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Dynamic connectedness between investors' sentiment and asset prices: A comparison between major markets in Europe and USA

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A R T I C L E I N F O

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TVP- VAR

A B S T R A C T

In this study, we use the GARCH-MIDAS model and its extensions to provide new insights on the impact of investor sentiment on asset prices focusing on major market indices in Europe and that of USA. Specifically, we account for leverage, thresholds, and structural heterogeneity in the volatility behaviour of the indices. Furthermore, we decompose the total conditional volatility of the indices into short- and long-term components. Our findings indicate that volatility of the sampled indices, at any given period, is notably characterized by the type of news (good/bad), extreme events, and more importantly, investors' sentiments. We also find that volatility in the United States conveys significant information to the UK and the Euro area. Although the volatility in the UK has little effect on the Euro area, the volatility from the latter however cascades to the UK significantly. Our findings are robust having passed through a battery of diagnostic tests.

1. Introduction

Over the years, traditional asset pricing models took the centre stage in measuring risk-return trade-offs. Concepts such as efficient market hypothesis (EMH) (Malkiel & Fama, 1970), capital asset pricing model (CAPM) (Sharpe, 1964) and arbitrage pricing theory (APT) (Ross, 1976) dominated the research space in financial markets. However, there has been a paradigm shift from traditional approaches to behavioural finance perspectives in recent years. As a modern approach to asset pricing, behavioural finance or, more colloquially, investor sentiment, has gained popularity due to the empirical support it provides for asset pricing. It accentuates the importance of human bias in market behaviour.

The foundation of sentiment studies lies in the modification of classical finance views on investors' rationality and market efficiency. Fundamentally, research on behavioural biases relies on the assumptions of investor normality, the presence of protracted market anomalies, and the extensive application of experimental psychology to support its proposition. Since its debut into the academic literature, scores of studies have explored the linkage between investor sentiments and financial market performance. Recent empirical contributions include those of Salhin et al., (2016), Sakariyahu et al., (2021), and Paterson et al., (2023). These studies and

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several others, while shedding light on the significance of investors' sentiments, focus on mean formation and conditional volatility, in contrast to earlier studies on asset pricing that primarily test the role of fundamental factors on stock market performance (see Kearney & Daly, 1998; Flannery & Protopapadakis, 2002; Lee & Gan, 2006; Kling & Gao, 2008).

In this paper, we explore new empirical pathways and address key questions in the nexus between behavioural finance and asset pricing: Is there a dynamic connectedness between investors' sentiments & asset prices, particularly in major markets such as Europe and USA? And if there is, why and what are the implications for investors and other stakeholders in the financial market? Due to globalisation, financial markets have become deeply connected and integrated such that the events in one market can easily transmit to other markets outside its borders. Consequently, based on cognitive thoughts, investors devise various trading strategies to immune their portfolio from the vicissitudes of global factors. We provide answers to the foregoing questions by examining (i) volatility components of the sampled indices, (ii) the roles of asymmetry, leverage, and investor sentiments, as well as (iii) the average joint connectedness of the sampled indices. The sampled stock markets, which include UK, Germany, Euronext, and USA, provide an empirical setting to investigate these questions, as these stock markets jointly account for about one-third of the global stock market activities (Sakariyahu et al., 2021). In addition, the preliminary evidence of interdependence depicted in Figs. 1 and 2 provides a significant basis for explaining this conundrum.

In comparison to previous research, our study is driven by three motivations. First, most studies (Edmans et al., 2007; Bollen et al., 2011; Akansu et al., 2017; Papakyriakou et al., 2019) on the impact of sentiment on market behaviour focuses particularly on mean–variance relation. Although estimating returns is of critical interest to both individual and institutional investors; nevertheless, the importance of accurate volatility forecasting, particularly in the face of political, socio-economic, and cultural dynamics, cannot be downplayed. Theoretically, the return on an asset should commensurate its risk level, to a reasonable extent (Sharpe, 1964). Hence, to an investor, an accurate measure of volatility provides insights into the appropriate pricing structure of an asset. Besides, capital projects are susceptible to financial volatility occasioned by policy uncertainties; thus, estimating future volatility of financial assets assist corporations to insulate against downside risks associated with financing and investment decisions. Furthermore, financial market volatility can create economic disruptions. Based on the supply-leading theory, finance and economic literature agree that financial markets propel growth in the real economy because it engenders efficient allocation of scarce resources among competing productive sectors. Hence, volatility associated with financial markets is capable of distorting macroeconomic fundamentals (Jurado et al., 2015; Berger et al., 2020). Moreover, when financial assets consistently increase in prices, it is a major indicator of a thriving economy, which further stimulates investors' optimism towards the market. As a result of the positive economic outlook, investors' wealth is improved in terms of capital gains, firms enjoy increased demand for goods and services while the economy experiences growth in its foreign direct and portfolio investments. Notwithstanding the above arguments, persistent volatility in the financial market can equally create investors' apprehension which may result in panic selling of assets. In fact, if the situation is not quickly put under control, it may lead to significant loss of capital and potential collapse of the market (Long et al., 2020; Rupande et al., 2019). Due to globalisation, financial market disruption can also be contagious; its effects can transmit to other sectors of the economy as well as other transnational borders, with adverse consequences. Therefore, to control the velocity of asset volatility, its source must be investigated, whether from fundamental or behavioural perspective. Many studies (Lee et al., 2002; Lemmon & Portniaguina, 2006; Humpe and Macmillan, 2009; Kasman et al., 2011; Patel, 2012; Ahmadi, 2016) have focused on the fundamental (or economic) perspectives of market behaviour, with conflicting outcomes; however, in this study, we explore the behavioural causes. Considering that all stakeholders in the market are usually concerned with the magnitude and direction of asset volatility, this study adopts modern volatility forecasting tools and provides accurate volatility estimates that will aid policy makers in financial regulations and reduce the severity of losses incurred by investors.

Second motivation stems from the selection of sentiment proxies. In sharp contrast to prior studies on investor sentiment

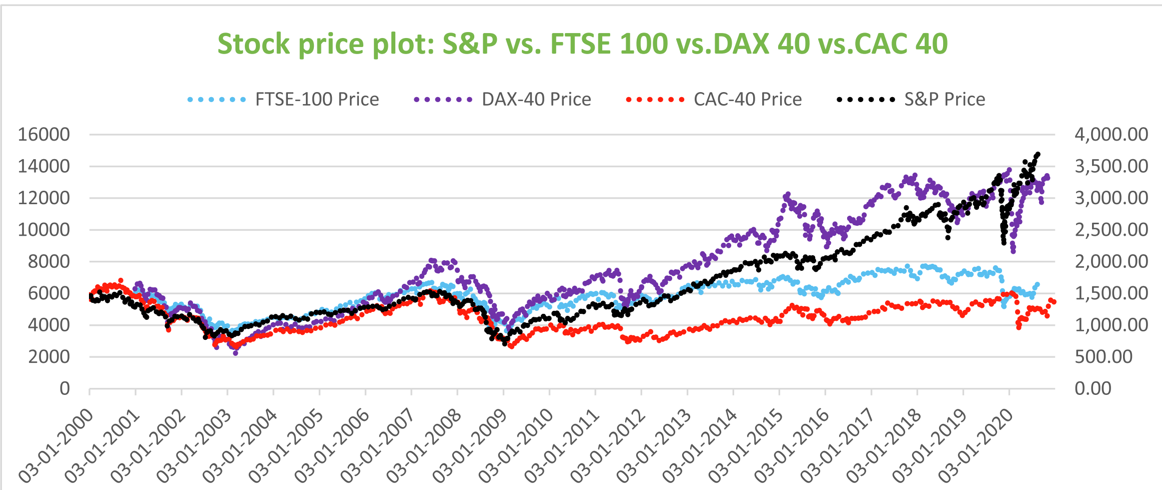

Fig. 1. Grouped price trend of the sampled indices.

