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USING INVESTORS' SENTIMENT TO FORECAST UK MARKET VOLATILITY

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ABSTRACT

This paper investigates the relationship between investors' sentiment and the future volatility of UK financial markets. It also examines the US-UK contagion theory and its impact on different UK market sizes.

The empirical results indicate that models that include investor sentiment proxies considerably enhance the explanatory power of future volatility. Moreover, sentiment significantly Granger-causes future volatility for both small and big companies, and vice-versa. Bidirectional relationships are predominant in the Small Cap Index. The variance of future volatility on both markets can be mainly explained by innovations on themselves as well as on lagged values of Dividend Premium and VIX. Future volatility responses to changes in investor sentiment are mainly positive and statistically significant for the first five days, gradually disappearing after. These innovations appear to affect small firms in a greater way.

Regarding American sentiment, the implied volatility index of S&P500 (VIX), has demonstrated to be a strong driver of UK financial market volatility.

Keywords: Investor Sentiment; Behavioral Finance; Contagion Theory; Future Volatility; Volatility Forecasting; Impulse Responses; Variance Decomposition

INTRODUCTION

Behavioural models of finance focus on psychological, emotional and sociological factors that affect the behaviours of investors and traders. They demonstrate that investor sentiment can influence financial markets.

This paper investigates the relationship between investors' sentiment and the future volatility of UK stock markets. It seeks to determine the relationship between levels of investor sentiments and future stock market volatility in the UK. It also examines the US-UK contagion theory and its impact on different UK market sizes.

The main purpose and contribution of this paper is to demonstrate the importance of including investor sentiment variables in volatility forecasting models. Investors and financial institutions forecast future stock market volatilities as an integral part of their risk analysis and trading strategies. However, most do not currently include investor sentiment variables as part of their forecasting. Instead, they tend to focus on historical patterns.

This paper finds that levels of investor sentiment can be strongly correlated with future stock market volatility. This paper therefore provides evidence that indicates how important it can be to include investor sentiment in models that forecast market volatility. The findings of this paper are relevant to investors and financial institutions that want to increase their returns.

LITERATURE REVIEW

Trying to explain and predict market behaviour has always been a topic of interest in finance. Modern financial theories such as Capital Asset Pricing Models (CAPM) or Efficiency Market Hypotheses (EMH) have struggled to clarify why sometimes markets behave irrationally (flash crashes, speculative bubbles or anomalies such as the January effect).

An alternative theory emerged at the end of the 20th century. **Behavioural finance** investigates agents' illogical response patterns using psychology and sociology in order to help explain market anomalies. Ricciardi and Simon (2000) define it as an 'attempt to explain and increase understanding of the reasoning patterns of investors, including the emotional processes involved and the degree to which they influence the decision-making process of individuals, groups, and entities' (Ricciardi and Simon, 2000, pp.2). In a market with rational and irrational investors' interaction, behavioural models recognise the importance of traders' irrationality, which results in asset mispricing as well as long-term significant effects on prices and volatilities (Barberis and Thaler, 2003).

However, how can investor sentiment be measured? Due to its qualitative features, it is naturally difficult to quantify. Nowadays, according to Hudson and Green (2015), the most common ways of determining sentiment are: 1) conducting individual **surveys** and compiling all the responses (i.e. the *American Association of Individual Investors, AAII*); 2) using objective **financial market indicators** such as the Put-Call ratio; or 3) using **composed indices** in order to extract a unique sentiment value from different sources of economic and financial data.

Many academics have examined relationships between investor sentiment and market returns.

For example, Baker and Wurgler (2006, 2007) found that low (high) investor sentiment has a statistically significant positive (modest) effect on the cross-section of future stock returns. They find evidence that smaller, more volatile American firms are more sensitive to investor sentiment.

Most research has focused on US markets. However, other markets such as UK (Baker et al., 2012), Europe (Bai, 2014) and several emerging markets have been studied.: Hong Kong (Chen et al., 2010), China (Chen et al., 2014), Taiwan (Sheu and Wei, 2011) or India (Kumari and Mahakud, 2016).

In addition, investor sentiment contagion between US and UK has also been in the spotlight. Hudson and Green (2015) have proved that US investors' individual and institutional sentiments direct UK market returns, but not conversely. They conclude that sentiments are more relevant to explain asset prices when the economy is stable or has an upward trend and investors are optimistic.

On the other hand, fewer papers have focused their attention on volatility forecasting using investor sentiment. De Long et al. (1990) introduce the idea that investors sentiment-based decisions may lead to excess volatility.

Campbell et al. (1993) argue that changes in investor sentiments can cause liquidity distresses and significant impacts on volatility. Moreover, Lee et al. (2002) also find this for conditional volatility and that the changes in sentiment increase when investors become more bearish and vice versa, being NASDAQ the most affected market.

