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An Extensive Analysis of FTSE 100 Realized Volatility with Different Information Channels

(Research Article)

FTSE 100 Gerçekleşen Volatilitenin Farklı Bilgi Kanallarıyla Kapsamlı Analizi

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ABSTRACT

***Keywords*:**
Volatility Forecasting, Realized Volatility, HAR-RV-X model, Information Channels, FTSE 100

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This paper investigates the influence of external information flows from the European Union and the United States on the volatility of the FTSE 100 index, using realized variance (RV) data derived from 5-minute intraday intervals. By categorizing external factors into UK-specific, neighbouring, and wider international groups, the study integrates these variables into the HAR-RV model to improve the accuracy of volatility forecasts. The empirical results indicate that interntional and neighbouring countries' factors, particularly US market indicators such as the S&P 500 and NASDAQ, significantly impact FTSE 100 volatility, whilst domestic UK factors contain no additional information. The international Kitchen-Sink model, which includes all international variables, proves to be the most effective in the in-sample and out-of-sample forecasting. The use of high-frequency data is crucial in this context, as it allows for more precise measurement and forecasting of market volatility. These findings emphasize the importance of incorporating a broad range of external factors in modelling and forecasting the volatility of internationally-oriented stock indices such as the FTSE 100.

ÖZET

***Anahtar Kelimeler*:**
Volatilite Tahmini, Gerçekleşen Volatilite, HAR-RV-X modeli, Bilgi Kanalları, FTSE 100

Bu makale, Avrupa Birliği ve Amerika Birleşik Devletleri'nden gelen dış bilgi akışlarının FTSE 100 endeksinin oynaklığı üzerindeki etkisini, 5 dakikalık gün içi verilerden türetilen gerçekleşen varyans (RV) verilerini kullanarak araştırmaktadır. Dış faktörler, Birleşik Krallık'a özgü, Avrupa bölgesi ve ABD odaklı gruplar olarak kategorize edilerek, bu değişkenler HAR-RV modeline entegre edilmiştir ve böylece oynaklık tahminlerinin doğruluğu artırılmıştır. Ampirik sonuçlar, küresel ve bölgesel faktörlerin, özellikle S&P 500 ve NASDAQ gibi ABD piyasa göstergelerinin, FTSE 100 oynaklığı üzerinde önemli bir etkisi olduğunu, ancak Birleşik Krallık'a özgü yerel faktörlerin ek bilgi içermediğini göstermektedir. Tüm ABD odaklı değişkenleri içeren ABD odaklı Kitchen-Sink modeli, hem örnek içi hem de örnek dışı tahminlerde en etkili model olduğunu kanıtlamıştır. Yüksek frekanslı verilerin kullanımı bu bağlamda kritik öneme sahiptir, çünkü piyasa oynaklığının daha hassas bir şekilde ölçülmesine ve tahmin edilmesine olanak tanımaktadır. Bu bulgular, FTSE 100 gibi uluslararası yönelimli hisse senedi endekslerinin oynaklığını modelleme ve tahmin etmede geniş bir dış faktör yelpazesinin dahil edilmesinin önemini vurgulamaktadır.

1. INTRODUCTION

Employing tick-by-tick data is quite important for generating more accurate measurement and forecasting of stock market volatility. However, the use of high frequency data in volatility estimation without aggregating it to a daily level has several challenges, such as market microstructure noise, large data volumes, timestamp accuracy, model selection, and computational complexity. To address these issues, Andersen & Bollerslev (1998) propose a method that aggregates intraday data to an inter-daily level, creating a volatility measure known as Realized Variance (RV), which is calculated by summing the squared intraday returns.

When it comes to analyzing stock market volatility, it is influenced not only by domestic factors but also by neighbouring and wider international factors, largely due to the growing internationalization and financialization of markets. Incorporating these external factors into volatility forecasting is essential for producing accurate forecasts, particularly for a international index such as the FTSE 100, which includes the largest and most internationally-focused companies in the United Kingdom (UK).

The HAR-RV specification, developed by Corsi (2009), is the prevailing approach for modelling and forecasting realized volatility. Most of the advancements in this field have focused on the baseline HAR-RV model, without incorporating any external variables (Gkillas, Gupta, & Pierdzioch, 2019; Wang et al., 2020; Christensen, Siggaard, & Veliyev, 2023). However, the role of various parameters in improving the forecasting performance of the HAR-RV model is quite important to obtain better volatility forecasts. Additionally, prior studies (Liang, Wei, Lei, & Ma, 2022; Asai et al., 2020; Bonato et al., 2020; Demirer et al., 2021; Bouri et al., 2021; Salisu et al., 2022; Luo et al., 2022) have shown the importance of macroeconomic, financial, behavioral, and climate-related factors in influencing market behaviour, yet the specific context of the FTSE 100 remains unaddressed as a internationally interconnected but UK-centric index. The innovative aspect of this paper lies in its ability to bridge this gap through a detailed integration of external volatilities, providing novel insights into volatility forecasting within the context of a major European stock market index.

In this regard, this paper uniquely contributes to the literature by adapting the HAR-RV model specifically to the FTSE 100 index and exploring its sensitivity to external volatilities categorized as local, neighbouring, and international. In doing so, the HAR-RV model with an exogenous parameter (i.e. HAR-RV-X) is employed to integrate these external factors into the baseline HAR-RV model for the FTSE 100. By analysing the in-sample and out-of-sample performance of various combinations of these variables, including individual factors, simple averages of group forecasts, and the comprehensive Kitchen-Sink approach, the research seeks to determine the most effective methods for forecasting FTSE 100 volatility. Domestic factors pertain specifically to the UK and include elements such as bond yields, the UK Economic Policy Uncertainty (UKEPU) index, and LIBOR rates. Neighbouring factors consist of key European stock indices, including Germany's GDAXI, France's FCHI, Italy's FTMIB, and the broader STOXX Europe index. The international category largely includes US indicators, such as the S&P 500 (SPX), Dow Jones Industrial Average (DJI), NASDAQ (IXIC), the CBOE Volatility Index (VIX), and commodity prices like oil and gold.

While existing research extensively explores the role of both international and neighbouring market information channels in shaping the dynamics of various stock market indices, a comprehensive investigation into how these external factors influence the FTSE 100 remains limited. Most studies have primarily focused on other major indices, often neglecting a detailed examination of the cross-market effects specifically affecting the FTSE 100. As a result, there exists a significant gap in the literature regarding the extent to which external information flows—originating from both geographically proximate and globally dominant financial markets—contribute to the predictability and volatility of this key index. Addressing this research gap is crucial for advancing the understanding of the FTSE 100’s response to external financial shocks and market developments.