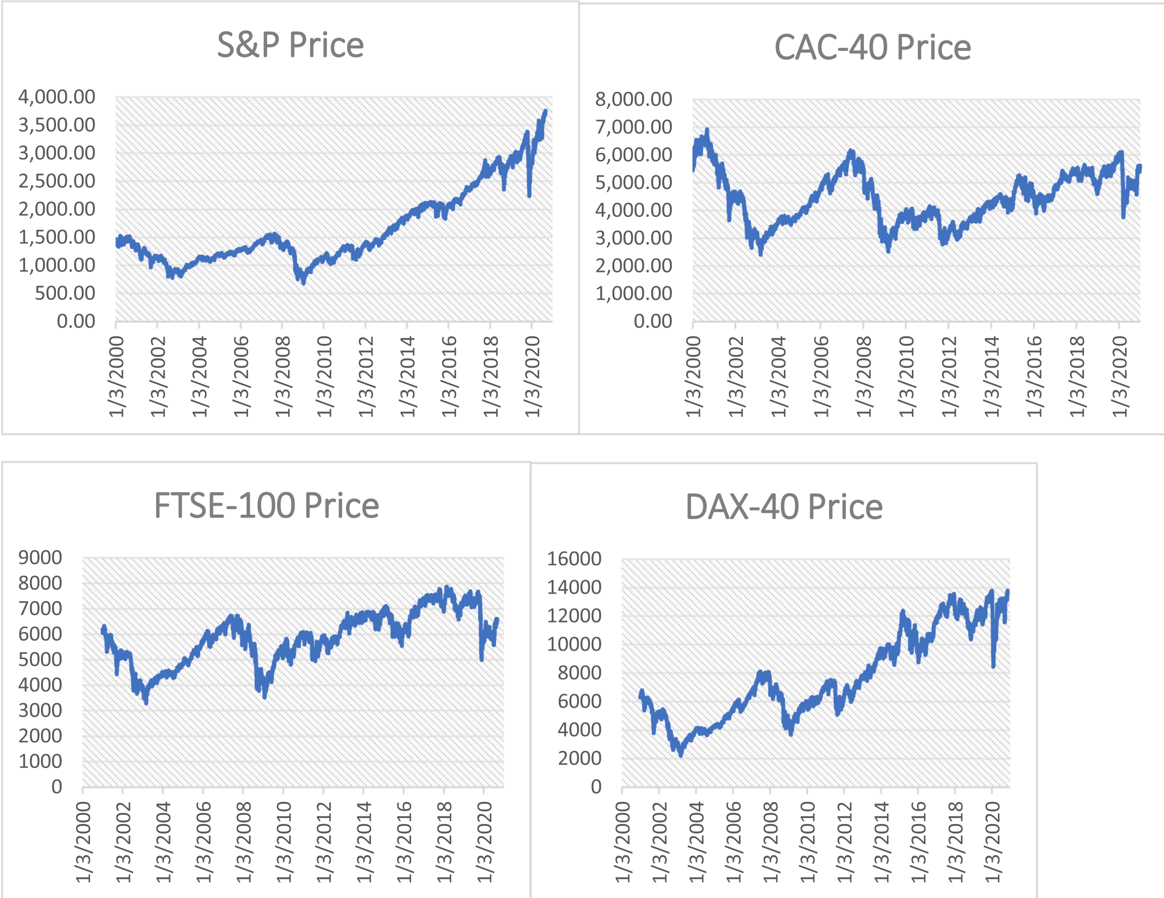

Fig. 2. Individual Price trend for each index.

(Sakariyahu et al., 2021; Dosumu et al., 2023; Sakariyahu et al., 2023), our study employs new sentiment index to explain how investors' mood and emotions influence volatility levels across global financial markets. Our first sentiment variable is the *lag-lead* data of the sampled indices. By lag-lead, we refer to emotional ambivalence exhibited by irrational investors towards a particular stock, sector, or market when the proportion of stocks declining in value exceeds the proportion of stocks advancing in value. Studies (such as Simon & Wiggins, 2001; Chang et al., 2012; Bathia & Bredin, 2013) note that this trading practise eventually upsets anticipated market norms by artificially inflating asset prices during bullish periods or severely depressing them during negative ones. Next, we adopt *liquidity* as another sentiment measure, which has also previously been used in the literature and found to influence investors' trading behaviours through determining information flow and diffusion (Zouaoui et al., 2011; Hu et al., 2022), market returns (Baker and Stein, 2004; Pan & Poteshman, 2006), efficiency (Garcia & Liu, 1999), and volatility (Baker & Stein, 2004). Lastly, we adopt *put-call ratio*, obtained from options of the sampled indices, as an indicator of market sentiment. Market players use the put-call ratio as a fear gauge, similar to the VIX, with greater levels signifying a pessimistic mood (Simon & Wiggins, 2001; Dennis & Mayhew, 2002; Pan & Poteshman, 2006; Umar et al., 2021). The put-call ratio is typically interpreted to mean that as market players become bearish, they buy puts to either hedge their portfolios or place bearish bets. A low put-call ratio, on the other hand, is linked to a reduced demand for puts, which would indicate a bullish attitude. The put-call ratio is therefore generally believed to be a 'contrarian investing tool' driven by demand rather than supply (Simon & Wiggins, 2001; Bandopadhyaya, & Jones, 2008; Houlihan, & Creamer, 2019). As a result, it is reasonable to assume that the relationship between the put-call ratio and volatility of the sampled indices will correlate.

The third motivation is based on methodological approach. Essentially, we observed that most studies explaining the interdependence between investor sentiment and market volatility used different approaches including the standard GARCH-models (Kearney & Daly, 1998; Flannery & Protopapadakis, 2002; Yaya & Shittu, 2010; Hsing, 2011; Ahmadi, 2016). However, the common drawback among these studies is the limited forecasting abilities of the standard GARCH models because of the use of same frequency data. Recent research (Engle & Rangel, 2008; Engle et al., 2013; Pan & Liu, 2018; Wang et al., 2020) on asset volatility have shown that the GARCH-MIDAS model and its extensions offer better predictive power as they decompose total conditional variance into short- and long-term volatility components. Besides, the GARCH-MIDAS model, through its asymmetric strands, has an advantage of diffusing volatility behaviour into leverage and thresholds. To the best of our knowledge, no study has used the GARCH-MIDAS model to connect investor sentiments with market volatility. To this end and as a novelty in the literature, we adopt this technique to provide fresh perspectives on volatility forecasting. This is necessary to furnish valuable information to policymakers and offer interesting insights into how investors can earn adequate returns on their investments, commensurate at least, to the risk they bear.

Using a collection of global stock markets, we discover differences in volatility and connectedness across markets, and to the extent that market similarities (or differences) are unveiled, we can investigate whether our sentiment variables play critical roles in driving the presented differences and/or connectedness. For estimation and forecasting purposes, we use the daily price data of three major European market indices: FTSE-100, DAX-40, and CAC-40, from 2000 to 2020. We also introduce price data for S&P 500 for out-of-sample performance check. The evidence in Figs. 1 and 2, which displays the price movement for each index, over our sample period (2000–2020) confirms a similarity in the movement of the indices. Following the approach of Pan & Liu (2018) and Wang et al. (2020), we employ the GARCH-MIDAS model and its modified extensions to generate forecasts. Similar to their findings, our results show that the variants accounting for asymmetry and extreme shocks provide superior forecast performance on market volatility than the standard GARCH- MIDAS model.

Additionally, we observe from the output of the asymmetric model, that bad news and perhaps negative shocks have significant influence on the markets than good news. Our findings provide new evidence suggesting that investor sentiments permeate financial markets through'noise' induced by good and bad news. Given that bad news often triggers stronger emotions and reactions than good news, the consequence is that it creates artificial volatility levels and persistent anomalies across the markets. Also, by applying time-varying structural framework in our analysis, we provide fresh information on the dynamic connectedness among major financial markets in the world. Our output also confirms that the asymmetric effect of news in the short term is greater than the long term. Interestingly, our main sentiment variable reveals significant influence on the volatility behaviour across the models. The outputs of other sentiment variables are also in tandem with the main estimations. Furthermore, our out-of-sample forecast performances prove that the models are convincing due to the introduction of leverage and threshold effects. Our results are crucial and provide relevant information to investors, academic community, industry practitioners and regulators.

This study renders some noteworthy contributions to the literature in different ways. First, we add to the extant research in behavioural finance literature which documents the predictive power of investor sentiments on market behaviour (Baker & Wurgler, 2006; Yu & Yuan, 2011; Salhin et al., 2016; Xiong et al., 2020). Different from the approach in prior studies (such as Sakariyahu et al., 2021; Paterson et al., 2023), applying new sentiment proxies allows us to make plausible cross-country comparison. Second, by adopting major markets in Europe and USA, we determine the dynamic interdependence among the indices of these markets. An intriguing contribution lies in the discovery that markets in Europe convey significant volatility information to the UK with the latter only providing little effects to those markets. Also, the US market is the major conveyor of volatility to other markets in Europe. Our findings reinforce similar positions of Xiong et al., (2020) who also provide evidence of connectedness among six G7 countries and five Asia pacific countries. Third, we contribute to the literature by shedding light on the predictive stability of our models. By applying the Diebold–Mariano test, we provide additional information on the performance of our models by showing out-of-sample results, whereas most previous studies do not consider this approach.

The remainder of this paper is structured as follows. Section 2 documents the review of past studies. Section 3 explains the data collection process and preliminary estimations. Section 4 provides details of the empirical strategy. Section 5 presents the empirical findings, and Section 6 concludes the paper, stating the significance of the main findings and outlining avenues for future research.

2. Review of past studies

Globalisation has made the world's financial markets deeply connected and integrated. This means that the events that occur in one market can easily transmit to other markets located outside of its borders. As a result, investors devise a variety of trading strategies to protect their portfolios from the uncertainties around global events. To this end, investors' emotions, and cognitive thoughts, generally described as investor sentiments, play a crucial role which, in recent times, have been found to have significant influence on asset pricing. Several academic papers have been put forward by researchers to explain the interaction between investors' sentiments and market behaviour, there is however, an apparent conflict of findings in the literature. While some papers have reported significant positive or negative impact of sentiment on market behaviour, others have discountenanced its predictive power. From a different perspective, some studies also provide evidence on how investors deduce sentiments from macroeconomic fundamentals and the resulting effect on market outcomes. For example, in an early study, Kearney & Daly (1998) examined factors contributing to the volatility of stock prices in the Australian stock market. Utilising the Generalised Least Squares (GLS) estimation approach to examine monthly data, they find that macroeconomic factors such as interest rates and inflation, directly influence investors' biases and affect the volatility of the Australian stock market. Additionally, they observed that industrial production, money supply, and current account deficit indirectly impact stock market volatility. In another study, Chiu et al., (2000) employed a two-factor process to examine the dynamic relationship among investor sentiment, macroeconomic fundamentals, and financial market volatility (bond and stock market volatility). By analysing economic indices, they decompose total market volatility into short and long run components and conclude that changes in investor sentiment arise from changes in macroeconomic indices with a significant impact on market volatility.