Chiu et al. (2018) believe that market volatility reveals the impact of investors behaviour which cannot be explained by economic activity. They find strong evidence of short-run cyclical volatility being a good forecaster of investor sentiment and vice versa.

Wang et al. (2006), however, find that sentiment does not have significant explanatory power for forecasting volatility nor returns. This is, traders' sentiment is caused by returns and realised volatility and not vice versa.

Incorporating social media, Siganos et al. (2014) observe a negative relation between sentiment on Facebook and volatility whereas it appears to be positive with stock market returns.

Moreover, Sheu and Wei (2011) create a trading strategy based on future volatility forecasting using Taiwan investors' sentiment. They find evidence of superior investment returns when including the explanatory power of investor sentiment levels.

The focus of this paper is to provide some clarification on the relationship between investors' sentiment and UK stock market volatility. It examines the causal effects of UK investor sentiment on market volatility as well as the US-UK contagion theory through the inclusion of American AAII and VIX proxies. Finally, it examines whether US and/or UK investor sentiment has a bigger impact on smaller British firms by comparing the Small Cap Index to the FTSE 100, as Baker and Wurgler (2006, 2007) evidenced for US financial market.

DATA

The analysis uses daily data from the Bloomberg database between January 2002 to April 2018, accounting for a total of 4126 trading days. Two UK financial markets are considered for the study based on their size: FTSE 100 and Small Cap Indexes (UKX and SMX Bloomberg acronyms respectively).

The models use levels in sentiment rather than changes in sentiment, as the latter did not have a significant correlation with future volatility. Some variables such as TPCO and DP have been first differenced in order to mitigate some unit root problems.

Volatility measures

In the context of volatility forecasting, **realized Future volatility (FV)** has been calculated as the sample standard deviation of daily returns from day t to t+h; where *h* is the h-day-ahead volatility (set as 5, 10, 15 and 20 trading days). It is based on Corrado and Miller (2005) and Sheu and Wei (2011) approach. Initially, it has been constructed using a rolling window of 90 days (from t to T).

$$FV_t = \hat{\sigma}_{t:T} = \sqrt{\frac{252}{h-1}\sum_{j=1}^{h}[Rtn_t - \overline{Rtn}_{t+h}]^2}$$

Where Rtn_t is the market return at time t and FV_t is the future volatility from time t to T, expressed in annual terms. $\overline{Rtn}_{t+h}$ is the mean of market returns during days t+h.

I include the **absolute daily returns (|R|)**, the **high-low range (HL)** and **VRS**, a volatility measure proposed by Rogers and Satchel (1991) in the benchmark forecasting model (defined in the methodology section). Please refer to the Appendix for a detailed explanation.

Investors sentiment proxies

Additionally, the following sentiment variables have been considered for this study (see Appendix for details):

1. The daily implied volatility of FTSE100 (VFTSE).
2. The Put-Call Volume Ratio (TPCV).
3. Put-Call Open Interest Ratio (TPCO).
4. Relative Strength Index (RSI) over 14 Days.
5. Dividend premium (DP).
6. American Association of Individual Investors survey (AAII).
7. Implied Volatility Index of the S&P 500 (VIX).

Even though data for constructing TPCV and TPCO ratios was not available for the Small Cap Index, they have been included in the FTSE 100 study due to their potential explanatory significance.

Summary statistics

Table 1 in Appendix summarises the main descriptive statistics of the previously mentioned variables for a 16-year period. The mean absolute returns seem to be higher and more volatile for larger firms. Regarding investors' sentiment, mean value of RSI is 52.24 percent, suggesting an overall stable market during the studied period. Skewness and Kurtosis values for the future volatilities indicate we are dealing with leptokurtic distributions when compared to the normal.

Moreover, the correlation matrices between volatilities and sentiment are in Appendix Table 2. Most of sentiment proxies appear to be significant at 10 percent level, however, the correlation values are not very high. The highest significant correlation is unsurprisingly for VTSE and VIX proxies (around 0.90 and 0.80, respectively, for FTSE 100; while they are a bit lower for SMX, 0.80).

Regarding the rest of the sentiment variables, only TPCO, AAII and DP seem to have higher correlation with future volatilities of FTSE 100, an average of around ± 0.35. Whereas RSI, AAII and DP seem to be the most correlated sentiment proxies for Small Cap firms' volatility.

It brings to attention that absolute returns for the FTSE 100 are poorly correlated to future market volatility, but are significant and more closely correlated for smaller firms. This suggests that absolute returns have no statistically significant explanatory power to forecast FTSE 100 volatility.

METHOLOGY

This paper uses Vector Autoregressive Models (VAR) for the analysis. They allow both forecast and predictor variables to have an identical influence on each other, this is, they are all considered as endogenous variables. Because no restrictions are imposed, more data characteristics may be captured using this technique.