This study aims to fill this void by systematically formulating and empirically testing two key hypotheses. The first hypothesis posits that incorporating local, neighbouring, and international information channels into forecasting models significantly enhances the predictive accuracy of the Heterogeneous Autoregressive Realized Volatility (HAR-RV) model when applied to the FTSE 100 index. In particular, the inclusion of these external information flows is expected to refine volatility forecasts, capturing the spillover effects and interdependencies that conventional models might overlook.

The second hypothesis examines the differential impact of various external factors on the FTSE 100’s volatility. Specifically, it assesses how the predictive significance of regional market indicators, such as key European stock indices, compares to that of broader international influences, including U.S. market indicators and global commodity price movements. By dissecting these relationships, the study aims to determine whether geographically closer financial centres exert a stronger influence on the FTSE 100 than distant but globally dominant markets, such as the U.S. Additionally, it investigates whether specific asset classes—such as commodities—play a meaningful role in shaping volatility patterns.

By focusing on these hypotheses, this research contributes to the broader literature on cross-market information transmission and provides valuable insights into the unique volatility dynamics of the FTSE 100. Understanding these interactions is particularly relevant in the context of growing global financial interconnectedness, where shocks and market movements in one region can quickly propagate across borders. The findings of this study underscore the importance of integrating a diverse set of external information variables when modelling volatility, ultimately offering a more comprehensive and nuanced framework for forecasting the behaviour of the FTSE 100 in relation to international financial developments.

This paper is organized as follows: Section 2 reviews the pertinent literature, while Section 3 describes the data and methodologies used in the research. Following that, Section 4 presents the empirical findings along with their analysis. Finally, Section 5 offers the concluding remarks.

2. LITERATURE REVIEW

Realized volatility (RV), first introduced by Andersen and Bollerslev in 1998, is calculated as the sum of squared intraday returns. This method provides a more accurate estimate of daily volatility compared to traditional measures. While early studies used the ARFIMA model to predict RV, Corsi (2009) identified its limitations, highlighting the model's lack of economic clarity. To address this, Corsi developed the Heterogeneous Autoregressive model of Realized Variance (HAR-RV), based on the Heterogeneous Market Hypothesis (HMH) proposed by Muller et al. (1997). The HAR-RV model has become foundational in volatility forecasting, modeling daily RV by incorporating past daily, weekly, and monthly components. It effectively captures different volatility patterns, reflecting the varied behaviors of market participants and aligning with both short-term and long-term trading strategies.

Recent progress in volatility modelling, particularly within the HAR framework, has emphasized enhancing the standard HAR model by integrating realized semi-variances, jump components, asymmetries, and leverage effects, which are regarded as being more closely connected to the dependent variable since these explanatory variables capture the well-established characteristics of volatility. Research by Barndorff-Nielsen et al. (2010) and Corsi & Reno (2012), among others, also points out the significance of these improvements in improving model performance. For instance, Gkillas, Gupta, & Pierdzioch (2019) demonstrate the inclusion of realized skewness and kurtosis to improve the model's explanatory power. Similarly, Wang et al. (2020) emphasizes leveraging high-frequency data from international indices, while Christensen, Siggaard, & Veliyev (2023) inspect the role of machine learning in enriching HAR models fort he Dow Jones Industrial Average index constituents.

Another strand of the research is the inclusion of exogenous variables into the HAR-RV model (known as HAR-RV-X) to improve forecasting accuracy. Studies by Peng et al. (2018) and Wang (2019) examine the benefits of incorporating international stock market indices and the CBOE VIX index, respectively, into the HAR-RV framework, finding improved volatility forecasts for Chinese stock market. Liu et al. (2019) further advances this methodology by employing a time-varying parameter model and combination strategies to address overfitting concerns. Similarly, Dutta & Das (2022) integrate time-varying jump information from the VIX into the HAR-RV framework, demonstrating a positive impact on the S&P 500 index, and applied it to short-, medium-, and long-term volatility components. Additionally, research by Duan et al. (2018) and Mei et al. (2017) examine the role of economic policy uncertainty (EPU), realized skewness, and kurtosis in improving volatility forecasts. Their findings suggest the value of these factors, particularly in the context of regime-switching models and long-term forecasting. In the scope of commodity markets, Degiannakis & Filis (2017) apply a similar methodology to forecast oil price volatility. Their methodology incorporates various exogenous volatilities from multiple asset classes, which informing its superior forecasting performance.

Kambouroudis et al. (2021) emphasizes the significance of implied volatility (IV) data in forecasting volatility, proposing an extended HAR-RV-IV model that enhanced volatility prediction across 10 international stock markets. This model outperforms the extended HAR models incorporating other variables such as leverage effects and overnight returns. Liang, Wei, Lei, & Ma (2022) bring new comprehensive evidence regarding HAR-RV-AVERAGE as an outperforming model for forecasting international equity market realized volatility. Liang, Li, Ma, & Zhang (2022) utilize the exponentially weighted moving average (EWMA) to redefine the weekly and monthly components of the HAR model, thereby increasing the use of both recent and historical information. They develop the EWMA-HAR-RV model to predict realized volatility (RV) in the international equity investment market. Korkusuz et al. (2023) uses various range estimators within the HAR-RV-X framework to forecast volatility in the Group of Seven (G7) stock markets, where the inclusion of exogenous overnight volatility variables improve forecasts for nearly all markets. One another study (Nishimura & Sun, 2024) employs HAR-RV model to analyze whether newly select U.S. President Trump’s tweets influence the EU stock market volatility. Their work finds that Trump's tweets significantly amplify stock market volatility in Germany and France, while their impact on the UK's stock market volatility is considerably weaker.

Prior studies have explored the predictive value of information derived from an extensive range of macroeconomic, financial, behavioral, and climate-related variables, utilizing a broad array of both linear and nonlinear univariate and multivariate models (see, for example, Asai et al., 2019; Asai et al., 2020; Bonato et al., 2020; Demirer et al., 2020; Demirer et al., 2021; Gkillas et al., 2020; Bouri et al., 2021; Gupta & Pierdzioch, 2021b; Salisu et al., 2022; Luo et al., 2022, along with references cited therein). Despite the extensive research on volatility forecasting models, particularly the advancements in incorporating exogenous variables into the HAR framework, there remains a notable gap in the literature regarding the FTSE 100 stock market. Whilst studies successfully improve volatility forecasts for various international (mostly Chinese and American) markets by integrating variables such as implied volatility, overnight returns, and time-varying jump information, the FTSE 100 has not been thoroughly examined in this context. Specifically, the impact of exogenous variables on the volatility forecasting of the FTSE 100 index is understudied. However, understanding the impact of cross-market information on the FTSE 100, is essential for investors, policymakers, and market participants who have certain levels of risk which they can bear. This highlights the need for further investigation in this area.