Using investors' intelligence sentiment index, Lee et al., (2002) explain the impact of sentiments on volatility and expected return. With the aid of GARCH-in-mean, they document that returns and volatility are determined by changes in sentiments and the magnitude of the changes in sentiments affect the state of the market (bearish or bullish). However, in testing for the usefulness of sentiment for volatility forecasting, the study of Wang et al. (2006), surprisingly, lends no support to the relationship between sentiment and market behaviour. They document that sentiment has no predictive capacity on returns and volatility. Similarly, Verma and Verma (2007) examine how conditional volatilities are influenced by fundamental and noise trading activities using DJIA and S&P 500 stocks returns. With the aid of multivariate EGARCH model, they document negative effects of institutional and individual sentiments on stocks returns' volatilities. Meanwhile, Yu & Yuan (2011) also demonstrate the influence of investor sentiment on the mean–variance trade-off in the United States. Their study divides investor sentiment into low and high periods. They find that during low-sentiment periods, stock market's conditional variance is positively related to stock market's expected excess return but not correlated with high sentiment-periods. Furthermore, they show that during low-sentiment periods, there is a strong negative correlation between contemporaneous volatility innovations and returns. Their study thus concludes that sentiment-prone investors, unlike rational investors, are naive investors who have low understanding of how to measure risk and could misestimate volatility.

The inconsistencies and diverse positions within literature have also been intensified by the various indicators used to measure investor sentiment. For example, advocates of media-driven sentiment offer rational justifications to substantiate the notion that discussions on social media platforms elicit investors' sentiments towards the market, thereby influencing the movement of stock prices. These studies propose that market sentiment can be influenced by the responsiveness of investors who depend on information obtained from widely read print and online media platforms such as Wikipedia, Investopedia, and Twitter. For instance, to provide a thorough understanding of the influence of tweet-induced sentiments on the financial market,

Rao & Srivastava (2012) conducted a comprehensive analysis of over four million tweets. Utilising Granger causality test, they explored how board tweets influence stock price behaviour, thus distinguishing between positive and negative tweets through a unique mood tracking measure. The findings of their study strongly indicate a significant positive correlation between board tweets and stock price activity. Providing further justification, Kim and Kim (2014) conducted a study utilising a vast dataset of over 32 million messages from the Yahoo Finance message board, encompassing discussions related to 92 firms, collected over a period spanning from 2005 to 2010. The findings of their study did not reveal any indications of predictability in trading volume, volatility, or stock returns, either at the individual firm level or when aggregated.

In another stream of research, proponents of market sentiments suggest monitoring and extracting information about investors' attitudes from a trading perspective. For instance, Bahloul and Bouri (2016) highlight the impact of trader-position based sentiment on the volatility of future markets. Constructing a new sentiment index to capture different positions of traders, their study reports that price volatility in major futures markets are positively related to sentiments which consequently leads to market instability. They also conclude that most traders are irrational investors whose activities are mainly sentiment-induced and when they appear bullish in transactions, they destabilize the market with irrational trades. Similarly, in a different study conducted by Frugier (2016) using a portfolio of large European stocks to examine the link between investor sentiment, stocks volatility and future returns, they observe that portfolios managed by active traders with positive sentiment produce higher returns and lower volatility than those managed passively. They thus opine that behavioural finance is an essential component in returns and volatility measurement.

Although it can be inferred that the influence of media sentiment studies on market behaviour is substantial. Nevertheless, the credibility of these measures has been tainted by the prevalence of fake news in the media and the fact that the impact of information disseminated through online media channels is mostly determined by factors such as the presence of positive or negative language, the popularity of the media sources, and the engagement of commenters. Consequently, other studies have devised new media sentiment proxies to explain market outcomes. For example, in contrast to the above studies on media sentiment, Naeem et al., (2020) explore the influence of Twitter based happiness as a sentiment proxy, on future stock market volatility. Focusing on major global stock markets around the world, such as Switzerland, Japan, China, UK, Germany, France, Netherlands, South Korea, Hong Kong, India, Brazil, USA, Canada, and South Africa, they show that the use of twitter happiness essentially captures investors' sentiments. Their study concludes based on both linear and non-linear tests that future volatility of some of the sampled countries are well influenced by twitter happiness. In recent times, Reis, and Pinho (2020) also introduced new media sentiment proxy (EUROSENT) to investigate the effect of investor sentiment on both returns and volatility in European markets. Applying vector autoregression model and other GARCH techniques, the study observes that its new sentiment measure strongly predicts market returns and volatility.

The above empirical reviews demonstrate that investor sentiment has been widely used to perform significant forecast on asset pricing. However, our study is distinct in two ways: first, we use a new sentiment proxy that provides fresh insight to volatility forecasting and secondly, in contrast to past papers, we employ GARCH-MIDAS model to properly account for episodic features associated with volatility forecasting and decompose the volatilities into short- and long-term components. This is in addition to the TVP-VAR model that shows joint interdependence of variables.

3. Data and preliminary findings

3.1. Data

Our data includes sentiment proxies and daily market data for three prominent European markets: the FTSE-100 index of the UK market, the DAX-40 index of the Frankfurt Stock Exchange, and the CAC-40 index of the Euronext market, which includes the France, Amsterdam, and Brussels Stock Exchanges. We introduce S&P 500 index data for continental comparison, robustness, and out-of-sample performance evaluations. We obtain daily market data, including market open and close prices, from DataStream and validate their quality using Bloomberg. Due to the availability of data, the beginning dates differ by market with the earliest being January 2000, whereas the ending dates are all at the end of 2020.

In terms of sentiment variables, we first employ the *lag-lead index*. Our selection of this proxy is based on the premise that sentiment-induced investors are noisy traders that react irrationally to market information, potentially altering expected volatility levels of the market (Simon & Wiggins, 2001; Wang et al., 2006; Yang & Wu, 2011; Stolbov et al., 2022). Using lag-lead as a new proxy for sentiment, we argue that investors crowd into a certain sector or index when the number of value-advancing stocks outnumbers value-declining stocks within the sector/index. As a result, sentiment-driven trading patterns increase the proportion of irrational trading to rational trading, thus reshaping projected market outcomes. Our lag-lead sentiment proxy for each index is calculated as the number of advancing stocks scaled by the trading volume of advancing stocks, divided by the number of declining stocks scaled by the trading volume of declining stocks. A high lag-lead means that the proportion of declining to advancing stocks is small. In addition to the lag-lead index, we follow extant studies in the literature by using *liquidity, measured by market turnover*, to proxy investor sentiment. Prior studies (see Baker & Stein, 2004; Pan & Poteshman, 2006; Baker & Wurgler, 2007; Liu, 2015; Chen & Sherif, 2016) document that liquidity has significant impact on asset pricing. Lastly, we adopt *put-call ratio* of the sampled indices as proxy for investor sentiment. We argue that put option buyers are potentially pessimistic investors because they are wagering on stock price declines. Conversely, call option buyers are placing a wager on rising stock prices and can be viewed as optimists. Studies in the literature acknowledge that the put-call ratio indicates investors' optimism/pessimism and different put-call ratios have been used (see Simon & Wiggins, 2001; Bandopadhyaya, & Jones, 2008; Umar et al., 2021). However, the most common is based on statistics collected from the Chicago Board Options Exchange (CBOE) which, on a daily basis, adds up all of the call and put options that are traded on specific stocks and on different indices (Simon & Wiggins, 2001; Seo and Kim, 2015). For the S&P index, we use data from CBOE while the put-call data for the European market indices were sourced from Eurex Exchange. The put-call ratio is calculated as trading volume of put option contracts divided by trading volume of call option contracts. A put-call ratio greater than 1 indicates that there are more pessimists in the market than optimists and if the value is less than one, then it suggests the pessimists are less than optimists (Simon & Wiggins, 2001).

Following prior studies in the literature (Shu & Chang, 2015; Sakariyahu et al., 2021; Dosumu et al., 2023), returns of the price index R_t are computed as the first order difference of the natural logarithm of the price index P_t and the value of volatility is captured by squared root of daily return:

$$R_t = 100^* [\Delta \log(P_t)] \tag{1}$$

We refine the daily price to returns using log changes and calculate the volatility of the returns. Furthermore, we document the statistical properties of the price index and the returns series therefrom. Specifically, we show that the descriptive statistics of the variables conform with the stylized facts of financial time series data. Also, we perform relevant tests for ARCH effects and auto-correlation. The descriptive statistics of the variables, the ARCH effects using ARCH-Lagrange Multiplier (ARCH-LM) test by Engle (1982) and auto-correlation tests using Ljung-Box Q- statistics are all shown in Table 1.

