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# Forecasting Pakistan stock market volatility: Evidence from economic variables and the uncertainty index

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ABSTRACT

This study examines the impact of the economic policy uncertainty index (EPU) and macroeconomic variables on the volatility of the Pakistan stock market using the GARCH-MIDAS (mixed data sampling) model. The model allows us to observe whether those variables contain valuable information to forecast stock market volatility. Our empirical findings show several outcomes. First, our out-of-sample results show economic policy uncertainty index has predictive power to forecast Pakistan stock market volatility. Second, among all variables, oil prices are the most powerful predictor of volatility with a higher out of sample *R* square value. Third, all macroeconomic variables including exchange rate, short-term interest rate, money supply M2, foreign direct investment, gold prices, inward remittances, industrial production, and consumer price index (proxy for inflation) contain useful information for stock market volatility forecasting. However, the long-run interest rate is an ineffective indicator of volatility during the sample period study. Finally, we find that the combination forecast information is also useful for volatility forecasting.

## 1. Introduction

Volatility in financial markets is an issue of great concern. As a risk measure, volatility considers an important state variable for asset pricing and investment. Additionally, the volatility dynamics are associated with portfolio allocation, risk management, hedging, and options pricing (Christoffersen & Diebold, 2000; Chun et al., 2020; Mei et al., 2017; Morales and Callaghan, 2011; Naeem et al., 2019; Wang and Nishiyama, 2015; Zhang et al., 2020). The higher volatility creates widespread panic and results in disorderly market situations that reduce investors' confidence and that lead to declines in business investments and economic growth. Therefore, understanding the mechanism of economic dynamics and accurately estimating future volatility is essential.

However, it is prudently observed by financial analysts, policymakers, and market practitioners. Nonetheless, before estimation, it is hard to find the main economic drivers of volatility. The seminal work of SCHWERT and WILLIAM (1989), who posits a time-varying link between stock market uncertainty and macroeconomic variables. Moreover, Paye (2012) examines the strong linear connection between macroeconomic indicators and stock market volatility. Both theoretical and empirical studies confirm that institutional and macroeconomic determinants are potential drivers of financial markets volatility (Engle et al., 2013; Bahloul et al., 2017; Fang et al., 2018; Hsu et al., 2019). The literature shows that financial market volatility and macroeconomic indicators are intrinsically associated

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(Chen et al., 1986; Mele, 2007; Christiansen et al., 2012).

Additionally, it is well documented that emerging financial markets are extremely volatile as compared to developed markets, and their volatility is mostly linked to the unstable macroeconomic environment (Muradoglu et al., 2000; Bilson et al., 2001; Kirui et al., 2014; Tiryaki et al., 2017). In this research, we provide a comprehensive outlook on the role of macroeconomic indicators in Pakistan's stock market volatility by employing the GARCH-MIDAS approach. The Pakistan stock market is Asia's third-largest and world-best 5th-performing stock market (Bloomberg, 2016).[1] According to the report of a US-based global financial markets research firm the Pakistan stock market is the 4th best performing market in the world for 2020 even during the turbulent period of COVID-19, the Pakistan stock market has been the best performer in Asia.[2] Moreover, the Pakistan stock market considers the world-leading emerging stock market to have the highest growth and liquidity, and also emerging markets are highly volatile market due to macroeconomic discrepancies and political uncertainty (Irtiza et al., 2021; Joyo, Shafique, & Lefen, 2019; Silva & Antunes, 2015). Furthermore, few studies show that Pakistan stock market performance is sensitive to macroeconomic volatility (Shahid 2015; Ahmad & Ramzan, 2016; Ghani, Ghulam, & Chaudhary, 2017). However, it is still unexplained, and only a handful of studies address this concern. This is our first motivation, how numerous macroeconomic determinants are associated with Pakistan's stock market volatility. The reason behind using macroeconomic variables for forecasting volatility is that it is associated with the financial valuation of companies and reflects economic activity and government policy action.

In addition, global factors also significantly affect Asian stock market returns. Due to globalization and liberalization, information transmission from developed markets to emerging markets is more rapid and strong. Furthermore, among global consumers, changes in commodity prices affect emerging economies through various channels. It is essential for policymakers and financial analysts to determine the dynamic behaviors of the equity market in concerning changes in global factors (Balcilar et al., 2015; Muradoglu et al., 2000; Ma et al. 2017, 2021; Dong & Yoon, 2019; Liang et al., 2020; Uddin et al., 2022; Cepni et al., 2022). Therefore, we consider global factors oil and gold prices to find whether global indicators have any significant effect on Pakistan stock market volatility.