This study investigates the cross-market information relationships of the FTSE100 from the perspective of local, neighbouring, and international information channels. By examining the FTSE 100 stock market, this work aims to uncover the unique volatility patterns the UK has and their relationship with international financial markets as well as local and neighbouring markets. The analysis provides a comprehensive view of how the FTSE100 reacts to and interacts with external market shocks. By doing so, this paper contributes to the ongoing debate in this related literature on volatility modelling and forecasting.

3. METHODOLOGY AND DATA

3.1. Methods: Realized volatility (RV) and HAR-RV model

3.1.1. Realized volatility (RV)

Volatility is not directly observable, making it necessary to use a proxy to estimate true volatility in financial markets. Previously, researchers rely on daily squared returns as a simple and accessible proxy. However, this measure is found to have significant limitations, particularly in its inability to capture the fluctuations that occur within a trading day. In their groundbreaking work, Andersen & Bollerslev (1998) demonstrate that daily squared returns are an inadequate representation of market volatility. Therefore, they introduce the idea that cumulative intraday squared returns provide a far more accurate and reliable measure of volatility.

Building on this concept, Andersen, Bollerslev, Diebold, & Labys (2003) formalize the method, known as "realized variance," which calculates volatility as the sum of squared intraday returns over a specified period. This methodology captures the richness of high-frequency data, providing a more detailed understanding of market dynamics. Realized variance effectively accounts for the variability that daily squared returns often miss, such as sudden price jumps and intraday trading patterns.

While both realized variance and daily squared returns are unbiased estimators of volatility, realized variance is widely considered far more efficient (Andersen & Bollerslev, 1998). This efficiency arises because realized variance incorporates information from high-frequency data, which reduces estimation error and enhances precision. Moreover, its reliance on intraday data allows it to respond more dynamically to market events, making it especially valuable for applications such as risk management, derivative pricing, and econometric modeling of volatility. The adoption of realized variance has thus become a standard in modern volatility research, highlighting its superiority over traditional methods.

$$RV_t = \sum_{i=1}^{m} r_{t,i}^2 \tag{1}$$

As shown in Equation 1, realized variance is computed as the sum of squared intraday returns, where m represents the number of intraday observations for day t. In theory, increasing the value of m improves the accuracy of daily volatility estimates. However, if m becomes too large, the efficiency of high-frequency data can be compromised due to the microstructure noise effect. Andersen, Bollerslev, Diebold, & Labys (2003) along with Hol & Koopman (2002) suggest an optimal frequency interval between 5 and 30 minutes. In a more recent study, Liu, Patton, & Sheppard (2015) compared over 400 realized measures and found that it is difficult to outperform five-minute realized variance. Additionally, Barndorff-Nielsen et al. (2010) introduced the decomposition of realized variance into positive and negative semivariances, or "good" and "bad" volatilities.

Barndorff-Nielson et al. (2010) decompose the realized variance into positive and negative realized semivariances or good and bad volatilities.

$$RSV_t^+ = \sum_{i=1}^{m} r_{t,i}^2 \, I\,\{ r_{t,i} > 0\} \tag{2}$$

$$RSV_t^- = \sum_{i=1}^{m} r_{t,i}^2 \, I\,\{ r_{t,i} < 0\} \tag{3}$$

where $I\{\cdot\}$ is an indicator function. We should also note that $RV_t = RSV_t^+ + RSV_t^-$.

3.1.2. HAR-RV model

The HAR-RV model stems from the heterogeneous market hypothesis introduced by Müller, Dacorogna, Dave, Olsen, Pictet, & von Weizsäcker (1997). This hypothesis suggests that there are three distinct types of investors, each with varying risk preferences and reactions to the same market information. Building on this hypothesis, the same researchers developed the Heterogeneous Autoregressive Conditional Heteroskedasticity (HARCH) model. Inspired by the HARCH model and its foundational hypothesis, Corsi (2009) introduced the HAR-RV model, which functions as an additive cascade model, incorporating different components of volatility. The model is formally defined as follows:

$$RV_{t+h}^d = \beta_0 + \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \varepsilon_{t+h} \quad (4)$$

where RV_t^d is daily realized volatility; RV_t^w refers to weekly realized volatility, and then RV_t^m indicates monthly realized volatility. RV_t^w and RV_t^m can easily be calculated as follows:

$$RV_t^w = \frac{1}{5}(RV_{t-5}^d + RV_{t-4}^d + \cdots + RV_{t-1}^d)$$

$$RV_t^m = \frac{1}{22}(RV_{t-22}^d + RV_{t-21}^d + \cdots + RV_{t-1}^d)$$

The main point of the HAR-RV model is to predict future volatility using three different volatility components: a daily (RV_t^d), a weekly (RV_t^w), and a monthly (RV_t^m) components. The HAR-RV model can simply be estimated by the ordinary least square (OLS) method. The model is such a good alternative to the ARFIMA model. The HAR-RV model can also capture long memory characteristics of volatility even though it is not in the class of long memory models. In practice, the HAR-RV model is found to be such a promising model as the model performance is remarkably good in spite of its simple structure.

In financial markets, different types of investors pursue various objectives. Some are primarily hedgers, while others focus on speculation. The HAR-RV model aims to capture these differing investor reactions through a straightforward autoregressive process. This model categorizes investors into three groups: short-term, medium-term, and long-term, represented by the components, RV_t^d, RV_t^w, and RV_t^m, respectively. Each of these components reflects how different investors influence current realized volatility. Essentially, the model's coefficients offer insight into how various market participants perceive and respond to volatility. Additionally, the HAR-RV model effectively captures the persistence of realized volatility.

In the HAR-RV-X framework, exogenous variables are incorporated in several ways, such as using each variable individually, combining forecasts, or employing the Kitchen-Sink approach, which includes a set of exogenous variables in the same model. The model specifications for individual forecasts and the Kitchen-Sink method are provided in Equations 5 and 6, respectively.

$$RV_{t+1}^d = \beta_0 + \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \boldsymbol{\beta_X X_t^d} + \varepsilon_{t+1} \quad (5)$$

$$RV_{t+1}^d = \beta_0 + \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \sum_{\boldsymbol{i=1}}^{\boldsymbol{K}} \boldsymbol{\beta_i X_{i,t}^d} + \varepsilon_{t+1} \quad (6)$$

In Equation 5, the exogenous component, $\beta_X X_t^d$, refers to the i^{th} individual exogenous volatility at day t. We can obtain 13 different individual HAR-RV-X model using this formula. For example, the HAR-RV-GDAXI, HAR-RV-FCHI, HAR-RV-SPX, HAR-RV-VIX, HAR-RV-GOLD, HAR-RV-BOND, HAR-RV-EPU … are obtained from the abovementioned Formula 5. Equation 6 implies the Kitchen-Sink models where $\sum_{i=1}^{K} \beta_i X_{i,t}^d$, represents the multi-exogenous variables.