3.2. Preliminary estimations

As shown in Table 1, the FTSE-100 index witnessed an average mean return of less than 1 % which represents the capital gain of the index for the sample period. For DAX-40, investors earned an average return of almost 3 % while CAC-40 and S&P indices recorded an average return of about 1 % and 3 % respectively. These figures suggest that both FTSE-100 and CAC-40 produced similar average returns for their investors during the sample period while DAX-40 and S&P investors had same mean returns. Furthermore, we observe a wide difference in the minimum and maximum values of the return series of all the indices. FTSE showed a minimum return of −11 % and maximum return of about 10 %; DAX-40 witnessed minimum and maximum return of −12 % and 11 % respectively. CAC-40 showed a minimum return of −12 % and maximum return of about 11 % while S&P witnessed minimum and maximum return of −12 % and 11.6 % respectively. As anticipated, the minimum returns for the indices were witnessed during the global financial crisis while the maximum returns were recorded prior to the crisis. This would suggest that a large dispersion exists in all the market indices. Consequently, we examine the standard deviation of the output. We notice that despite having the lowest mean returns, FTSE-100 documented a high standard deviation compared to other indices, which further accentuates that the UK financial market is indeed highly volatile.

The result of the skewness statistic shows that the returns series are negatively skewed across the indices. This implies that there is a high tendency to obtain negative extreme values of returns, perhaps given that the sample period covers the era of 2007 global financial crisis. In addition, the kurtosis value of returns across the indices largely exceeds the conventional standard of 3 and implies that the returns are leptokurtic (high-peaked). Intuitively, the kurtosis statistic shows the relative difference in the tailedness (or peakedness) of a normal distribution with that of a probability distribution. According to stylized facts, financial time series data are mostly leptokurtic, that is, having fat tails and high peaks. Hence, the returns series are not normally distributed and the probability

Table 1
Descriptive statistics.

Statistics	FTSE-100 P_t	FTSE-100 R_t	DAX-40 P_t	DAX-40 R_t	CAC-40 P_t	CAC-40 R_t	S&P P_t	S&P R_t
Mean	5876.69	0.008	7686.00	0.025	4468.39	0.009	1653.67	0.026
Std. Dev.	1022.41	1.197	3076.75	1.491	918.77	1.445	674.39	1.253
Minimum	3287	−10.87	2202.96	−12.24	2403.04	−12.28	676.53	−11.98
Maximum	7877.45	9.84	13,790	11.40	6922.33	11.18	3756.07	11.58
Skewness	−0.23	−0.16	0.35	−0.02	0.15	−0.02	1.03	−0.15
Kurtosis	2.26	11.11	1.88	9.17	2.21	9.28	3.07	13.72
Observations	5049	5049	5082	5082	5370	5370	5284	5284

that there would be outliers in the returns is higher compared to a normal distribution. The p-value of the Jarque-Bera statistic (not reported) is less than 0.01 significance level, hence, the rejection of the null hypothesis of normal distribution. Jarque-Bera statistic is essentially used to further clarify the normality results reported by the skewness and kurtosis statistics.

To further verify the stylized facts on financial time series data, we examine the presence of autocorrelation using Ljung-Box Q-statistic and the time-varying conditional heteroscedasticity using ARCH-LM test proposed by Engle (1982). In the case of ARCH-LM test of the return series, the null hypothesis of the test is specified as no presence of autoregressive conditional heteroscedasticity (ARCH), that is, there's homoscedasticity. Table 2 shows that at 0.01 level of significance, the ARCH-LM test of return series rejects the null hypothesis of no ARCH effects at different lag order. This implies that there's volatility clustering in the indices which further affirms the use of volatility modelling tool. Volatility clustering in financial time series data implies period(s) of large changes followed by further large changes (wildness) and period(s) of small changes followed by further small changes (calmness).

In Table 3, the Q-statistic reveals that the returns series of the indices exhibit statistically significant autocorrelation at higher order. The presence of autocorrelation confirms that volatility in the series at a time period is significantly influenced by the volatility in the preceding period(s). Essentially, this is not uncommon to time series financial data and the use of ARCH or GARCH models correctly deals with the issue of autocorrelation.

3.3. Empirical models

This section explains the procedures for estimating the conditional volatility in this study. Generally, volatility can be estimated using different approaches; they include simple historical volatility method, moving average approach, rolling window, equally weighted moving average (EWMA) approach, Vector Autoregression model (VAR) and Generalized Autoregressive Conditional Heteroskedasticity (GARCH) methods. Of all these methods, GARCH is widely embraced in literature because of the limitations in the model performance of the other techniques (Piccoli et al., 2017; Wang et al., 2020). For instance, while some of these methods estimate volatility as a constant time invariant series, ARCH/GARCH techniques estimate volatility from the viewpoint of a conditional autoregressive time varying equation. More so, compared to other volatility techniques, GARCH variants systematically capture the essential features of financial time series such as volatility clustering, thick tailed returns and mean reverting tendencies. Besides, estimates generated through GARCH process reflect real world situations (Angelidis et al., 2004).

3.3.1. GARCH-MIDAS process

We use GARCH-MIDAS model of Engle et al. (2013) to explain the impact of investor sentiment on the volatility of the FTSE-100, DAX-40, CAC-40, and S&P indices. The standard GARCH-MIDAS model employs mixed frequency sampling to decompose the total conditional volatility of the assets into both short- and long-term components. We estimate the model for the indices' returns as:

$$r_{i,t} - E_{i,t}\left(r_{i,t}\right) = \sqrt{\tau_t g_{i,t}} \epsilon_{i,t}, \forall_i = 1, 2, \cdots, N_t, \tag{2}$$

$$\varepsilon_{i,t} | \Psi_{i-1,t}\ N(0,1), \tag{3}$$

$$r_{i,t} = \mu + \sqrt{\tau_t g_{i,t}} \epsilon_{i,t}, \forall_i = 1, 2, \cdots, N_t, \tag{4}$$

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i,t} - \mu)^2}{\tau_t} + \beta g_{i-1.t} \tag{5}$$

$$with \alpha > 0, \beta > 0, \alpha + \beta < 1.$$

In the above model, $\Psi_{i-1,t}$ represents the set of information available up to day i-1 of period t. N_t denotes the GARCH process which is used to capture the short-term volatility component shown in model 2 above, while the long-term volatility component τ_t is explained by a MIDAS regression procedure shown below.

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_1) SENT_{t-k}, \tag{6}$$

where m represents the constant term, θ denotes the coefficient of long term and *SENT* stands for each of the sentiment proxies: lag-lead index, liquidity (market turnover) and put-call ratio.

Table 2
ARCH-LM test.

	FTSE-100		DAX-40		CAC-40		S&P	
Statistics	F-stat	nRˆ2	F-stat	nRˆ2	F-stat	nRˆ2	F-stat	nRˆ2
ARCH-LM test [1]	280.60*	270.80*	184.80*	178.26*	7.543*	7.490*	178.725*	164.64*
ARCH-LM test [5]	214.25*	943.00*	136.82*	602.10*	13.754*	63.634*	49.609*	221.97*
ARCH-LM test [10]	134.85*	1151.68*	86.70*	739.70*	8.999*	81.643*	27.427*	243.16*

Table 3
Ljung-Box Q Autocorrelation test.

Statistics	FTSE-100	DAX-40	CAC-40	S&P
LB-Q [5]	41.476*	19.557*	12.45*	23.058*
LB-Q [10]	56.111*	33.653*	19.56*	29.272*
LB-Q [20]	90.167*	54.897*	37.85*	41.602*
LB-Qˆ2 [5]	1653.0*	1092.5*	89.35*	353.11*
LB-Qˆ2 [10]	3127.1*	2017.5*	172.4*	500.61*
LB-Qˆ2 [20]	5120.4*	2873.9*	283.1*	635.62*
Observations	5049	5082	5370	5284

3.3.2. *GJR GARCH-MIDAS model: Asymmetry effect*

As additional regressors, we modify the above model to capture both short- and long-term leverage (or asymmetry) effects. This is appropriate for explaining the impact of positive (good news) and negative (bad news) shocks. Incorporating the asymmetry terms using GJR GARCH-MIDAS model, we follow the procedures of Pan and Liu (2018) to estimate the short- and long-term volatility components as shown below. In the model, the asymmetry term which separates positive and negative returns, is also captured below.

$$g_{i,t} = \omega + [\alpha + \gamma \mathrm{I}(\varepsilon_{t-1} < 0)]\frac{(r_{i,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t}, \tag{7}$$