Moreover, we use economic policy uncertainty indexes for Pakistan, which is recently proposed by Choudhary et al. (2020). The author constructed the uncertainty index for Pakistan by following the procedure of Baker et al. (2016), to cover more historical background, an index construct based on two newspapers from 2010 to 2020. From the past three decades, Pakistan's economy has been severely affected by war and terrorism, political instability and some natural disasters. This index captures the following main uncertainty events in Pakistan, such as high terrorism activity, political turmoil, great floods of 2010, exchange rate volatility, and the IMF program of 2019, and covers the most recent outbreak of the COVID-19 pandemic. Additionally, the literature shows that economic policy uncertainty has a notable influence on the equity market returns and macroeconomic fundamentals and considers it a key determinant of the economic cycle (Alexopoulos & Cohen, 2015; Arouri et al., 2016; Karnizova & Li, 2014).

Furthermore, our work is related to Asgharian et al. (2013) and Conrad and Loch (2015) who investigate the relation among US stock market volatility with macroeconomic variables by employing the GARCH-MIDAS method. Both studies show, macroeconomic indicators provide useful information for volatility forecasting and find that some macroeconomic variables are key determinants of risk. We extend the abovementioned studies in twofold aspects. First, in our study we use economic policy uncertainty index along with domestic and global macroeconomic variables to determine whether the EPU index holds valuable information for volatility prediction, while the aforementioned studies emphasize only macroeconomic variable information. In addition, we investigate the effect in an emerging economy, whereas the existing studies focus on developed economies.

The GARCH-MIDAS model has gained much attention in emerging literature because of its substantial benefit for volatility forecasting, as it distributes volatility in short- and long-term components (Asgharian et al., 2015; Yu et al., 2018; Xu et al., 2019; Conrad & Kleen, 2020; Wang et al., 2020; Zhou et al., 2020). Following this stream of literature, we employ the GARCH-MIDAS model to investigate the effect of macroeconomic variables on equity market volatility. Since, this model distributes volatility into short- and long-run components, the short-term volatility component uses mean-reverting daily unit GARCH practice, and the MIDAS polynomial applies to monthly macroeconomic variables to investigate the long-term volatility component.

We find several outcomes from our empirical analysis. First, we find that the economic policy uncertainty (EPU) index is useful predictor of volatility in Pakistan stock market. Second, we find the impact of global indicators oil and gold prices for Pakistan stock market volatility forecast. Regarding global indicators we find some remarkable results among all variables, oil prices are more powerful predictor of stock market volatility with a higher $R^2$ value. Third, all macroeconomic variables contain useful information for Pakistan stock market volatility forecasting except long run interest rate. Additionally, combination forecast models also contain useful information for stock market volatility prediction.

This research contributes to the literature in the following aspects. First, to our knowledge this is the first study in the context of Pakistan in which we use both domestic and global macroeconomic variables to predict the volatility of the equity market. Second, we use the economic policy uncertainty index for Pakistan, which is recently introduced by Choudhary et al. (2020). The uncertainty index captures the main uncertain events during the last ten years and also covers uncertainty during the COVID-19 pandemic. Furthermore, according to the author's best information, this is the first study that uses local economic policy uncertainty (EPU) for Pakistan to estimate stock market volatility. Additionally, this study enhances the literature, especially in the context of emerging economies.

The remaining section of the paper is organized as follows Section 2 contains a related literature review. Section 3 describes the methodology. Section 4 provides the data description. Section 5 presents the empirical results, in-sample estimation. Section 6 provides out-of-sample findings. Section 7 contains the conclusion of the study.

[1] https://www.bloomberg.com/news/articles/2016-06-14/best-performing-asian-stock-market-may-get-extra-boost-from-msci.

[2] https://www.rt.com/business/499762-pakistan-best-performing-market/.

## 2. Literature review

Our research is based on two strands of literature. The first is concerned with the role of macroeconomic variables in equity market returns and volatility. The second literature strand reviews the connection between economic policy uncertainty and equity market returns and volatility. A considerable strand of financial literature shows the connection between macroeconomic variables and stock markets (Engle & Rangel, 2008; Engle et al., 2013; Ma et al., 2018; Bhuiyan & Chowdhury, 2020; Chen et al., 2022). The earlier work of Liljeblom and Stenius (1997) investigates the correlation among macroeconomic variables with equity market volatility in Finland for the period of 1920–1991 by using the GARCH model. The empirical findings show the significant impact of equity market volatility on macroeconomic variables, and the result also supports the converse relationship.