The combination method simply takes the average of all the individual forecasts in groups. The forecast combinations are the simple average of all included forecasts, which can be calculated as follows: the sum of individual forecasts is divided to the numbers of individual forecasts.

3.1.3. Rolling Window and Forecast Evaluation Criteria

The rolling window technique is widely used in forecasting, and this study adopts it to generate volatility forecasts for stock markets. To begin, the entire dataset is divided into two parts: an initial sample and an out-of-sample window. There is no established consensus in the literature on the optimal selection of a forecasting window. However, given the primary aim of assessing out-of-sample model performance, we arbitrarily select the initial and out-of-sample windows, ensuring a length that allows for a proper regression fit while also maximizing the out-of-sample period. The rolling window method operates by sequentially adding a new observation and removing the oldest one, thus keeping the size of the estimation sample consistent. We focus on producing only one-step-ahead volatility forecasts, as multi-step-ahead forecasts are more likely to be less accurate due to the reduced availability of information for further predictions.

For evaluating the out-of-sample accuracy of the models, we utilize three widely recognized loss functions: quasi-Gaussian log-likelihood (QLIKE), heteroskedasticity-adjusted mean squared error (HMSE), and heteroskedasticity-adjusted mean absolute error (HMAE), aligning with recent research practices. (e.g. Zhou, Pan, and Wu, 2019; Ma et al., 2018; Liu et al, 2019).

$$QLIKE = \frac{1}{\tau}\sum_{t=T+1}^{T+\tau}[log\widehat{RV_t^2} + \frac{\widehat{RV_t^2}}{RV_t^2}] \tag{7}$$

$$\text{H}MSE = \frac{1}{\tau}\sum_{t=T+1}^{T+\tau}[1 - \widehat{RV_t^2}/ RV_t^2]^2 \tag{8}$$

$$\text{H}MAE = \frac{1}{\tau}\sum_{t=T+1}^{T+\tau} | \, 1 - \frac{\widehat{RV_t^2}}{RV_t^2} | \tag{9}$$

where $\widehat{RV_t^2}$ denotes the out-of-sample volatility forecast from competing models and RV_t^2 is a proxy for true market volatility. τ is the number of out-of-sample forecasting days. Each one of the loss functions have a specific calculation method to measure the forecast error. According to Patton (2011), these three well-established loss functions can provide consistent rankings for competing volatility models in the case of a noisy volatility proxy.

3.1.4. MCS procedure

Hansen et al. (2011) introduce the well-known Model Confidence Set (MCS) procedure, which employs a specific elimination algorithm to identify a set of superior models. This algorithm evaluates models within a competitive group at a designated confidence level, determining which ones remain robust when tested against a particular loss function, all without relying on a predetermined benchmark model. Models that exhibit weak predictive capabilities are systematically excluded from the initial pool of candidates. Among the six statistics available for identifying superior models, Hansen et al. (2003) particularly advocate for using the range and semi-quadratic statistics. A brief overview of the MCS procedure is provided below.

Let $L_{i,k}$ denote the criterion of model i and $d_{i,j,k} = L_{i,k} - L_{j,k}$ is the differential. The null hypothesis of MCS procedure is $H_{0,M} = E(d_{i,j,k}) = 0, for\ i,j\ \in M,\ M \subset M^0$ and the null is tested against the alternative $H_{1,M} = E(d_{i,j,k}) \neq 0, for\ some\ i,j\ \in M.$

3.1.5. Research Hypotheses

This study investigates the role of external information flows in forecasting the volatility of the FTSE 100 index by testing two key hypotheses. These hypotheses are formulated based on the premise that financial markets are highly interconnected, with both regional and international factors influencing stock market dynamics.

Hypothesis-1:
The inclusion of external market information enhances the forecasting accuracy of the HAR model for FTSE 100 volatility.

The first hypothesis examines whether integrating domestic, neighbouring, and international market information channels improves the predictive performance of the Heterogeneous Autoregressive Realized Volatility (HAR-RV) model when applied to the FTSE 100 index.

To test this hypothesis, different model specifications will be estimated, incorporating various external predictors alongside the standard components of the HAR-RV model. The predictive accuracy of each specification is evaluated using out-of-sample forecasting metrics, such as the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE). Improvements in forecast performance indicate the relevance of cross-market information in modelling the FTSE 100's volatility.

Hypothesis-2:
The predictive significance of European market indicators differs from that of U.S. market indicators and co mmodity prices in forecasting FTSE 100 volatility.

The second hypothesis assesses whether different categories of external factors—such as regional European indices and global market indicators (e.g., U.S. stock indices and commodity prices)—exert varying degrees of influence on the FTSE 100's volatility.

This hypothesis is tested by incorporating different external variables into the HAR-RV model and assessing their relative contributions to volatility prediction. The model's parameters will be evaluated to determine whether neighbouring indices or wider international indices (e.g., U.S. stock market) plays a greater role in shaping FTSE 100 volatility patterns. To test these hypotheses, the study does employ an econometric approach that integrates realized volatility modelling with external market variables. The HAR-RV model will serve as the baseline framework, augmented with additional terms representing external spillover effects. Alternative specifications will be considered to ensure robustness, and a comparative model performance analysis will be conducted to validate the findings.

3.2. Data

Daily realized variance series are collected from the Oxford-Man Institute's Quantitative Finance Realized Library. According to the seminal paper of Liu, Patton, & Sheppard (2015), no measure significantly outperforms the 5-minute realized variance among a set of 400 different volatility estimators. Therefore, 5-min realized variance series are employed, which is a widely accepted robust volatility measure. Of note, employing high-frequency data, especially for minute-wise data, brings an important challenge in data curation process such as microstructure noise effect caused by bid-ask spreads, order flow irregularities, and latency issues. This difficulty could distort realized variance calculations to a certain extent. By adapting a 5-minute frequency that is suggested by the seminal paper of Liu, et al. (2015), this work minimises such distortions while ensuring that significant market movements are adequately captured. This study also includes a wide range of different financial and economic data.

A diverse set of financial and economic variables is included to provide a comprehensive analysis. The data consists of the following stock market indices, financial variables, and economic indocators. Eight international stock market indices are FTSE 100 (UK), GDAXI (Germany), FCHI (France), FTMIB (Italy), STOXX50E (Euro Stox 50), SPX (S&P 500), DJI (Dow Jones Industrial Average), and IXIC (Nasdaq 100). Additional financial variables are collected from the Federal Reserve Bank of St. Louis (FRED) database, which contains the data of the CBOE volatility index (VIX), the Crude Oil Prices (WTI; West Texas Intermediate), the CBOE Gold ETF Volatility Index, the UK Government 10-year Treasury Bond Yields, and the London 12-month Interbank offered rates based on POUND (LIBOR-POUND). The economic indicator, the index of UK Economic Policy Uncertainty (EPU), is provided by the webpage of the Economic Policy Uncertainty.