The aim of this study is to analyse whether investor sentiment has a causal influence in future market volatility or vice-versa. Consider for instance a negative change in investor sentiment, one may expect a decrease on market returns but it could also still result in a slight increase due to a change from very bull to a bull market position. Following this, a simple version of this model can be written as a bivariate VAR with one lag VAR(1):

$$FV_{1,t} = c_1 + \sum_{p=1}^{L} \phi_{11,p} \, FV_{1,t-p} + \sum_{p=1}^{L} \phi_{12,p} SI_{2,t-p} + \varepsilon_{1,t}$$

$$SI_{2,t} = c_2 + \sum_{p=1}^{L} \phi_{21,p} \, FV_{1,t-p} + \sum_{p=1}^{L} \phi_{22,p} \, SI_{2,t-p} + \varepsilon_{2,t}$$

where FV_t denotes the future volatility and SI_t the sentiment proxy. C_t is a constant value and ε_t is the white noise.

A common problem in VAR studies is finding the most appropriate number lags (p) and variables (K) in order to get the best results. Two popular model selection metrics are employed: Final Prediction Error (FPE) and Akaike Information Criterion (AIC), in order to find the model which minimises the estimation errors and produces superior forecasts.

Joint and Granger Causality tests are conducted to examine the level of correlation between present and past values of the variables. The hypotheses test that investor sentiment does not granger-cause future volatility and vice versa.

Nevertheless, these tests may not be enough to explain the entire relationship. Impulse responses and variance decompositions are examined in order to check the responsiveness of one variable to a sudden change in the error term of another. The impulse analysis is performed by exercising single shocks in a proxy's noise term separately and recording the impact on the rest of indicators over time, while keeping the rest of the error terms in the system constant.

On the other hand, variance decompositions study the dynamics of those innovations but given a shock in their **own** variable. Movements in each explanatory proxy can describe the degree of error variance in other equations, for every different h-step-ahead forecast.

Because these analyses cannot be calculated without the correct ordering of the variables, two orders are analysed. In addition, due to possible error correlations, shocks need to be handled in an orthogonal way. This means that the errors' common element will be randomly associated to the first variable in the model, so that the first equation in the system is estimated initially, and then the second. Ideally, the ordering implies that innovations in one proxy are expected to follow others and not lead them.

Benchmark model

For comparison reasons, our own benchmark model BMK for future volatility is built:

$$FV_t = c_1 + \phi_1 \, HL_{t-1} + \phi_2 \, |R_{t-1}| + \phi_3 \, VRS_{t-1} + \varepsilon_t$$

Where FV_t is the future volatility, HL_{t-1}, $|R_{t-1}|$ and VRS_{t-1}, are the one-day lagged high-low range, absolute returns and VRS respectively. C_t is a constant value and ε_t is the error term.

Dynamic forecasts

Assuming the principle of stationarity, each equation in the VAR model is estimated repetitively using Ordinary Least Squares (OLS), minimising the sum of squared error parameters. This is known as VAR in levels. Forecasts for each variable in the system are generated using h-step-ahead method up to time T. This paper estimates out-of-sample volatility forecasts of 5, 10, 15 and 20 days-ahead, starting in May 2018.

In the previously stated VAR model, one-step-ahead forecasts could be expressed as:

$$\widehat{FV}_{1,T+1|T} = \hat{c}_1 + \hat{\phi}_{11,1} \, FV_{1,T} + \sum_{p=1}^{L} \hat{\phi}_{1p} \, Vol_{2p}$$

$$\widehat{Vol}_{2,T+1|T} = \hat{c}_2 + \hat{\phi}_{21,1} \, FV_{1,T} + \sum_{p=1}^{L} \hat{\phi}_{2p} \, Vol_{2p}$$

Where $\widehat{FV}_T$ represents the forecasts of the future volatility at time and $\widehat{Vol}_T$ includes the forecasts of all the volatility measures HL, |R| and VRS at time

T+1. $\hat{\phi}_{ii,l}$ and $\hat{c}_t$ are the parameters' and constants' estimates respectively, there are no error terms.

From these dynamic forecasts the future volatility (FV) is calculated using the formulation previously illustrated. In addition, bootstrapped prediction intervals from the estimated error terms are also calculated.

Finally, forecasts accuracy is evaluated through Mean Absolute Percentage Error and the results are compared to the benchmark model BMK. MAPE is constructed by:

$$MAPE_t = \frac{1}{N}\sum_{i=1}^{n}\left|\frac{FV_i - \widehat{FV_{\iota,M}}}{FV_i}\right|$$

Where $\widehat{FV_{\iota,M}}$ is the estimated future volatility of model M in day i and FV_i is the actual realized future volatility in day i. N is the number of days forecasted.