Table 4
In-Sample estimation results for the GARCH-MIDAS model and its variants: FTSE-100 This table shows the output of the seven sentiment-augmented GARCH-MIDAS models. We report the coefficients and their significance levels, while the standard errors are shown in parentheses. ***, **, * refer to statistical significance level at 1 %, 5 %, and 10 % respectively. X, Y, Z represent the sentiment variables: lag-lead index, liquidity (market turnover) and put-call ratio. Model 1: Standard GARCH-MIDAS model, Model 2: GJR GARCH-MIDAS model with short-term asymmetry effects, Model 3: GJR GARCH-MIDAS model with long-term asymmetry effects, Model 4: Threshold GARCH-MIDAS model with short-term extreme event effects Model 5: Threshold GARCH-MIDAS model with long-term extreme event effects, Model 6: GJR- Threshold GARCH-MIDAS model with short-term asymmetry and extreme event effects and Model 7: GJR-Threshold GARCH-MIDAS model with long-term asymmetry and extreme event effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
μ	0.044***	0.023**	0.065***	0.045*	0.056**	0.035***	0.056**
	(0.013)	(0.012)	(0.012)	(0.009)	(0.011)	(0.012)	(0.009)
α	0.513**	0.534*	0.525***	0.553*	0.551**	0.535***	0.460***
	(0.000)	(0.003)	(0.000)	(0.000)	(0.002)	(0.004)	(0.011)
β	0.420*	0.438***	0.450*	0.422***	0.436*	0.455***	0.444
	(0.013)	(0.011)	(0.009)	(0.011)	(0.012)	(0.009)	(0.011)
ω	2.59***	2.38**	1.57*	1.55***	1.63***	2.35	2.19
	(0.480)	(0.299)	(0.172)	(0.138)	(0.156)	(0.221)	(0.065)
m	0.433*	0.398	0.541***	0.250**	0.681***	0.567***	−0.613
	(0.036)	(0.058)	(0.073)	(0.058)	(0.042)	(0.055)	(0.039)
θ	0.177**	0.114**		0.143***		0.113*	
	(0.003)	(0.008)		(0.003)		(0.003)	
θ^*					0.203**		
					(0.010)		
$\theta+$			−0.003***				−0.042***
			(0.010)				(0.025)
$\theta-$			0.046**				0.055*
			(0.009)				(0.015)
$\theta+^*$					−0.530**		−0.384
					(0.16)		(0.13)
$\theta-^*$					0.209*		0.401
					(0.006)		(0.17)
γ		−0.216**					
		(0.100)					
$\gamma+$						−0.223*	
						(0.009)	
$\gamma-$						0.530**	
						(0.021)	
$\gamma+^*$					−0.219*		0.401
					(0.022)		(0.013)
$\gamma-^*$					0.217**		−0.091
					(0.020)		(0.15)
X	0.14*	0.20**	0.09*	0.55*	0.36	0.59***	0.56**
	(0.003)	(0.022)	(0.012)	(0.020)	(0.017)	(0.022)	(0.009)
Y	0.410*	0.299**	0.331*	0.275*	0.266	0.337**	0.177*
	(0.003)	(0.002)	(0.012)	(0.020)	(0.000)	(0.021)	(0.032)
Z	0.314**	0.220*	0.095	0.157*	0.126*	0.134*	0.160**
	(0.009)	(0.011)	(0.028)	(0.022)	(0.007)	(0.004)	(0.000)

$$\tau_t = m + \theta \sum_{k=1}^{K} \varphi_k(\omega_1, \omega_1) SENT_{t-k}. \tag{8}$$

3.3.3. Threshold GARCH-MIDAS model: Extreme even effect

In recent times, studies (Piccoli et al., 2017; Wang et al., 2020) have demonstrated the importance of modelling volatility from the viewpoint of extreme events such as persistent abnormal returns given that such events, particularly during financial crises, have crucial impact on market volatility. In this study, we use the threshold GARCH-MIDAS model to also account for the effect of extreme shocks on the volatility of the indices. The short- and long-term components are shown below.

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{9}$$

$$\tau_t = m + \theta^{-*} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{i-k} + \theta^{+*} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{i-k} + \theta^{*} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{i-k} \tag{10}$$

3.3.4. GJR-threshold GARCH-MIDAS model: Combining both asymmetry and extreme event effects

As part of the estimations, we introduce, simultaneously, both the asymmetry and extreme event effects in the model. We test whether combining the two variants (GJR-Threshold GARCH-MIDAS) in a single regression model will produce higher performance. To this end, we estimate in equations (12) and (13) below, the short- and long-term volatility components of the four indices, concurrently capturing the effect of bad and good news (asymmetry) and the effect of extreme events (threshold).

$$g_{i,t} = \left(1 - \alpha - \beta - 0.5\gamma^{-} - 1_{\{r_{i,t} < q_1\}} \gamma^{-*} - 0.5\gamma^{+} - 1_{\{r_{i,t} > q_2\}} \gamma^{+*}\right) + \left(\alpha + 1_{\{r_{i,t} < 0\}} \gamma^{-} - 1_{\{r_{i,t} < q_1\}} \gamma^{-*} + 1_{\{r_{i,t} > 0\}} \gamma^{+} + 1_{\{r_{i,t} > q_2\}} \gamma^{+*}\right) \times \frac{(r_{i,t} - \mu)^2}{\tau_t} + \beta g_{i-1,t} \tag{11}$$

$$\tau_i = m + \theta^{-} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{I-k} + \theta^{-*} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{I-k} + \theta^{+} \sum_{k=1}^{K} \varphi_k(\omega) SENT^{-}_{I-k} + \theta^{+*} \sum_{k=1}^{K} \varphi_k(\omega) SENT_{I-k.} \tag{12}$$

From equations (2)–(12) above, our results contain seven (7) different model estimations, in the following order: Model 1: Standard GARCH-MIDAS model, Model 2: GJR GARCH-MIDAS model with short-term asymmetry effects, Model 3: GJR GARCH-MIDAS model with long-term asymmetry effects, Model 4: Threshold GARCH-MIDAS model with short-term extreme event effects Model 5: Threshold GARCH-MIDAS model with long-term extreme event effects, Model 6: GJR- Threshold GARCH-MIDAS model with short-term asymmetry and extreme event effects and Model 7: GJR-Threshold GARCH-MIDAS model with long-term asymmetry and

Table 5

Out-of-sample forecasting performances for the FTSE-100 index using D–M and MCS tests. This table reports the forecasting performances of the FTSE-100 index using the D–M and MCS tests. The outputs of the D-M test for each model are shown in the first two rows while the values on the third row are the p-values of the MCS test. For the D-M test, we report the coefficients of the loss function with their significance levels while the t-statistics are shown in parentheses. The corresponding model has better predictive ability than the standard model if all loss functions have a value lower than 1. For the MCS test, p-values larger than 0.10 indicate that the corresponding model has an efficient forecast power. ***, **, * refer to statistical significance level at 1%, 5%, and 10% respectively.

	MSE	MAE	HMSE	HMAE	R2LOG	QLIKE
Model 1	1.040	1.091**	1.147	1.200	1.225	1.011
	(0.194)	(0.436)	(-2.105)	(-5.033)	(-1.011)	(-0.439)
	0.301	1.100	0.021	0.019	0.005	0.001
Model 2	1.012	1.304	1.120	0.457**	0.900*	0.309*
	(-0.090)	(-0.221)	(-1.045)	(-0.034)	(-0.160)	(-0.201)
	0.105	0.021	0.313	0.331	0.432	0.001
Model 3	0.969*	0.902*	0.961	0.909**	0.980	0.950
	(-0.258)	(-0.611)	(-0.550)	(-0.404)	(-0.622)	(-0.412)
	0.291	0.128	0.220	0.191	0.540	0.001
Model 4	0.940	0.929**	0.922*	0.950	0.890*	0.951*
	(-0.622)	(-0.405)	(-0.099)	(-1.223)	(-1.306)	(-0.122)
	0.199	0.201	0.108	0.330	0.001	0.000
Model 5	1.090*	1.455	1.078**	1.054*	1.089	1.710*
	(-1.220)	(-0.254)	(-1.500)	(-0.431)	(-0.610)	(-0.411)
	0.201	0.145	0.001	0.102	0.015	0.001
Model 6	0.905	0.968*	0.933	0.950*	0.900**	0.990*
	(-0.668)	(-0.625)	(-1.133)	(-1.140)	(-0.688)	(-0.544)
	0.330	0.291	0.918	0.701	0.667	0.001
Model 7	0.983*	0.804	0.921*	0.935*	0.820**	0.600
	(-0.530)	(-0.556)	(-2.053)	(-0.498)	(-0.642)	(-0.518)
	0.991	1.003	0.665	0.991	1.470	0.863

extreme event effects.

4. Empirical findings

In this section, we provide the in-sample estimation results of the seven models described above, starting with the standard GARCH-MIDAS model. To test the forecasting ability of our sentiment-augmented models, we further estimate the out-of-sample performance of the seven models. The results of the in-sample estimation are reported in tables 4, 6, 8 and 10 for the four indices.

4.1. In-sample results: Short-term volatility components

The coefficient of the standard GARCH-MIDAS models (without leverage and asymmetry), are all significantly positive, indicating their predictive ability for stock volatility. Additionally, we observe that the coefficients of α and β are jointly close to 1, suggesting the strong presence of volatility persistence. The asymmetric parameter γ of the short-term volatility component shows significantly negative impact on volatility. This indicates that bad news has huge impact on the volatility levels of the indices than good news, in the short-term. To better understand this parameter, we explore the stylized fact which requires that the values of $\alpha + \beta + \gamma /2$ must be close to 1 (Wang et al., 2020). Our output concurs with this apriori expectation and are consistent with the findings of Xie et al., (2021), thus indicating that there is a strong presence of short-term volatility persistence.