Table 1. Descriptive statistics of the series

		Mean	Std. Dev.	Skew.	Ex. Kur.	Jarque-Bera	Q(5)	ADF
Indices								
Stock Markets	1. FTSE	9.91E-05	0.00024	14.986***	314.99***	1.09E+07***	2602.15***	-7.975***
	2. GDAXI	0.000110	0.00017	7.7620***	87.446***	863110***	5541.95***	-7.163***
	3. FCHI	0.000112	0.00020	10.123***	150.49***	2.52E+06***	5376.08***	-7.934***
	4. FTMIB	0.000122	0.00017	6.2168***	58.473***	390868***	4748.29***	-6.651***
	5. STOXX50E	0.000131	0.00026	10.683***	156.23***	2.71E+06***	4174.94***	-9.508***
	6. SPX	8.31E-05	0.00021	10.834***	154.84***	2.67E+06***	4770.71***	-9.261***
	7. DJI	8.50E-05	0.00024	12.721***	224.01***	5.55E+06***	3718.72***	-9.684***
	8. IXIC	7.45E-05	0.00019	15.448***	353.84***	1.37E+07***	4368.95***	-9.128***
	9. VIX	17.908	7.3291	2.7481***	13.057***	21950.5***	11127.8***	-5.664***
	10. OIL	-7.52E-06	0.01265	1.4177***	45.893***	231243***	104.958***	-10.28***
	11. GOLD	17.555	5.2736	1.0482***	2.0058***	920.793***	11536.8***	-4.377***
	12. BOND	-0.00109	0.03915	-0.8040***	33.515***	123090***	15.8668***	-9.577***
	13. UKEPU	331.66	206.34	2.4136***	14.328***	25003.1***	4862.01***	-4.916***
	14. LIBOR	-0.00042	0.01175	-1.0463***	85.886***	806962***	255.72***	-8.677***

Source: *GRETL software's output.* **Note:** *Asterisk *,**, and *** denote rejections of null hypothesis at 10%, 5%, and 1% significance levels, respectively. The null hypothesis of the third and fourth moments are "Skewness = 0" and "Excess Kurtosis = 3". Indices; Neighbouring (1-5), International (6-10), Local (12-14).*

The study spans the period from July 1, 2009, to April 10, 2020. Given that stock markets in different regions operate on different trading calendars, it is necessary to align the datasets to shared trading days across all series. To address this, the following data-cleaning and alignment procedures are applied: Firstly, unmatched trading days (i.e., days where any market or variable lacks data) were removed, ensuring that each row corresponds to the same date point across all series. Secondly, cleaning procedure deals with missing or anomalous data points, which is addressed by cross-verification of data sources to ensure reliability. Outliers caused by sudden market closures or extreme events are carefully evaluated for their inclusion or exclusion to maintain dataset integrity.After alignment and data cleaning procedure, the final dataset consists of 2,600 observations across 12 variables, ensuring uniformity and consistency in analysis.

Table 1 presents the descriptive statistics of the dataset. The data show significant skewness and leptokurtosis at the 99% confidence level, indicating that all the series have fat-tailed distributions. The Jarque-Bera test statistics confirm the non-normality of the series, also at the 99% confidence level. Additionally, the Ljung-Box statistic reveals the presence of autocorrelation, as the null hypothesis of no autocorrelation up to the 5th order is rejected across all series. The Augmented Dickey-Fuller (ADF) test results suggest that each series is stationary, with the null hypothesis of a unit root being rejected for all. These results are also supported by the KPSS test, which is not given in the table but available upon request from the author. Line graphs are provided in Figure 1 to visually demonstrate these findings.

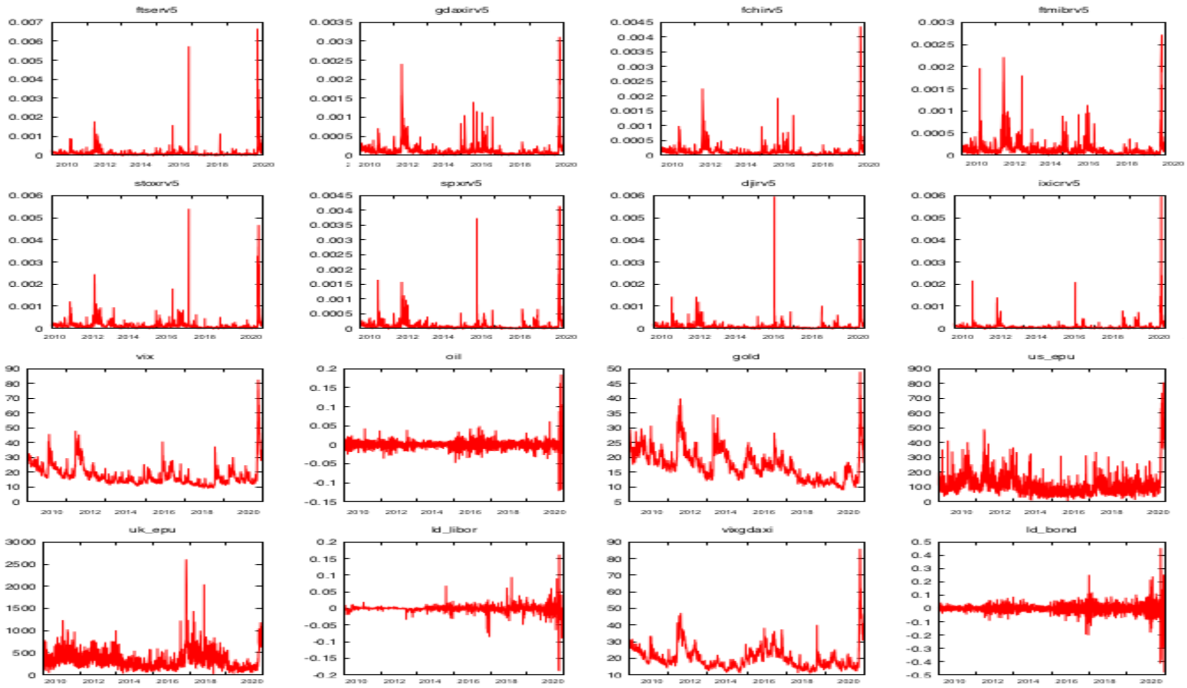

Figure 1. Line graphs of the series

Source: Figure 1 is illustrated using *GRETL software, (Line graphs of the series between 2009-2020).*

4. EMPIRICAL RESULTS

The study examines how information flows from the EU and US stock markets influence volatility forecasts of FTSE 100 index. The external factors are categorized as local, neighbouring, and international. Local factors include BOND, UKEPU, and LIBOR, whilst neighbouring factors are represented by EU stock indices (GDAXI, FCHI, FTMIB, and STOXX). International factors are mainly based on US data (SPX, DJI, IXIC, VIX, OIL, and GOLD). This classification helps determine the importance of these external volatilities in enhancing the accuracy of stock market predictions.