RESULTS

To begin with, Augmented Dickey-Fuller (ADF) tests for unit roots are run for all lagged variables in order to verify that mean and variance are constant over time. The 16-lagged p-value is not significant at 5% level (0.05>0.00) for most of the indicators. However, there is evidence that TPCO and DP contained unit roots so they are first differenced to make them stationary.

Before running any VAR models, future volatilities are regressed with sentiment proxies in order to examine their relationship. The analysis has been divided into Models 1 and 2 as well as benchmark models to facilitate the comparisons. All models include lagged values of the control variables based on the benchmark model (|R|, HL and VRS) plus different sentiment proxies depending on their degree of correlation/significance. Models 1 include both UK and US sentiment proxies whereas Models 2 only include local sentiment through VTSE (as it is the variable with the most explanatory power when individually regressed) (see Table 3 Appendix).

For all models, variables seem to be jointly significant. As per results below, adjusted R^2 do increase when sentiment proxies are included in the models. Proposed models explain around 80 percent of FTSE 100 and 63 percent of Small Cap variation of future volatility. This explanatory power is weaker for smaller companies, meaning that future volatilities' variation may depend on other indicators not included in our models.

Individually, most of the variables seem to be high-statistically significant at five percent confidence level. As per Wang et al. (2006), I also find predictive power in market returns. VFTSE is positive and highly significant for all models, even at the 1 percent level. This means that a unit increase in VFTSE, results in an average increase of 0.94 (0.32) points of FTSE 100 (Small Cap) future volatility, ceteris paribus. On the other hand, American investor sentiment proxies (AAII and VIX) are also statistically significant, confirming at a first glance the contagion theory demonstrated by Hudson and Green (2015).

In general, investor sentiment proxies considerably enhance the explanatory power of models 1 when compared to the benchmark models.

With the intention of answering previously stated research questions, VAR methodology is now applied. Models 1 for both markets are selected as the ones with lowest forecasting errors (see Table 4) and will serve for illustration purposes going forward. The number of lags that minimises AIS and FPE is 11 for FTSE 100 and 16 for Small Cap Index. The number of VAR parameters estimated for each market is 123 and 145 respectively. Residual diagnosis shows that VAR satisfies the stability condition (see Appendix Figure 1).

There is evidence to suggest that all variables are jointly significant for FTSE 100 and Small Cap, meaning that the proposed VAR models capture the dynamics of each indicator.

Table 5. Granger Causality tests

		FTSE 100		Small Cap	
Eq	Excl	Prob	Relationship	Prob	Relationship
FV	|R|	0.145	Unidirectional	**0.000**	Unidirectional
FV	HL	0.796	Unidirectional	**0.000**	Bidirectional
FV	VRS	0.851	Unidirectional	0.078	Unidirectional
FV	VFTSE	**0.001**	Bidirectional	**0.020**	Bidirectional
FV	TPCV	0.303	None		
FV	TPCO	0.659	None		
FV	RSI	**0.000**	Unidirectional	**0.000**	Bidirectional
FV	AAII	0.648	None	0.250	Unidirectional
FV	DP	**0.000**	Bidirectional	**0.035**	Bidirectional
FV	VIX	**0.000**	Bidirectional	**0.000**	Bidirectional

Moreover, there is proof to say that, overall, investor sentiment significantly Granger-causes future volatility for Small Cap Index at five percent confidence level (through VFTSE, RSI, DP and VIX). Reversely, variations in future volatility appear to lead those of traders' sentiments (VFTSE, RSI, AAII, DP and VIX), demonstrating a predominantly bidirectional relationship between future volatility and sentiment for smaller firms.

Regarding FTSE 100, it can be said that, in general, investor sentiment seems to significantly Granger-cause future volatility at five percent level, however, there are fewer relations. The evidence suggests that future volatility is likely to Granger-cause only VFTSE, DP and VIX. Lastly, TPCV, TPCO and AAII do not seem to be useful for predicting future volatility of FTSE 100.

Nevertheless, previous tests do not entirely explain this relationship sign nor the variables' responsiveness to shocks. A deeper analysis of variance decomposition and impulse responses is performed. Table 6 shows the variance decomposition of the future volatility VAR equation for 20-days-ahead. A considerable limitation of VAR models' decomposition is the importance of the right arrangement of the proxies. That is the reason why order I and its reverse (Order II) are imposed:

FTSE 100 Order I: FV, |R|, HL, VRS, VFTSE, TPCV, TPCO, RSI, AAII, DP, VIX

Small Cap Order I: FV, |R|, HL, VRS, VFTSE, RSI, AAII, DP, VIX

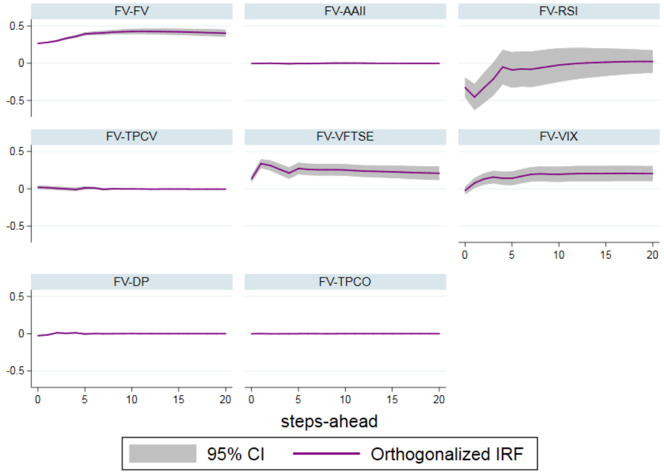
Results show that around 80% of the 20-day-ahead future volatility variance is explained by innovations on its own error. For FTSE100, 8% and 10% of the FV variance can be explained by lagged values of Dividend Premium and VIX. Whereas the variance effect of these sentiment proxies is a bit lower for smaller companies. In contrast with the Granger causality tests, these outcomes leave out the significant influence of VFTSE, RSI and AAII on future volatility. Lagged shocks to these variables do not influence current values of FV. A possible explanation for this is that the effect on volatility may be incorporated immediately rather than in a delayed way.

Table 6. Variance Decomposition for 20-days-ahead FV residuals

		FTSE 100		Small Cap	
	Variable	Order I	Order II	Order I	Order II
Explained by innovations in	FV	0.8392	0.7953	0.8756	0.8220
	|R|	0.0005	0.0008	0.0103	0.0099
	HL	0.0097	0.0000	0.0334	0.0090
	VRS	0.0000	0.0047	0.0000	0.0418
	VFTSE	0.0314	0.0096	0.0026	0.0006
	TPCV	0.0020	0.0026	-	-
	TPCO	0.0005	0.0014	-	-
	RSI	0.0027	0.0044	0.0104	0.0070
	AAII	0.0027	0.0054	0.0014	0.0023
	DP	0.0124	0.0794	0.0001	0.0347
	VIX	0.0989	0.0963	0.0662	0.0727

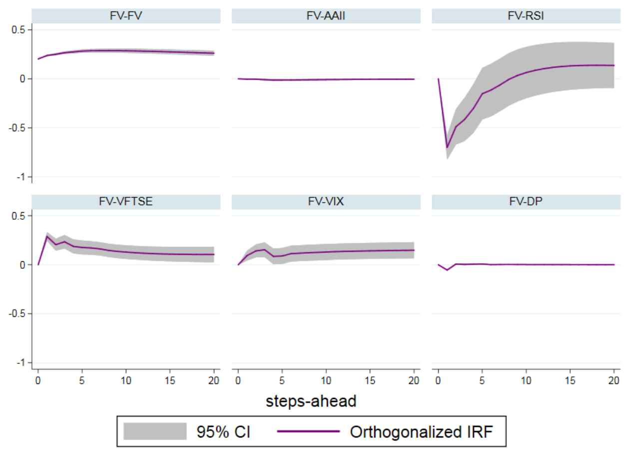
Furthermore, impulse responses help examine the dynamic relationship between sentiment and future volatility. Figures 2 and 3 illustrate the impulse responses of the Indexes' future volatility associated with different innovations to both themselves and to investor sentiment proxies. Unlike previous regressions, there only appears to be statistically significant responses to shocks in RSI, VFTSE and VIX for the first 5 days. After that, innovations gradually disappear in the long-term. Now DP is not significant at all for FTSE100. TPCO, TPCV and AAII have slightly positive to no effects on FV. Taking the responses' signs into account, unitary shocks to RSI seem to always have a negative impact on future volatility, whereas all other sentiment indicators seem to have positive effects.

Figure 2. Orthogonalised IRF for FTSE100



The graphs above (below) represent the daily evolution of future volatility variation of FTSE 100 (Small Cap) to one-unit shock in itself as well as to other investor sentiment indicators up to 20-days-ahead. Vertical axis stands for future volatility and the horizontal is the number of days ahead. The purple line is the Orthogonal Impulse Response Function. The shaded area denotes the confidence intervals at 95% level.

Figure 3. Orthogonalised IRF for Small Cap Index



Finally, a forecast accuracy diagnosis is completed for the 5-, 10-, 15- and 20-days-ahead volatility forecasts (see Table 7 in Appendix). Looking at the average forecasting errors, 5-day-ahead predictions appear to especially minimise the errors of the estimations. However, one notices that including US and UK traders' sentiment proxies versus only including VFTSE (i.e. model 1 vs 2) give very similar results. This confirms the importance of VFTSE forecasting ability.

CONCLUSIONS

Nowadays, behavioural finance is becoming more important in explaining financial markets performance. This paper investigates the causal relationship of local investors' sentiment on UK stock market volatility. This paper also analyses the US-UK contagion theory and examines its impact on smaller firms (Small Cap Index) versus FTSE 100 companies.