4.2. In-sample results: Long-term volatility components

Turning attention to the long-term volatility component, our findings reveal inconsistent results for the parameters of θ^{+} and θ^{-} under different models. For the θ^{+}, we find that the coefficient produced significantly negative results suggesting that the parameter has low impact on long-term volatility. Meanwhile, we find significantly positive results for the negative parameter θ^{-}. The findings indicate that long-term volatility can increase in the future due to the sign of this parameter. Also, the coefficient of the long-term

Table 6
Estimation results for the GARCH-MIDAS model and its variants using DAX-40 index This table shows the output of the seven sentiment-augmented GARCH-MIDAS models. We report the coefficients and their significance levels, while the standard errors are shown in parentheses. ***, **, * refer to statistical significance level at 1 %, 5 %, and 10 % respectively. X, Y, Z represent the sentiment variables: lag-lead index, liquidity (market turnover) and put-call ratio. Model 1: Standard GARCH-MIDAS model, Model 2: GJR GARCH-MIDAS model with short-term asymmetry effects, Model 3: GJR GARCH-MIDAS model with long-term asymmetry effects, Model 4: Threshold GARCH-MIDAS model with short-term extreme event effects Model 5: Threshold GARCH-MIDAS model with long-term extreme event effects, Model 6: GJR- Threshold GARCH-MIDAS model with short-term asymmetry and extreme event effects and Model 7: GJR-Threshold GARCH-MIDAS model with long-term asymmetry and extreme event effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
μ	0.053**	0.021*	0.057***	0.051*	0.064*	0.044*	0.331**
	(0.021)	(0.035)	(0.056)	(0.029)	(0.022)	(0.002)	(0.021)
α	0.611*	0.055*	0.409*	0.366*	0.521*	0.6044**	0.691*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)	(0.042)
β	0.239*	0.811	0.560**	0.541**	0.322*	0.109*	0.264*
	(0.032)	(0.066)	(0.017)	(0.145)	(0.068)	(0.031)	(0.078)
ω	1.560*	2.110	1.606**	1.053**	0.321*	0.441*	2.11*
	(0.401)	(0.120)	(0.221)	(0.300)	(0.168)	(0.110)	(0.052)
m	0.210	0.221	0.109**	0.250*	0.820**	0.722*	−0.309
θ*	(0.006)	(0.050) 0.420* (0.002)	(0.032)	(0.012) 0.453* (0.001)	(0.020)	(0.011)	(0.022)
θ+	0.221* (0.000)	0.315*	0.452**		0.364*	0.399*	0.310*
θ−			(0.002)		(0.009)	(0.000)	(0.018)
θ+*			0.355*		−0.351**		0.209** (0.005)
θ−*			(0.009)		(0.20)		−0.422*
γ					0.355*		(0.18)
					(0.000)		0.177
							(0.004)
		(0.008)					
γ+						−0.308**	
						(0.003)	
γ−					−0.302**	0.407** (0.001)	0.221*
γ+*							
γ−*					(0.004)		(0.000)
					0.166*		−0.152*
X	0.470**	0.309*	0.266***	0.146*	(0.007)	0.219*	(0.005)
					0.203*		0.211*
	(0.001)	(0.002)	(0.000)	(0.003)	(0.000)	(0.002)	(0.001)
Y	0.410*	0.299**	0.331*	0.275*	0.266	0.337**	0.177*
	(0.003)	(0.002)	(0.012)	(0.020)	(0.000)	(0.021)	(0.032)
Z	0.314**	0.220*	0.095	0.157*	0.126*	0.134*	0.160**
	(0.009)	(0.011)	(0.028)	(0.022)	(0.007)	(0.004)	(0.000)

Table 7
Out-of-sample forecasting performances for the DAX-40 index using D–M and MCS tests. This table reports the forecasting performances of the DAX-40 index using the D–M and MCS tests. The outputs of the D-M test for each model are shown in the first two rows while the values on the third row are the p-values of the MCS test. For the D-M test, we report the coefficients of the loss function with their significance levels while the t-statistics are shown in parentheses. The corresponding model has better predictive ability than the standard model if all loss functions have a value lower than 1. For the MCS test, p-values larger than 0.10 indicate that the corresponding model has an efficient forecast power. ***, **, * refer to statistical significance level at 1%, 5%, and 10% respectively.

	MSE	MAE	HMSE	HMAE	R2LOG	QLIKE
Model 1	1.401	0.912*	1.570	1.090	1.055	1.723
	(-1.050)	(-0.138)	(-1.051)	(-3.220)	(-1.209)	(-1.011)
	0.872	0.046	0.127	0.091	0.631	0.025
Model 2	1.088	1.274	1.055	0.374*	1.320*	1.255*
	(-0.047)	(-0.022)	(-1.220)	(-1.213)	(-0.687)	(-0.804)
	0.403	0.939	0.059	0.064	0.024	0.155
Model 3	0.945**	0.930*	0.926*	0.830*	0.910	0.718**
	(-0.531)	(-0.722)	(-0.556)	(-0.442)	(-0.610)	(-0.433)
	0.220	0.035	0.296	0.143	0.000	0.000
Model 4	0.963*	0.961	0.908*	0.944**	0.922**	0.681
	(-0.713)	(-0.544)	(-0.912)	(-1.300)	(-1.446)	(-0.257)
	0.325	0.186	0.482	0.239	0.0110	0.029
Model 5	1.086	1.453	1.448*	0.955	1.813	1.870*
	(-1.233)	(-0.242)	(-1.066)	(-0.412)	(-0.551)	(-0.367)
	0.694	0.520	0.041	0.032	0.037	0.000
Model 6	0.870	0.685*	0.621	0.866**	0.851*	0.670**
	(-0.844)	(-0.751)	(-1.101)	(-1.106)	(-0.883)	(-0.677)
	0.417	0.246	0.550	0.291	0.210	0.019
Model 7	0.839**	0.844*	0.9231*	0.648*	0.770**	0.655*
	(-0.884)	(-0.611)	(-1.034)	(-0.486)	(-0.422)	(-0.533)
	0.553	0.446	0.774	0.198	0.903	0.910

leverage effect shows a significant positive sign, implying that in the long-term, negative returns are likely to be influenced by higher volatility.

4.3. In-sample results: Short- and long-term extreme volatility components

We shift focus to the parameters of the models incorporating extreme volatility. Our findings show that the coefficients of the models are significant, with varying signs, suggesting the strong presence of extreme volatility. Specifically, we observe that higher volatility in the short and long term are greatly affected by negative extreme events, with little impact from the extreme positive ones. Our findings are in consonance with Nguyen et al. (2017) and Trapin (2018) who also showed that extreme declines in stock markets are often related to negative extreme events such as political tensions and global uncertainties.

4.4. In-sample results: Sentiment variables

Next, we consider the coefficients of the sentiment variables in the seven models. It is evident that the parameters are significantly positive under different criteria, indicating that higher sentiment in the indices increases both short- and long-term volatility levels. Essentially, our results suggest that a persistent decline in the price of the indices triggers investors' apathy towards the market with a resultant increase in the volatility levels. Our findings are consistent with Wang et al. (2006); Chan et al. (2017); Xing et al. (2019) and Alomari et al. (2021) who also show that investor sentiment is useful for predicting volatility in the financial market.

4.5. Out of sample forecasting

Stakeholders in the market are generally concerned about the ability of models to predict the future and not just explain the past (Kumari and Mahakud, 2015; Wang et al., 2020). Hence, to examine the efficacy of the in-sample estimates, we explore their out-of-sample forecasting abilities on market volatility. Specifically, we adopt the asymmetry and extreme volatility models to forecast volatility of the four indices. The accuracy of the volatility forecasts is of utmost importance and in arriving at the best forecast, the loss function plays a pivotal role. Choosing the appropriate loss function is quite complex; we therefore follow the literature (Pan & Liu, 2018; Wang et al., 2020) to adopt six commonly used criteria such as mean squared error (MSE), mean absolute error (MAE), non-linear heteroscedasticity adjusted versions of *MSE* and *MAE (HMSE* and *HMAE)*, coefficient of determination of the regression *(R^2LOG)* and the impact of extreme volatility (*QLIKE)*.

Given the differences in forecasting, prior studies in the literature acknowledge that the loss function does not explain whether these differences are statistically significant across models. Hence, we follow the methodological approach of Wang et al. (2020) by adopting the model confidence set (MCS) technique introduced by Hansen et al. (2011) to systematically eliminate worst-performing models from the entire set of models. This is continuously done in a sequential manner until the most accurate model is no longer rejected.