4.1. In-Sample Analysis of FTSE 100 Using HAR-RV-X Models

This section presents the in (full) sample volatility estimation results of various HAR-RV-X models for the FTSE 100 stock market index. In this regards, various combinations of these external factors are integrated into the baseline HAR-RV model, including individual variables, a simple average of group forecasts, and Kitchen-Sink model that includes all additional variables at once.

Table 2. Full sample volatility estimation results of various HAR-RV-X models

Models	$Constant$	β_1	β_2	β_3	β_X	$Adj.R^2$
HAR-RV (Benchmark)	2.01E-05***	0.772***	-0.017	0.041	-	0.35
Neighbouring information						
HAR-RV-GDAXI	9.06E-06***	-0.024	0.621***	-0.018	0.296***	0.37
HAR-RV-FCHI	1.29E-05***	-0.027	0.601***	-0.011	0.270***	0.37
HAR-RV-FTMIB	5.42E-06	0.0002	0.648***	-0.003	0.241***	0.37
HAR-RV-STOXX	1.11E-05***	-0.211***	0.611***	0.018	0.353***	0.38
International information						
HAR-RV-SPX	2.06E-05***	-0.082**	0.530***	0.031	0.371***	0.39
HAR-RV-DJI	2.07E-05***	-0.062	0.623***	0.013	0.252**	0.38
HAR-RV-IXIC	1.84E-05***	-0.028	0.537***	0.038	0.354***	0.39
HAR-RV-VIX	-0.00012***	0.011	0.626***	-0.249*	1.06E-05***	0.38
HAR-RV-WTI	2.02E-05***	0.027	0.769***	-0.002	-0.001	0.35
HAR-RV-GOLD	-3.31E-05**	0.037	0.756***	-0.069	3.44E-06***	0.36

			Domestic information			
HAR-RV-BOND	2.01E-05***	0.019	0.809***	-0.038	-0.0005	0.36
HAR-RV-UKEPU	3.73E-05**	0.044	0.772***	0.008	-6.08E-08	0.35
HAR-RV-LIBOR	2.06E-05***	0.044	0.763***	-0.014	0.0005	0.35

Source: *GRETL software's estimation output.* ***Note:*** *Asterisk *,**, and *** denote rejections of null hypothesis at 10%, 5%, and 1% significance levels, respectively. Therefore, the parameters with the asterisk (***) mean the significance of the corresponding coefficients at 1% significance level.*

4.1.1. Benchmark Model (HAR-RV)

The benchmark HAR-RV model provides a foundation for understanding the volatility dynamics of the FTSE 100 without considering any exogenous variables. The constant term is significant at the 1% level, and the model indicates that daily volatility (βd) has a strong and significant impact on the overall volatility, with a coefficient of 0.772. However, the weekly and monthly (βw and βm) components are not statistically significant. The adjusted R-squared (Adj. R^2) value of 0.35 suggests that the baseline model explains 35% of the variance in FTSE 100 volatility. The equation for the HAR-RV model is as follows:

$$RV_{t+h}^{d} = \beta_0 + \beta_d RV_t^d + \beta_w RV_t^w + \beta_m RV_t^m + \beta_X X_t^d + \varepsilon_{t+h} \quad (10)$$

where βd stands for daily volatility part; βw denotes to weekly component, and lastly βm is monthly volatility component.

4.1.2. The impact of Domestic, Neighbouring and International Information on FTSE index

The models in the local information group focus on UK-specific factors, including bond yields, UK economic policy uncertainty (EPU) index, and LIBOR rates. Table 2 indicates that the local group factors such as Bond, the UKEPU and LIBOR do not significantly impact FTSE 100 volatility in the in-sample results.

The neighbouring information group incorporates information from other European stock markets, including GDAXI (Germany), FCHI (France), FTMIB (Italy), and STOXX (Europe). Each of these cross-market information is represented by an exogenous variable (β_x) in the model, which accounts for the influence of a specific neighbouring market on the FTSE 100. The GDAXI, FCHI, FTMIB, and STOXX indices all significantly impact FTSE 100 volatility, but their effects vary. When the GDAXI, FCHI and FTMIB indices attached to the benchmark model, the weekly component has a significant impact on to the extended models. However, their daily and monthly effects become less significant. The STOXX index, however, has the strongest overall effect in the group of neighbouring information, notably on a daily and weekly basis, though its daily impact is negative. The model's accuracy improves slightly better with the STOXX index (38 per cent), whilst it remains consistent with the other indices (37 per cent).

The group of the international information contains information from major international indices, including SPX (US), DJI (US), IXIC (US), VIX (US), WTI (Oil prices), and gold prices. The SPX index has the strongest influence on FTSE 100 volatility with the coefficient 0.371. It also improves the model's explanatory power with 39 per cent. Similarly, The IXIC index also has a significant positive effect, though slightly less impactful than SPX. The DJI index shows a similar pattern to SPX and IXIC, but its influence is not much notable as the other two American stock indices. The VIX index, which measures market volatility in the US, has a lesser effect than the American stock indices, though its impact is based on the results of full-sample estimation. Oil prices (WTI) does not significantly affect to FTSE 100 volatility, whilst gold prices (gold) have a significant but little effect. This would indicate a possible hedging behaviour of oil and gold prices to FTSE 100 volatility.

4.1.3. Kitchen-Sink Approach

The best results come from the Kitchen-Sink model that combines various neighbouring, international, and local factors. These combined models in Table 3 ensure the most comprehensive explanation of FTSE 100 volatility, with the international model providing the strongest fit amongst the others. The neighbouring group also shows notable improvements in explaining volatility, whereas the local factors do not have a significant impact on FTSE 100 volatility. For example, the final (overall) model combines neighbouring, international, and local information to provide a comprehensive view of volatility drivers. The overall model shows the highest adjusted R^2 values of 42 per cent. However, HAR-RV-INTERNATIONAL is at 0.41 per cent alone, indicating that a mix of factors from different regions and markets provides the best explanation of FTSE 100 volatility, whilst majority of this improvement seems to stem from the international factors.