The empirical results suggest that investor sentiment proxies can help to explain future stock market volatility. This effect is greater for FTSE100 companies. Moreover, investor sentiment significantly Granger-causes future volatility for both small and big companies, and vice versa. Bidirectional relationships are predominant in the Small Cap Index.

The variance of future volatility on both markets can be mainly explained by innovations on themselves as well as on lagged values of Dividend Premium and VIX. Future volatility responses to changes in investor sentiment are mainly positive and statistically significant for the first five days, they gradually disappear after this. Only unitary shocks to RSI have a negative impact on future volatility. These innovations appear to affect small firms in a greater way.

Regarding American individuals' sentiment, past values of AAII do not seem to be correlated with current values of future volatility on any of the markets. Nonetheless, VIX, the implied volatility index of S&P500, has demonstrated to be a strong driver of UK volatility.

These findings, however, differ from Hudson and Green (2015) who find UK investor sentiment insignificant once American sentiment proxies are introduced. I find that local sentiment still plays a relevant role in forecasting future volatility.

These results may be of interest to many investors and financial institutions who forecast volatility for their investment and risk strategies as well as constructing financial models such as Value-at-Risk.

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APPENDIX

Detailed explanation of volatility measures used:

Following Sheu and Wei (2011), I examine the **absolute daily returns (|R|)** and the **high-low range (HL)** in the benchmark forecasting model (defined in the methodology section). The high-low range includes the market fluctuation limits which have been set up as 20% of the daily price variation (±10% of the previous day closing price, as per the London Stock Exchange Halting Rules).

$$|R_t| = \left|\ln \frac{C_t}{C_{t-1}}\right| \qquad HL_t = \frac{H_t - L_t}{C_{t-1} * 20\%}$$

Where $|R_t|$ is the absolute daily returns at time t and HL_t is the daily high-low range at time t. C_t is the closing price on trading day t whereas C_{t-1} is the one on the previous trading day. H_t is the daily highest index price on trading day t, while L_t is the lowest one.

Another volatility measure proposed by Rogers and Satchel (1991) is considered. It uses daily high (H), low (L), open (O) and closing (C) prices to estimate market variance in time series. **VRS** is constructed as:

$$VRS_t = \sqrt{252 * \sum_{t=1}^{n} ln\left(\frac{H_t}{O_t}\right) * ln\left(\frac{H_t}{C_t}\right) + ln\left(\frac{L_t}{O_t}\right) * ln\left(\frac{L_t}{C_t}\right)}$$

Detailed list of investor sentiment proxies analysed in this study:

1. The daily **implied volatility** of the FTSE100 index options **(VFTSE),** which is the local equivalent of the American investor fear index VIX, has previously been contemplated as a good forecaster of future volatility in financial markets (Corrado and Miller (2005)). The VFTSE represents the market expectation of stock market price variance over a period of 30 days.

2. The **Put-Call Volume Ratio (TPCV),** a common proxy for determining the current condition of the options market. It is useful to understand whether possible a reversal is approaching. The ratio has been calculated as the put trading volume divided by the call volume on day t. If the ratio is closer to one, it means that traders are buying more put than call options. Thus, this could be a possible bearish trend in a falling market, and conversely with low values. Extreme numbers suggest a change in the market mid-term trend.

3. **Put-Call Open Interest Ratio (TPCO)**. An alternative way of calculating the previous Ratio is by using the number of open or outstanding option contracts instead. It can be interpreted as a signal of trend strength. It is obtained by dividing the number of open interest in a put contract by the number of open interest in call option with the same strike price and expiry date on day t. Increasing open interests indicates new traders are trading in the market (thus, more money is entering the market), a sign of rising momentum and/or trend continuation.

4. **Relative Strength Index (RSI)** over 14 Days. This ratio reveals whether an Index is overbought or oversold in a given timeframe. The RSI is similar to a market momentum indicator. From a ratio 0 to 100, a value around 70-80 (30-20) considers the market to be overbought (oversold). Extreme values could be interpreted as a sign of imminent reversal (downwards or upwards, respectively).
5. **Dividend premium (DP)** has been also used by scholars such as Baker and Wurgler (2007) as a measure of investors' demand for income stability. It has been calculated as the difference between the *Total Return Index (Gross Dividends)* minus the *Total Return Index (Net Dividends).*

6. The **American Association of Individual Investors survey (AAII)** is also included. Recently, academics such as Hudson and Green (2015), have demonstrated that US individual investor´s sentiment contagion can spread to other countries, including the UK. Calculated as the percentage change from bullish over bearish sentiment (excluding neutral investors), a high AAII ratio represents an overall bull market, whereas a low ratio indicates the presence of more bearish traders. Any extreme value might suggest the proximity of a market direction change in the following days. I use daily values from the weekly survey.