Engle and Rangel (2008) explore the link between macroeconomic volatility and stock market volatility in 50 countries, including both developed and emerging economies, by applying the Spline GARCH Model. The empirical results show that low-frequency components of volatility are higher in response to greater volatility of macroeconomics indicators, including short-term interest rate, inflation and GDP, and these are significant explanatory indicators of volatility forecasting. Additionally, Engle et al. (2013) investigate the relation among macroeconomic indicators with equity market volatility in the short and long run. The results show that macroeconomic volatility influences stock market volatility in both short and long runs.

Asgharian et al. (2013) use macroeconomic variable information to estimate the US equity market volatility by employing the GARCH-MIDAS model. The empirical findings show that macroeconomic variables provide valuable information for volatility prediction and the GARCH-MIDAS model performs better than the traditional GARCH model. Asgharian et al. (2015) employ the macroeconomic uncertainty index (MUI) to estimate bonds and equity market volatility. Findings show flight to quality behavior (like herd behaviors) in which investors shift risky assets during a financial downturn from stock to bond. Mo et al. (2018) investigate the impact of domestic and global macroeconomic variable information to forecast commodity market volatility in emerging economies (China and India) by employing the GARCH-MIDAS model. The results show that both domestic and global macroeconomic variables are valuable in forecasting the volatility of commodity markets.

Asravor, Kofi, and Fonu (2021) examine the dynamic connection among macroeconomic variables with stock market returns in the long and short run by using the ARDL model. The empirical findings show that foreign direct investment and interest rates have a positive influence on equity market returns, while inflation and money supply negatively affect stock market returns. Cheng, Wui Wing, Wing, and Yip (2017) explore the role of macroeconomic variables in estimating Chinese equity market volatility. The study findings show that macroeconomic variables play an essential role in equity market volatility estimation. Overall, the literature shows the vital role of macroeconomic variable information in equity market volatility estimations.

In this section we review the literature regarding economic policy uncertainty (EPU) and its connection with equity market volatility. Economic policy uncertainty has attracted much attention in research because this index gauges economic activities and uncertainties in government policies. Liu and Zhang (2015) investigate the economic policy uncertainty index used to estimate future stock market volatility. Interestingly, both in-sample and out-sample findings show that economic policy uncertainty considerably increases the fluctuation, and has predictive power to forecast future volatility. Arouri et al. (2016) examine the influence of economic policy uncertainty (EPU) on the US stock market returns by using linear and switching models. Their findings show that stock market returns decrease in response to an upsurge in policy uncertainty and that the effect is stronger during periods of high volatility.

Moreover, Liang et al. (2020) use five economic policy uncertainty indexes to estimate oil market volatility by employing predictive regression with a combination forecast method. The empirical findings show that international economic policy uncertainty and the US equity market index can forecast oil market fluctuations. Additionally, studies show the important role of EPU (Sin & Chor yiu, 2015; Fang et al., 2018; Hoque, Enamul, & Azlan, 2019; Li et al., 2020; Yao et al., 2020) Thus, the above literature shows the significance of economic policy uncertainty for equity market volatility estimations.

## 3. Methodology

In our research, we use the GARCH-MIDAS, mixed data sampling volatility component model, introduced by Engle et al. (2013). This new class model gains much attention in recent literatures for volatility estimations (Fang et al., 2020; Jiang et al., 2021; Pan et al., 2017). The GARCH-MIDAS model statistically denoted as:

The conditional mean equation is,

$$r_{i,t} = \mu + \sqrt{\tau_i s_i}\varepsilon_{i,t},\ \forall i = i, \ldots, N_i, \tag{1}$$

In equation (1), $r_{i,t}$ is the returns, and $\sqrt{\tau_i s_i}\varepsilon_{i,t}$ , $\tau_t$ is long run volatility component $S_i$ is short-term variance and $\varepsilon_{i,t}\Phi_{i-1,t} \sim |N(0,1)$, and $\Phi_{i-1,t}$ is set of information on particular day in sample period. Further, the conditional variance equation can be presented as follow:

$$\sigma_{it}^2 = \tau_t . s_{it}, \tag{2}$$

The short-term daily conditional variance component $s_{i,t}$ is a GARCH (1, 1) procedure as:

$$s_{i,t} = (1 - \alpha - \beta) + \alpha \frac{\left(r_{i-1,t} - \mu\right)^2}{\tau_i} + \beta s_{i-1,t}\ , \tag{3}$$

where $s_{i,t}$ *is* conditional variance GARCH component and $\alpha$ , $\beta$ are ARCH and GARCH component, these parameter should be fulfilled