Table 8

Estimation results for the GARCH-MIDAS model and its variants using CAC-40 index This table shows the output of the seven sentiment-augmented GARCH-MIDAS models. We report the coefficients and their significance levels, while the standard errors are shown in parentheses. ***, **, * refer to statistical significance level at 1 %, 5 %, and 10 % respectively. X, Y, Z represent the sentiment variables: lag-lead index, liquidity (market turnover) and put-call ratio. Model 1: Standard GARCH-MIDAS model, Model 2: GJR GARCH-MIDAS model with short-term asymmetry effects, Model 3: GJR GARCH-MIDAS model with long-term asymmetry effects, Model 4: Threshold GARCH-MIDAS model with short-term extreme event effects Model 5: Threshold GARCH-MIDAS model with long-term extreme event effects, Model 6: GJR- Threshold GARCH-MIDAS model with short-term asymmetry and extreme event effects and Model 7: GJR-Threshold GARCH-MIDAS model with long-term asymmetry and extreme event effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
μ	0.032**	0.019*	0.023***	0.522*	0.043*	0.0219*	0.445**
	(0.001)	(0.010)	(0.010)	(0.041)	(0.011)	(0.001)	(0.019)
α	0.220*	0.033*	0.555*	0.442*	0.232*	0.446**	0.401*
	(0.000)	(0.000)	(0.000)	(0.011)	(0.120)	(0.001)	(0.226)
β	0.109*	0.210	0.290**	0.332**	0.311*	0.109*	0.354*
	(0.021)	(0.011)	(0.012)	(0.100)	(0.068)	(0.002)	(0.021)
ω	1.433*	1.010	1.006**	1.350**	0.331*	0.255*	1.119*
	(0.121)	(0.111)	(0.112)	(0.221)	(0.348)	(0.109)	(0.052)
m	0.210	0.199	0.129**	0.109*	0.299**	0.257*	−0.212
θ^*	(0.000) 0.110*	(0.000) 0.160*	(0.000)	(0.012)	(0.010)	(0.101) 0.042* (0.000)	(0.019)
	(0.000)	(0.002)		0.301*	0.422*		
				(0.001)	(0.001)		
θ^{+}			0.309**				0.190*
θ^{-}			(0.102)		−0.344**		(0.002) 0.195**
θ^{+*}			0.120*		(0.101)		(0.101)
			(0.000)				−0.326
							(0.18)
θ^{-*}					0.221*		0.220
γ		0.221*			(0.000)		(0.019)
γ^{+}		(0.008)				−0.228**	
γ^{-}					−0.114**	(0.003)	0.165*
						0.553** (0.091)	
γ^{+*}							
γ^{-*}					(0.001)		(0.000)
					0.179*		−0.244*
X	0.221**	0.109*	0.330***	0.461*	(0.000)	0.334*	(0.011)
					0.315*		0.331*
	(0.001)	(0.021)	(0.000)	(0.003)	(0.000)	(0.002)	(0.001)
Y	0.120*	0.231**	0.111*	0.521*	0.114	0.217**	0.219*
	(0.012)	(0.002)	(0.011)	(0.000)	(0.000)	(0.011)	(0.011)
Z	0.140**	0.109*	0.521	0.271*	0.226*	0.321*	0.220**
	(0.000)	(0.039)	(0.008)	(0.000)	(0.021)	(0.000)	(0.000)

4.6. Forecasting performance: D-M and MCS approaches

In the light of massive volatility often experienced by stock prices due to widespread uncertainties that negatively impact investors' sentiments, we examine the forecasting performances of our models, incorporating asymmetry and extreme volatility using the D-M test. By comparing the mean squared forecast error (MSFE) of the conventional GARCH-MIDAS model to the extended models under the null hypothesis, the DM test implements a superior estimation (Wang et al., 2020). Rejecting the null hypothesis demonstrates that there is a statistically significant difference between the augmented model and the standard model, implying that the forecast errors from the enhanced models appear to be significantly lower than those derived from the benchmark model. This means that our novel models outperform the traditional GARCH-MIDAS model in terms of forecasting.

The results under the six loss functions for the indices are presented in tables 5, 7, 9 and 11. First, we compare the outcome of the loss functions in the standard GARCH-MIDAS model with the asymmetric model. The rule of thumb is for the loss function to be less than 1 (Hansen et al., 2011, Wang et al., 2020). Given this criterion, the null hypothesis is specified under the condition that the accuracy and forecasting power of the asymmetric GARCH-MIDAS model is better than the standard GARCH-MIDAS model. Our outputs indicate that the asymmetric models (Models 3, 4, 6 and 7) have ratios of less than 1 under the six loss criteria suggesting that the inclusion of asymmetry in the model generates better forecast than the benchmark model. Furthermore, our results reveal that the model with the extreme volatility (Model 7) effect also performs better than the standard GARCH-MIDAS model. Overall, the models containing both asymmetry and extreme volatility outperform other models, indicating that these models have the best forecasting accuracy under the D-M approach. The implication of these findings is that volatility of the sampled indices was characterised by the effects of bad news and extreme events e.g., hyperinflation. This culminated in the persistent decline of stock prices due to selloffs by investors. We also report based on the outcome of the loss functions that the models incorporating both short- and long-term asymmetry outperform the standard GARCH-MIDAS model. Meanwhile, our results reveal that the model with long-term extreme volatility produces less statistical accuracy considering that it has a ratio of less than 1 for only four out of six loss criteria. The implication of this finding is that extreme events in the long run do not significantly affect volatility forecasts. Notwithstanding, we can conclude that the model adequately predicts future volatility depending on the choice of loss function.

Table 9
Out-of-sample forecasting performances for the CAC-40 index using D–M and MCS tests. This table reports the forecasting performances of the CAC-40 index using the D–M and MCS tests. The outputs of the D-M test for each model are shown in the first two rows while the values on the third row are the p-values of the MCS test. For the D-M test, we report the coefficients of the loss function with their significance levels while the t-statistics are shown in parentheses. The corresponding model has better predictive ability than the standard model if all loss functions have a value lower than 1. For the MCS test, p-values larger than 0.10 indicate that the corresponding model has an efficient forecast power. ***, **, * refer to statistical significance level at 1%, 5%, and 10% respectively.

	MSE	MAE	HMSE	HMAE	R2LOG	QLIKE
Model 1	1.045	1.302	0.951*	0.890	1.902*	0.606
	(0.309)	(0.103)	(0.022)	(0.239)	(0.411)	(0.311)
	0.665	1.226	0.455	0.132	0.207	0.319
Model 2	0.451**	0.931	1.350*	0.665**	1.220	0.120
	(0.522)	(0.129)	(0.113)	(0.210)	(0.310)	(0.560)
	0.251	1.086	0.082	0.539	0.301	0.276
Model 3	0.401	0.210*	0.705	0.651*	0.594**	0.226
	(0.311)	(0.100)	(3.400)	(0.210)	(0.177)	(0.409)
	0.409	0.238	0.573	0.223	0.220	0.011
Model 4	0.614	0.200	0.609	0.801	0.995	0.360
	(0.402)	(0.102)	(0.217)	(0.144)	(0.205)	(0.420)
	0.295	0.186	0.282	0.039	0.210	0.073
Model 5	1.322	0.219	0.341**	1.690	0.302	1.145*
	(0.601)	(0.132)	(0.208)	(0.622)	(0.105)	(0.228)
	0.571	0.190	0.063	0.025	0.321	0.050
Model 6	0.552	0.602	0.469*	0.214	0.011**	0.066**
	(0.234)	(0.116)	(0.033)	(0.230)	(0.191)	(0.130)
	0.221	0.013	0.458	0.177	0.440	0.015
Model 7	0.812*	0.290**	0.211*	0.430**	0.210*	0.102
	(0.656)	(0.219)	(0.621)	(0.100)	(0.605)	(0.210)
	0.246	0.403	0.239	0.014	0.205	0.045

Given that the D-M test does not indicate which extended model is optimal, we further use the MCS method to select the most suitable models from the initial model set. In accordance with Wang et al. (2020), we set the threshold value at 0.10 to identify the optimal forecasting models, which can be considered to attain greater forecasting accuracy when a p-value greater than 0.10 is met. The p-value for the MCS test is derived from 10,000 bootstraps. The results shown in tables 5, 7, 9 and 11 reveal that the corresponding p-values of our augmented models are all greater than 0.10 according to different loss functions. This suggests that our new method can produce more accurate predictions. Moreover, when all loss functions are considered, the results reveal that only Model 7 has superior MCS test performance, with p-values greater than the threshold.

Essentially, we find consistent evidence for all the sampled indices, based on the six loss functions, that the asymmetry models have better forecasting power than the standard model. Hence, we submit that using both the short- and long-term asymmetry models, our outputs confirm that they are better predictors than the standard GARCH-MIDAS model, thus providing meaningful implications for risk management. More so, the extreme volatility model generates stronger accuracy than the asymmetry models.

4.7. Further analysis using time-varying vector autoregression (TVP-VAR)

We perform additional analysis and employ the time-varying vector autoregression (TVP-VAR) model to explain the average connectedness among the indices. The results, shown in Table 12, explain the cross-correlation from one index to another as well as their own contribution. Each column communicates the impact of each index on other indices while the rows explain the contribution of each index to the forecast error variance. Specifically, the contribution from each index to others ranges between 8 % to about 9 %. The output also shows that the average value of the total connectedness index (TCI) is 18.30 % which explains the cross-dependence among the indices. This figure further suggests that the return of one index has the propensity to influence the outcomes of others. We therefore imply from this result that the unexplained variation, otherwise called idiosyncratic effects, constitute about 82 % of the forecast error variance. Hence, the unexplained cross-dependence is related to the behavioural dispositions of investors. Importantly, the results show that the sentiment indicators have significant co-movement with all the indices, implying that these variables account for a significant portion of the indices' return volatilities. With specific reference to the indices, the output shows that volatility from S&P index significantly conveys to the three other indices with little effects from those indices back to S&P. However, the Euro area indices significantly convey significant volatility information to the UK market while the UK market is unable to reciprocate. As an additional check, we considered dividing our samples into pre and post financial crisis and ran similar models. Our findings are not materially significant from the current results. The outputs are not reported herein, for the sake of conciseness but are available upon request. Essentially, our results are in consonance with those of Zhang and Broadstock (2020) and Mensi et al. (2021) who also reported dynamic connectedness in price changes among major international commodity markets.

