocks. Consequently, the IVOL-returns inverse relationship emerges in the market. With these findings, this study contributes to the literature by evidence regarding the pricing efficiency in one of the largest stock markets outside the US equity market. The results are consistent with the previous evidence, from the US and the UK samples, regarding the failure of investors to fully incorporate the information related to the persistent components of cash flow, especially for the loss firms (see, Jiang et al. 2016, Naoum & Papanastasopoulos 2018, and Papanastasopoulos 2020).

Consistent with cross-sectional analysis, the time series analysis shows that adding the pricing factors that mimic the predictive power of the expected profitability and the 52-week high ratio could help to price the anomalous behaviour of the IVOL-based strategy. The risk-adjusted alpha of the zero-cost strategy is substantially lower after considering the profitability factor and the 52-week factor. Therefore, adding these two factors could improve the general pricing ability of the widely used asset pricing model (eg., the CAPM and the Fama-French three-factor model)

The findings in this work have some important implications for both the practitioners and the academics. The evidence cast doubt on the pricing efficiency with the UK market. This evidence indicates the possible opportunity to build a profitable strategy based on the revealed information. Going long on the stocks with low IVOL and good signals (i.e. high 52-week high ratio and high expected profitability) and shorts the stocks with high idiosyncratic volatility and bad signals (low 52-week high ratio and low expected profitability) would be a lucrative strategy to the investors in the UK market. Generally, screening out the stocks with high IVOL from the winners could generate a more stable momentum strategy. Also, the results suggest that using the standard tools of finance theory may lead to inefficient capital allocation by the investment managers.

Moreover, results from the time-series analysis show that considering additional factors (i.e. the profitability and the 52-week high) to the available pricing model (i.e. Carhart 4-factor model) would be useful in different asset pricing applications to the equity in the UK market. For the academic community, the results point out some important directions for future research. The relationships highlighted in this work may explain some of the anomalous pricing behaviour documented in the UK market recently. For example, Lu and Hwang (2007) and Foran et al. (2015) document a counter-intuitive underperformance of illiquid stocks in the UK market. Stocks with poor performance signals and high IVOL are expected to be illiquid. Also, the empirical findings in this work encourage future studies to extend the pricing characteristics analysis by testing the ability of the factors based on the expected profitability and the 52-week high ratio to explain other pricing anomalies that have been reported in the financial markets.

Regarding the policy makers, the results reported under this study should attract their attention to some important issues. For the financial managers, the reported market inefficiency and the price overvaluation are significant for many of the value-relevant decisions such as the merger and the acquisition. In specific, employing the market price to measure the value could lead to an erroneous decision. Considering the returns predictability by the IVOL, the ES, and the other characteristics shown in this work would improve the decision-making efficiency as a whole. On average, improving the information environment for the firm and the whole market would generate value for the investors. Tackling the speculative behaviour would protect the market from the misleading behaviour. For example, Stigltiz (1989) demonstrates the social costs of speculative behaviour and suggests a tax on the turnover to curb such nonstandard behaviour.

Although the work employs a robust and suitable methodology, it should be noted that the results are not guaranteed and there are some limitations that may affect significance of the revealed patterns in this study. The stocks sorting technique is too simple and the multivariate cross-sectional regression is functionally restricted and linear, however the relationship may take other forms. The analysis does not account for some of the plausible stories behind the revealed evidence. Interestingly, previous studies highlight the ability of the growth option and the related risk to explain the IVOL puzzle. Also, the analysis does not consider one of the widely cited underreaction proxies, namely, the analyst coverage. Regardless of the availability problem that may defects this variable, considering it should provide support to credibility of the evidence reported in this study. In this work, I only use the Carhart asset pricing model as a risk benchmark to analyse the performance of the suggested strategies. It is not clear which model is more appropriate for pricing of the UK stocks, therefore employing an alternative risk adjusting method may affect the findings reported in this work, for example see, Daniel et al. (1997). Last but not least, the analysis accounts for the transaction costs indirectly in the double-sort approach and the cross-sectional regression (e.g., accounting for the bid-ask spread). Applying the transaction costs directly to the portfolio returns would significantly affect the reported pricing anomalies (see, Soares and Stark 2009).

In sum, through the main three chapters, this empirical work uncovers many interesting predictable patterns in the behaviour of the UK stock prices. These patterns contradict the widely accepted risk aversion hypothesis. It appears that the investors in the UK market prefer stocks with speculative features (e.g., high IVOL) thereby overvaluing these stocks. Furthermore, the existence of the arbitrageurs (e.g., institutional investors) in this market fails to short such overvaluation. This anomalous pricing behaviour is complex and generated by multiple channels. In specific, underreaction-related behaviour (e.g., low attention) and overreaction-related behaviour (e.g., lottery-like trading). Generally, the findings in this work are crucial for the investment and the legislation tasks targeting the UK stock market.

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