**Table 1**
Models description.

| Models Numbers | Model Name |
|---|---|
| Model-0 | GARCH-MIDAS |
| Model-1 | GARCH-MIDAS-x1 |
| Model-2 | GARCH-MIDAS-x2 |
| Model-3 | GARCH-MIDAS-x3 |
| Model-4 | GARCH-MIDAS-x4 |
| Model-5 | GARCH-MIDAS-x5 |
| Model-6 | GARCH-MIDAS-x6 |
| Model-7 | GARCH-MIDAS-X7 |
| Model-8 | GARCH-MIDAS-X8 |
| Model-9 | GARCH-MIDAS-X9 |
| Model-10 | GARCH-MIDAS-X10 |
| Model-11 | GARCH-MIDAS-X11 |
| Model −12 | GM-Mean |
| Model-13 | GM-Median |
| Model-14 | GM-Trimmed |
| Model-15 | GM-DMSP-1 |
| Model-16 | GM-DMSPE(0.9) |

**Note:** This table contains the benchmark model and extended model with each variable x1 to x11 and five combination forecast models from 12 to 16. Following the work of (Fang et al., 2018; Asgharian et al., 2015; Li et al., 2020), we construct these models in our study, and the combination forecasting model constructs following the work of (Zhang et al., 2018; Liang, Wei, et al., 2020; Li et al., 2020).

with $\alpha > 0$ *and* $\beta > 0$. The long-term component $\tau_i$ is defined as smooth realized volatility in the MIDAS framework, and the long-term component $\tau_i$ is represented as:

$$\log(\tau_i) = m + \theta \sum_{k=1}^{k} \varphi_k(w_1, w_2) RV_{t-k} \,, \tag{4}$$

$$RV_t = \sum_{k=1}^{N_t} r_t^2 j,$$

where $k$ is the maximum lag order of the low-frequency variables, which is 20 in this paper one month. Furthermore, we modify equation (3) and add macroeconomic variables along with realized volatility to examine the effect of macroeconomic variables on long-run volatility. In equations (3) and (4), the beta weighting scheme can be presented as:

$$\varphi_k(w) = \frac{\left(k/k\right)^{w_1-1}\left(1-k/k\right)^{w_1-1}}{\sum_{j=1}^{k}\left(j/K\right)^{\omega 2-1}} \tag{5}$$

In this paper, GARCH-MIDAS[3] is the benchmark model and in extended model we add macroeconomic variables. Following the work of (Asgharian et al., 2015; Fang et al., 2018; Li et al., 2020), we construct extended models, which are presented in Table 1.

## 4. Data

This research examines the important role of macroeconomic variables and economic policy uncertainty (EPU) in forecasting the volatility of the Pakistan stock market. Therefore, we use macroeconomic variables, EPU index and stock market index data set. First, we obtained the KSE 100 index (Pakistan) data from the stock market website. Second, we collected data sets of macroeconomic variables, including exchange rate (EX), consumer prices index (CPI) proxy for inflation, long term interest rate (INT), T-bill rate proxy for short term interest rate, money supply (M2), and industrial production foreign direct investment (FDI) data from trading economic, inward remittances data from State Bank of Pakistan (website).[4] Additionally, we use global indicators oil prices and gold prices, and the data set for global indicators is collected from the Federal Reserve economic database.[5] Third, economic policy uncertainty index

[3] More technical details of the GARCH-MIDAS model documented in (Asgharian et al., 2013) and (Engle, 2020).
[4] https://www.sbp.org.pk/.
[5] https://fred.stlouisfed.org/tags/series?t=pakistan.

data obtained from the EPU website[6]. All variables were selected by following the mainstream literature (Asgharian et al., 2013; Liu & Pan, 2020; Raza et al., 2015). The sample period was selected from August 2010 to December 2020, according to data availability for all variables. The descriptive statistics are presented in Table 2.