Table 3. Full sample volatility estimation results for various Kitchen Sink models

	$Constant$	β_1	β_2	β_3	β_{GDAXI}	β_{FCHI}	β_{FTMIB}	β_{STOXX}	$Adj. R^2$
HAR-RV-NEIGHBOURING	6.14e-06	-0.174**	0.593***	0.011	0.136*	-0.074	0.065	0.268	0.37

	$Constant$	β_1	β_2	β_3	β_{SPX}	β_{DJI}	β_{IXIC}	β_{VIX}	β_{OIL}	β_{GOLD}	$Adj.R^2$
HAR-RV-INTERNAT.	-7.03E-05***	-0.062*	0.436***	-0.101	0.507**	-0.289**	0.119	7.15E-06***	-0.0008	-6.76E-07	0.41

	$Constant$	β_1	β_2	β_3	β_{BOND}	β_{EPU}	β_{LIBOR}	$Adj.R^2$
HAR-RV-DOMESTIC	3.84E-05**	0.025	0.800***	-0.008	-0.0006	-6.23E-08	0.0007	0.36

	$Constant$	β_1	β_2	β_3	β_{GDAXI}	β_{FCHI}	β_{FTMIB}	β_{STOXX}	β_{SPX}	β_{DJI}	β_{IXIC}	
HAR-RV-OVERALL	-6.63E-05***	-0.209***	0.473**	-0.089	0.022	-0.196**	0.049	0.240***	0.328*	-0.159	0.133	⇒

	β_{VIX}	β_{OIL}	β_{GOLD}	β_{BOND}	β_{EPU}	β_{LIBOR}	$Adj.R^2$
⇒	6.96E-06***	-0.0006	-6.17E-07	-0.0005	-2.32E-08	0.0005	0.42

Source: *GRETL software's estimation output*. **Note:** *Asterisk *,**, and *** denote rejections of null hypothesis at 10%, 5%, and 1% significance levels, respectively. Therefore, the parameters with the asterisk (***) mean the significance of the corresponding coefficients at 1% significance level.*

The analysis of the FTSE 100 using HAR-RV-X models highlights the significant role of exogenous volatilities. Notably, neighbouring and international markets are important in determining the volatility of the FTSE 100. The models suggest that cross-market information from major European and US indices are crucial in explaining FTSE 100 dynamics, especially with the inclusion of STOXX and SPX that provide the most substantial improvements in model fit. Local factors, while important for the country, play a less dominant role in this modelling study. These findings underline the cross-market information flow of international financial markets and the importance of considering a wide range of factors in volatility modelling.

4.2. Out-of-sample Analysis of FTSE 100 Using HAR-RV-X Models

The dataset, consisting of 2,600 trading days, is divided into in-sample and out-of-sample periods. The in-sample period is 400 observations, selected to provide a solid foundation for model fitting while leaving a significant out-of-sample period, which is the primary focus of this study. The out-of-sample period covers 2,200 days, offering an extensive timeframe for testing. To produce one-step-ahead volatility forecasts for the FTSE 100, a rolling window method is employed. In this approach, the in-sample data size remains constant as new data points are added, and the oldest ones are removed (with the estimation sample rolling forward each time to generate new forecasts). This method enables a consistent assessment of the model's out-of-sample performance. The evaluation of forecast accuracy is conducted using three established loss functions—QLIKE, HMSE, and HMAE—as well as the MCS procedure, to identify the best-performing models. To ensure robustness, this forecasting exercise is also repeated using two additional forecasting windows of 200 and 600 observations.

The purpose of the MCS test is to evaluate the forecasting accuracy of a set of competing models using a specific elimination algorithm. This algorithm identifies, at a given confidence level, which models remain in the selection. Models with poor predictive performance are excluded from the initial set, as indicated by the term 'eliminated' in the tables below. There are six different statistics used to identify the superior models, with the range statistic being chosen based on the recommendation of Hansen et al. (2003). The results are interpreted by noting that models with the lowest loss function values should have higher p-values (a p-value of one) and lower ranks, signifying often superior predictive models. If the outcomes of the loss functions and the MCS test are entirely contradictory, the results may be unreliable, though minor discrepancies do not necessarily matter.

The top-performing extended forecasting model for the FTSE 100 index based on the selected evaluation criteria is the international Kitchen-Sink model, which incorporates all members of the international group simultaneously. The inclusion of (international group) variables such as SPX, DJI, IXIC, VIX, WTI, and GOLD enhances performance compared to individual models. This is because the simultaneous inclusion of variables contains more comprehensive information. After the international Kitchen-Sink model, the next best performers for the FTSE index are the gold model, the international combination model, and the VIX model, respectively.

Individually, the gold volatility index and the VIX, both part of the international information class, contain valuable information for forecasting UK stock market volatility. These two factors are recognized as significant influences on international stock markets. Typically, gold prices inversely correlate with stock markets; when stock prices fall, gold prices tend to rise. As a result, during periods of market risk, investors might diversify into gold to offset potential losses in stocks. The leverage effect also plays a crucial role during stock market declines, as negative returns often lead to sharper volatility spikes than positive returns. The asymmetric downside risks in the markets can be captured by including gold volatility as an exogenous variable in the model, which helps improve the predictive accuracy of FTSE 100 volatility.

This indicates that U.S. market information significantly impacts UK stock market volatility. SPX, DJI, and IXIC individually perform well for FTSE forecasting. Therefore, their joint information content contributes to the effectiveness of the international Kitchen-Sink model. Overall Kitchen-Sink and Overall combination methods provide relatively better forecast accuracy for the FTSE index, even though they are not among the top competing models.

Table 4. Out-of-sample one-step-ahead rolling window forecasting and MCS results

FTSE 100	QLIKE	p-value	Rank	HMSE	p-value	Rank	HMAE	p-value	Rank
HAR-RV (Benchmark)	-8.5838	0.0000	20	2.3436	0.0842	16	0.9087	eliminated	–
NEIGHBOURING INFORMATION									
HAR-RV-GDAXI	-8.5947	0.4578	9	2.1983	1.0000	6	0.8341	eliminated	–
HAR-RV-FCHI	-8.4747	0.8848	4	1.8077	1.0000	7	0.7933	0.4756	5
HAR-RV-FTMIB	-8.5993	0.5268	6	1.8782	1.0000	10	0.8056	0.3862	6
HAR-RV-STOXX50E	-8.5166	0.1938	12	1.9507	1.0000	12	0.8369	eliminated	–
NEIGHBOURING K.S.	-8.5866	0.4022	10	2.1549	1.0000	8	0.8318	eliminated	–
NEIGHBOURING COMB.	-8.6082	0.7980	5	1.8041	0.0000	9	0.8028	0.3520	7
INTERNATIONAL INFORMATION									
HAR-RV-SPX	-8.6003	0.0110	17	2.5611	0.0244	21	0.8773	eliminated	–
HAR-RV-DJI	-8.5810	0.1988	11	2.5441	eliminated		0.8943	eliminated	–
HAR-RV-IXIC	-8.6081	0.1052	13	2.4727	1.0000	15	0.8647	eliminated	–
HAR-RV-VIX	-7.7259	0.4862	8	1.7674	1.0000	4	0.7546	0.7306	4
HAR-RV-WTI	-8.5527	0.0002	19	2.4896	0.0286	20	0.9262	eliminated	–
HAR-RV-GOLD	-8.3386	0.0734	15	1.4750	1.0000	2	0.7434	0.9872	2
INTERNATIONAL K.S.	-8.2100	0.4950	7	**1.1990**	**1.0000**	**1**	**0.7034**	**1.0000**	**1**
INTERNATIONAL COMB.	**-8.6326**	**1.0000**	**1**	1.7744	1.0000	3	0.7568	0.9094	3
DOMESTIC INFORMATION									
HAR-RV-BOND	-8.5381	0.0912	14	2.4231	0.0410	19	0.9378	eliminated	–
HAR-RV-UKEPU	-8.5759	0.0004	18	2.2753	1.0000	14	0.8826	eliminated	–
HAR-RV-LIBOR	-8.5843	0.0000	21	2.3346	0.0774	17	0.9045	eliminated	–
LOCAL K.S.	-8.4818	0.0294	16	2.2989	0.0542	18	0.9177	eliminated	–
LOCAL COMB.	-8.5464	0.0000	22	2.2336	1.0000	13	0.8895	eliminated	–
OVERALL INFORMATION									
OVERALL K.S.	-6.6819	0.9970	2	1.8931	1.0000	11	0.8220	0.0036	9
OVERALL COMB.	-8.6358	0.9312	3	1.7861	1.0000	5	0.7878	0.1076	8