7. Finally, a second US sentiment proxy has been incorporated. The **Implied Volatility Index of the S&P 500 (VIX)** is famous for his quality forecasts for future volatility estimation, as previously said.

Table 1. Descriptive Statistics of FTSE 100 and Small Cap Indexes.

	FTSE 100 Index (UKX)							Small Cap Index (SMX)					
Proxy	**N**	**Mean**	**σ**	**Min**	**Max**	**Skew**	**Kurt**	**Mean**	**σ**	**Min**	**Max**	**Skew**	**Kurt**
FV	4126	16.676	8.590	7.264	54.904	1.883	7.476	10.175	4.640	3.591	29.605	1.598	6.385
|R|	4126	1.339	2.160	0.000	27.913	3.771	22.452	0.483	0.518	0.000	6.147	2.938	17.367
HL	4126	13.695	10.059	1.213	101.95	2.747	15.586	3.096	2.648	0.200	29.806	3.120	19.089
VRS	4126	6.768	5.112	0.003	50.977	2.611	14.841	3.618	3.991	0.000	59.237	3.705	30.220
VFTSE	4126	19.097	8.854	6.194	78.690	2.021	8.740	19.097	8.854	6.194	78.690	2.021	8.740
TPCV	4126	1.514	0.796	0.044	11.533	2.627	19.378	-	-	-	-	-	-
TPCO	4126	1.352	0.313	0.019	2.239	0.805	2.990	-	-	-	-	-	-
RSI	4126	52.239	10.703	14.680	84.020	-0.274	2.780	55.426	17.645	9.110	98.610	-0.123	2.460
AAII	4126	0.063	0.483	-2.714	0.880	-1.369	5.858	0.063	0.483	-2.714	0.880	-1.369	5.858
DP	4126	28.769	9.368	12.325	50.345	0.376	2.226	36.713	16.478	12.747	78.108	0.743	2.602
VIX	4126	19.243	8.911	9.140	80.860	2.294	10.592	19.243	8.911	9.140	80.860	2.294	10.592

This study has been divided by market size: FTSE 100 Index and the Small Cap Index. The variables object of study are the future volatility (FV), the market absolute return (|R|), high-low range (HL), the volatility suggested by Rogers and Satchel (1991) (VRS) and several investor sentiment proxies such as the FTSE 100 Volatility Index (VFTSE), the Put-Call Volume Ratio (TPCV), the Put-Call Open Interest Ratio (TPCO), the Relative Strength Index (RSI), the Dividend Premium (DP) and two American sentiment proxies: American Association of Individual Investors survey (AAII) and the Implied Volatility Index of the S&P 500 (VIX). Data available from January 2002 to April 2018.

Table 2. Pairwise Correlation Matrix for FTSE 100 and Small Cap Indexes

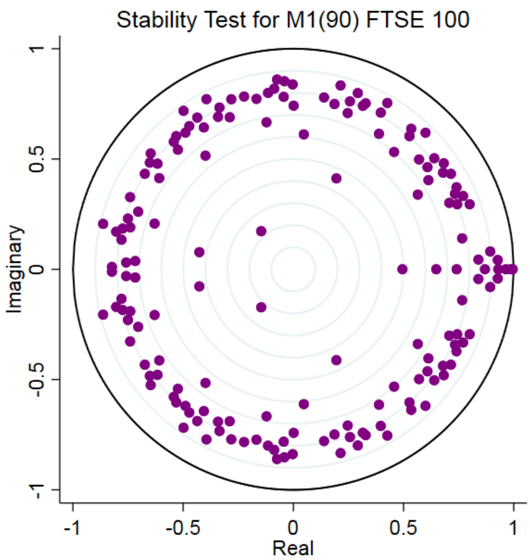
FTSE 100 Index (UKX)