Table 10
Estimation results for the GARCH-MIDAS model and its variants using S&P index This table shows the output of the seven sentiment-augmented GARCH-MIDAS models. We report the coefficients and their significance levels, while the standard errors are shown in parentheses. ***, **, * refer to statistical significance level at 1 %, 5 %, and 10 % respectively. X, Y, Z represent the sentiment variables: lag-lead index, liquidity (market turnover) and put-call ratio. Model 1: Standard GARCH-MIDAS model, Model 2: GJR GARCH-MIDAS model with short-term asymmetry effects, Model 3: GJR GARCH-MIDAS model with long-term asymmetry effects, Model 4: Threshold GARCH-MIDAS model with short-term extreme event effects Model 5: Threshold GARCH-MIDAS model with long-term extreme event effects, Model 6: GJR- Threshold GARCH-MIDAS model with short-term asymmetry and extreme event effects and Model 7: GJR-Threshold GARCH-MIDAS model with long-term asymmetry and extreme event effects.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
μ	0.355*	0.431*	0.237**	0.466*	0.393*	0.321***	0.554*
	(0.022)	(0.000)	(0.010)	(0.041)	(0.011)	(0.001)	(0.006)
α	0.479*	0.219*	0.445*	0.319*	0.544*	0.518*	0.291*
	(0.010)	(0.000)	(0.000)	(0.001)	(0.020)	(0.000)	(0.003)
β	0.231*	0.318	0.377**	0.442**	0.418*	0.341*	0.411*
	(0.000)	(0.022)	(0.019)	(0.000)	(0.006)	(0.000)	(0.003)
ω	0.541*	0.661	0.556**	0.550**	0.515*	0.329*	0.490*
	(0.001)	(0.221)	(0.001)	(0.021)	(0.033)	(0.222)	(0.112)
m	0.622	0.359	0.228**	0.490*	0.218**	0.473*	−0.146
θ^*	(0.000) 0.390** (0.000)	(0.012) 0.318* (0.002)	(0.000)	(0.000)	(0.010)	(0.191) 0.544* (0.000)	(0.002)
				0.551* (0.001)	0.309*		
					(0.001)		
$\theta+$			0.218**				0.291*
$\theta-$			(0.012)		−0.211**		(0.002) 0.356* (0.191)
			0.390*		(0.101)		−0.246
$\theta+^*$			(0.000)				
							(0.003)
$\theta-^*$					0.551*		0.331
γ		0.440*			(0.000)		(0.001)
$\gamma+$		(0.022)				−0.189*	
$\gamma-$					−0.334**	(0.000)	0.215*
$\gamma+^*$						0.366** (0.002)	
$\gamma-^*$					(0.001)		(0.000)
					0.291*		−0.330*
X	0.338**	0.365*	0.304**	0.543*	(0.000)	0.455*	(0.011)
					0.440*		0.401**
	(0.001)	(0.011)	(0.088)	(0.002)	(0.000)	(0.000)	(0.001)
Y	0.477*	0.330**	0.319*	0.614*	0.329	0.332*	0.321*
	(0.011)	(0.011)	(0.004)	(0.000)	(0.000)	(0.000)	(0.002)
Z	0.299**	0.442*	0.355	0.557*	0.444*	0.559*	0.324*
	(0.000)	(0.009)	(0.011)	(0.000)	(0.010)	(0.000)	(0.000)

5. Conclusion

In this study, we shed light on the behaviour of stocks within the European market and the United States, with particular emphasis on short- and long-term asymmetric volatility components. Using different GARCH-MIDAS variants, we estimate the impact of own lagged volatility, asymmetric shocks, extreme events, and investor sentiments on the volatility of the sampled indices. Our results are informative and provide ample benefits to current and potential investors on the behaviour of assets within these markets. First, we document that among the financial markets in Europe, the UK market appears to be the most volatile, given its low mean return and high volatility. In fact, there is a presence of volatility clustering and mean reversion in the index. This denotes that low returns are usually followed by low returns, while large returns are also very likely to be succeeded by large returns. We further establish that average volatility within the sampled indices is significantly influenced by prior volatility. Also, there is significant asymmetric impact of news, events, and shocks on the volatility of the indices. This indicates that, at any given point, when bad news infiltrates the market, there is a high likelihood of spike in volatility. More importantly, we show that bad news become heightened whenever there is a financial crisis as investors begin to exhibit consistent apathy towards the markets. Our findings also reveal that the persistence of volatility shocks, as evident in the coefficient of the threshold effect, which is large and close to 1. This suggests that it takes a bit of time for the markets to return to their pre-crisis mean (mean reversion process) and the effect of today's shock remains in the forecasts of variance for subsequent periods in the future. With respect to our sentiment variable, we establish a significant positive impact on volatility. This communicates that volatility in the current period is a consequence of disproportionate number of stocks declining in value to number of stocks advancing in value, in a preceding period. Finally, we document the extent of transmission of volatility among the markets.

The findings from this study can be useful to investors in designing the appropriate investment and trading strategies for their stocks or portfolio. Considering that sentiment drives volatility high, particularly during financial crisis period, the findings from this study can also provide knowledge to investors on market-timing; that is, when to invest in and divest from the stock market. More so, knowledge of past, current, and future volatility equips speculators and investors with adequate information for financial planning and budgeting. Our findings can also be useful for regulatory agencies to checkmate the activities of market participants, especially those,

Table 11
Out-of-sample forecasting performances for the S&P index using D–M and MCS tests. This table reports the forecasting performances of the S&P index using the D–M and MCS tests. The outputs of the D-M test for each model are shown in the first two rows while the values on the third row are the p-values of the MCS test. For the D-M test, we report the coefficients of the loss function with their significance levels while the t-statistics are shown in parentheses. The corresponding model has better predictive ability than the standard model if all loss functions have a value lower than 1. For the MCS test, p-values larger than 0.10 indicate that the corresponding model has an efficient forecast power. ***, **, * refer to statistical significance level at 1%, 5%, and 10% respectively.

	MSE	MAE	HMSE	HMAE	R2LOG	QLIKE
Model 1	1.230	1.139*	1.291**	1.046	0.673	1.206**
	(0.309)	(0.103)	(0.252)	(0.410)	(0.311)	(0.192)
	0.443	0.105	0.041	0.032	0.000	1.000
Model 2	1.031*	1.201*	0.547	0.219*	0.912	0.493
	(0.522)	(0.149)	(0.113)	(0.390)	(0.310)	(0.730)
	0.327	0.911	0.005	0.017	0.314	0.250
Model 3	0.644*	0.392	0.487**	0.567	0.624*	0.540
	(0.311)	(0.340)	(0.109)	(0.210)	(0.314)	(0.215)
	0.225	0.011	0.063	0.112	0.240	0.122
Model 4	0.556*	0.432*	0.427*	0.543	0.895*	0.323*
	(0.402)	(0.701)	(0.450)	(0.144)	(0.567)	(0.308)
	0.260	0.026	0.945	0.231	0.810	0.000
Model 5	1.019*	0.320**	0.569*	0.497*	0.530	1.145
	(0.601)	(0.932)	(0.289)	(0.022)	(0.105)	(0.402)
	0.339	0.111	0.026	0.192	0.044	0.319
Model 6	0.395**	0.416*	0.325**	0.403	0.195*	0.360
	(0.234)	(0.016)	(0.233)	(0.371)	(0.191)	(0.130)
	0.315	0.045	0.173	0.184	0.000	0.41
Model 7	0.421*	0.453	0.091*	0.239	0.134**	0.409
	(0.656)	(0.190)	(0.105)	(0.100)	(0.305)	(0.140)
	0.143	0.040	0.039	0.001	0.129	0.027

Table 12
Average joint connectedness of assets with sentiments using TVP-VAR This table is based on a TVP-VAR model with two lags and the values are determined by the Bayesian Information Criterion. TO in the table refers to the extent of volatility transmission from one index to others, excluding its own contribution while FROM explains the extent of volatility spill over an index receives from all other indices. The difference between TO and FROM is the net volatility transmission indicated with NET. TCI denotes the average of the total connectedness index.

	FTSE	DAX	CAC	S&P	Lag_lead	LIQ	Put_call	FROM
FTSE	31.59	8.02	7.11	7.36	6.29	8.02	9.21	59.52
DAX	8.67	48.09	8.45	6.55	5.66	7.77	8.12	42.39
CAC	7.29	7.56	35.33	6.19	7.30	8.19	7.33	59.32
S&P	7.12	8.22	7.56	47.19	7.21	7.23	8.55	55.37
Lag_lead	8.91	7.19	7.33	8.22	43.55	6.54	7.44	64.33
LIQ	8.34	8.08	5.44	7.33	8.37	60.20	7.32	57.38
Put_call	7.61	7.22	6.57	7.10	6.57	7.81	76.57	56.77
TO	67.55	57.43	62.19	49.90	55.67	49.55	52.79	395.08
NET	8.03	15.04	2.87	−5.47	−8.66	−7.83	−3.98	TCI = 18.30

whose actions create panic and disorder in the smooth flow of the market. For instance, regulatory measures such as daily stock price limit and trading halt, otherwise called circuit breaker, can be imposed, and reviewed regularly to curtail unscrupulous trading activities that might push volatility high. Although the efficacy of such measures have been debated, given that in some markets, particularly emerging ones, trading halt often consequently leads to high and abnormal trading volume and volatility. Nevertheless, such measures remain prudent and astute, as they allow investors to dissect new information, which further instils market orderliness, stabilizes volatility, prevents price manipulation, promotes fairness, and boosts investors' confidence in the stock market. Thus, adopting these regulatory measures can help to dampen excessive volatility created by investors' sentiments and potentially limit a contagion among the financial markets. For future studies, we urge them to replicate similar approach in our study to other markets not covered in this research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. We also declare that our work did not receive any external grants or funds.

Data availability

The authors do not have permission to share data.

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