Source: *GRETL software's estimation output*. ***Note:*** *"K.S." stands for Kitchen-Sink model and "COMB." denotes combination model. The respective p-values which are higher and closer to one mean the models with higher forecasting power, where their ranks are indicated in the rank column.*

International information plays a crucial role in influencing the volatility of the FTSE 100 stock market, given that it is composed of large companies with an international focus. This suggests that the FTSE 100 is highly responsive to international news, and incorporating various international data sources can be beneficial for forecasting the market's future volatility. The neighbouring information, particularly from Germany and France, emerges as the second most important group after international information. Germany is the UK's second-largest export market after the US, while France, as a neighbouring country and significant trading partner, also plays a key role. These econometric findings align with the real-world economic relationships of the UK. Local UK data might be expected to have a direct impact on the FTSE 100, whereas the performance of the local information group seems to be poor with forecasting the market's future volatility.

Figure 2 illustrates a significant rise in cumulative forecast errors in June 2016, attributed to the Brexit referendum. Another sharp increase is observed in 2018, likely due to concerns about a potential no-deal Brexit and the Bank of England's recession warning. Notably, the figure indicates that the HAR-RV-INTERNATIONAL-KITCHEN-SINK model is more resilient during turbulent periods compared to the HAR-RV-GOLD and HAR-RV-INTERNATIONAL-COMBINATION models. Conversely, the cumulative forecast errors for the benchmark HAR-RV model are higher than those of the other models throughout this time interval.

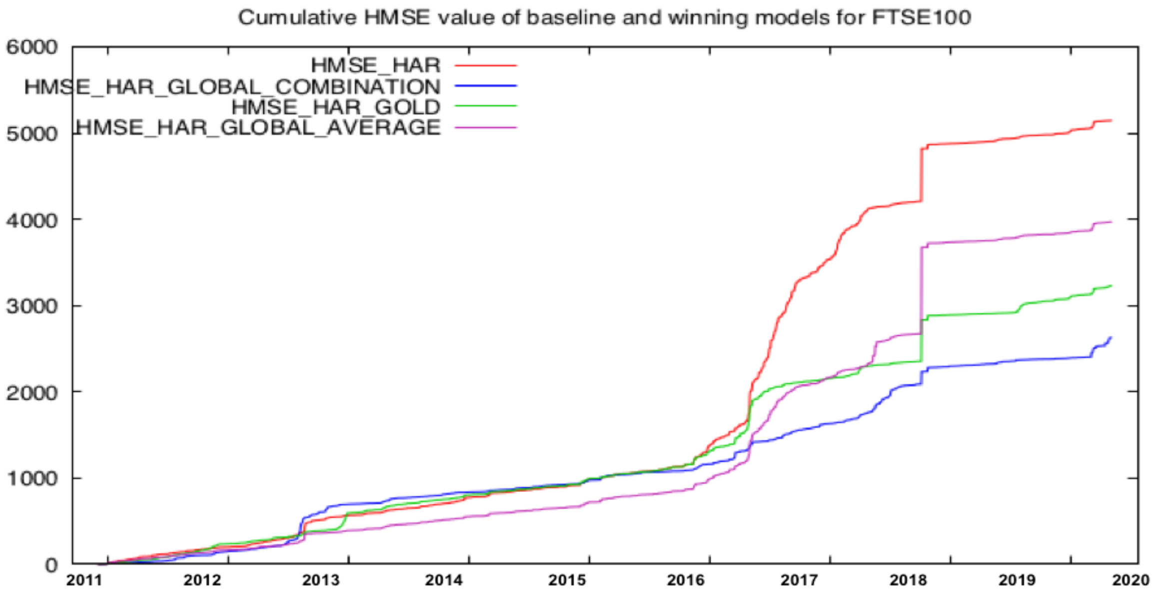

Figure 2. Cumulative HMSE line graph for different models.

Source: *GRETL software's plot, (2009-2020).*

5. CONCLUSION

This study addresses the significant role of external information, particularly from international and neighbouring markets, in forecasting the volatility of the FTSE 100 index. The empirical analysis reveals that the FTSE 100, being composed of large, internationally-focused companies, is highly sensitive to international news, especially from the U.S. stock markets. Models incorporating international information, such as the HAR-RV-INTERNATIONAL-KITCHEN-SINK model, demonstrate superior performance in forecasting volatility, pointing out the importance of a comprehensive approach that includes a wide range of international factors.

Neighbouring information, particularly from Germany and France, also plays a crucial role, reflecting the deep economic ties between the UK and these European nations. The findings suggest that while local UK-specific factors such as bond yields and economic policy uncertainty have no significant impact on FTSE 100 volatility, neighbouring and international factors provide more substantial predictive power.

The resilience of the HAR-RV-INTERNATIONAL-KITCHEN-SINK model during turbulent periods, such as the Brexit referendum and subsequent economic uncertainties, further emphasizes the value of integrating international data in volatility forecasting. This model's ability to maintain lower cumulative forecast errors compared to others, including the benchmark HAR-RV model, suggests that a broader, more inclusive approach to information gathering yields more accurate and robust predictions.

Overall, the study stresses the importance of the cross-market information amongst international financial markets. This further necessities incorporating diverse information sources to improve the predictive accuracy of stock market volatility models. The insights gained from this research have important implications for investors and policymakers, particularly in understanding the dynamics that drive the volatility of internationally-focused stock indices such as the FTSE 100.

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