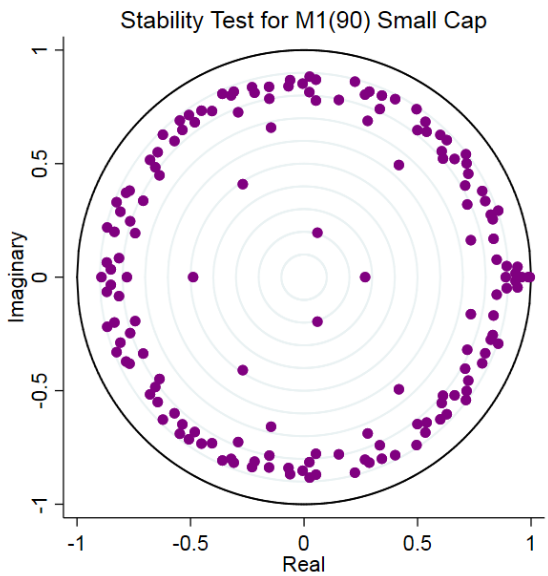
Variables	FV	|R|	HL	VRS	VFTSE	TPCV	TPCO	RSI	AAII	DP	VIX
FV	1.0000										
|R|	-0.058*	1.0000									
HL	0.626*	0.105*	1.0000								
VRS	0.628*	0.044*	0.997*	1.0000							
VFTSE	0.859*	-0.0070	0.796*	0.796*	1.0000						
TPCV	-0.130*	0.0100	-0.063*	-0.064*	-0.097*	1.0000					
TPCO	-0.361*	0.235*	-0.264*	-0.277*	-0.410*	0.137*	1.0000				
RSI	-0.160*	-0.134*	-0.400*	-0.388*	-0.395*	-0.116*	-0.0080	1.0000			
AAII	-0.324*	-0.072*	-0.373*	-0.371*	-0.408*	0.040*	0.0000	0.354*	1.0000		
DP	-0.390*	0.437*	-0.342*	-0.373*	-0.459*	0.041*	0.674*	0.081*	0.045*	1.0000	
VIX	0.818*	0.0020	0.703*	0.700*	0.895*	-0.101*	-0.411*	-0.298*	-0.353*	-0.422*	1.0000

Small Cap Index (SMX)

Variables	FV	|R|	HL	VRS	VFTSE	RSI	AAII	DP	VIX
FV	1.0000								
|R|	0.381*	1.0000							
HL	0.468*	0.918*	1.0000						
VRS	0.319*	0.161*	0.502*	1.0000					
VFTSE	0.751*	0.467*	0.520*	0.319*	1.0000				
RSI	-0.272*	-0.284*	-0.319*	-0.226*	-0.504*	1.0000			
AAII	-0.352*	-0.236*	-0.309*	-0.244*	-0.409*	0.461*	1.0000		
DP	-0.335*	-0.151*	-0.105*	0.0010	-0.473*	0.084*	0.062*	1.0000	
VIX	0.754*	0.431*	0.485*	0.288*	0.895*	-0.409*	-0.354*	-0.444*	1.0000

Figure 1. Stability Graphs of selected models





All the eigenvalues lie inside the circles; thus, VAR satisfies the stability condition.

Table 3. OLS Regressions

	FTSE 100			Small Cap		
Proxy	BMK	**M1**	M2	BMK	**M1**	M2
|R|	-0.77** (0.071)	**-0.21** (0.033)**	-0.21** (0.032)	-2.19** (0.308)	**-4.33** (0.444)**	-5.83** (0.464)
HL	1.512** (0.208)	**-0.07** (0.010)**	-0.10** (0.011)	1.11** (0.062)	**1.06** (0.099)**	1.40** (0.103)
VRS	-1.88** (0.408)	**-0.261 (0.042)**	-0.17** (0.021)	0.18** (0.017)	**-0.15** (0.026)**	-0.23** (0.027)
VFTSE		**0.905** (0.020)**	1.009** (0.014)		**0.221** (0.012)**	0.369** (0.006)
TPCV		**-0.224* (0.078)**				
TPCO		**1.314** (0.278)**				
RSI		**0.150** (0.006)**			**0.036** (0.003)**	
AAII		**-0.295** (0.145)**			**-0.743** (0.107)**	
DP		**0.031* (0.010)**			**2.736** (0.328)**	
VIX		**0.189** (0.015)**			**0.190** (0.011)**	
Cons	9.774** (0.181)	**-12.05** (0.625)**	0.313 (0.172)	7.110** (0.102)	**0.3790 (0.267)**	2.447** (0.111)
N	4125	**4124**	4124	4125	**4125**	4125
Adj R^2	41.10%	**79.40%**	75.30%	25.60%	**64.32%**	59.20%

Standard errors are in parentheses. (*) and (**) mean significant at 5% and 1% levels, respectively. TPCV and TPCO variables are not available for SMX. Models with lowest MAPE values have been marked in bold.

Table 4. Forecasts evaluation summary for all volatility models (MAPE)

FTSE 100 Index (UKX)				**Small Cap Index (SMX)**			
BMK	**M1**	**M2**	**Mean**	***BMK***	**M1**	**M2**	**Mean**
5-Day-Ahead Forecasting							
0.0053	**0.0140**	0.0144	**0.0112**	*0.0034*	**0.0048**	0.0049	**0.0044**
10-Day-Ahead Forecasting							
0.0124	0.0386	0.0287	0.0266	*0.0045*	0.0100	0.0090	0.0078
15-Day-Ahead Forecasting							
0.0189	0.0537	0.0388	0.0372	*0.0048*	0.0164	0.0134	0.0115
20-Day-Ahead Forecasting							
0.0319	0.0734	0.0542	0.0532	*0.0065*	0.0267	0.0220	0.0184