## 5. In sample estimation results

Our in-sample estimate results are presented in Table 3. We carry out parameter estimation results obtained from the GARCH-MIDAS model. This model distributes volatility into the short and long runs. We obtained the following in the sample estimation results. First, in our model the parameter $\mu$ is the unconditional mean of stock returns $\alpha$, $\beta$ are ARCH and GARCH terms both are short term components that are positive, whereas our fourth parameter $\theta$ is the sum of weighted rolling window realized volatility of each variable which is highly significance level 1% it indicates the predictability of monthly macroeconomic variables for daily stock returns, it also consistent for all variables. Furthermore, $\omega 1$ and $\omega 2$ are beta polynomial weights for the long-run component in the model, which is significant for most of the variables, showing that macroeconomic variables have the ability to forecast long-run volatility. Our in-sample estimations results comprise only 0.3% of the total observations. Therefore, main findings are presented in the out-of-sample evaluation.

## 6. Out of sample estimation

Out-of-sample predictive performance is more essential than in the sample because market participants are more concerned about model performance for future forecasting rather than analyzing past performance. In our research, to evaluate the predictive power of variables we use R square ($R^2_{oos}$) out of sample technique following existing studies (Liang, Ma, et al., 2020; Liang, Wei, et al., 2020; Li et al., 2020; Lu et al., 2021). The $R^2_{oos}$ test evaluates the predictability of the extended model. Statistically, it can be presented as:

$$R^2_{oos} = 1 - \frac{\sum_{t=1}^{M}\left(RV_t - RV_t^j\right)^2}{\sum_{t=1}^{M}\left(RV - RV_t^0\right)2}, \; j = \text{model}\ (1, 2 \ldots 16), \tag{6}$$

where $RV_t$ is actual realized volatility and $RV_t^j$ is the valuation from the extended model with variables j and $j \in$ Model (1, 2, 3 … 16). $Rv_t^o$, $i$ s the volatility calculated from the benchmark model. The GARCH-MIDAS is our benchmark model and extended model constructs by adding macroeconomic variables. If $R^2_{oos}$ value is positive and higher than zero in extended models, it indicates the extended model outperform than the benchmark model.

We find several compelling results from our analysis. First, we notice that the $R^2_{oos}$ value for the first model GARCH-MIDAS- x1 (EPU) is 2.31, positive and also significant at 5%, which shows economic policy uncertainty index contain useful information for Pakistan stock market volatility. Second, the global indicator oil price $R^2_{oos}$ value is 3.97 which is positive, and highest among all extended models also significant at 10%, that indicates the important role of oil prices information for Pakistan stock market volatility forecasting. Third, all macroeconomic variables including exchange rate, money supply M2, foreign direct investment, gold prices, inward remittances, industrial production, short term interest rate, and consumer prices index (proxy for inflation) $R^2_{oos}$ values are positive and significant at 5% and 10%. These results show all macroeconomic variables contain useful information for stock market volatility prediction, except long run interest rate. The $R^2_{oos}$ value of long run interest rate is (−1.86224) negative and insignificant, that indicates the model worst predicting performance during sample period of study.

Additionally, it is well documented that the combination forecast gives more consistent and accurate predictions (Liang, Ma, et al., 2020; Zhang et al., 2018). Therefore, we employ the combinations forecast approach, which is the weighted average of $N$ individual estimates, statistically denoted as:

$$\widehat{RV_C}_{,t} = \sum_{k=1}^{N} \omega_{k\ ,t-1}\ \widehat{RV_K}, t, \tag{7}$$

where $\widehat{RV_c}_{,t}$ is the forecast from the combination method, $\widehat{RV}_{K,t}$ is the forecast from the GARCH-MIDAS model, and $\omega_{k\ ,t-1}$ is the collective weight of the $k$th individual estimate formed at $t$. Thus, by following the work of Rapach et al. (2010), we use five combination models: first, the mean combination prediction from the equal-weighted average of $N$ individual predictions; second, the median combination estimate is the median value of forecasts; and third, the trimmed mean combination is $\omega_{k,t} = {}^{1}/_{N} - 2$ when eliminating the higher and lower predictions. Further fourth and fifth is DMSPE1, and DMSPE2 is denoted as:

$$\omega_{k,t-1} = \frac{\varnothing_{i,t-1}^{-1}}{\sum_{K=1}^{N}\varnothing_{i,t-1}^{-1}} \tag{8}$$

[6] www.policyuncertainty.com.

**Table 2**
Descriptive statistics.

| Statistics | Stock-r | x1 | x2 | x3- | x4- | x5 | x6 | x7 | x8 | x9 | x10 | x11 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Observations | 2578 | 125 | 2578 | 125 | 125 | 125 | 2578 | 2578 | 125 | 125 | 125 | 125 |
| Mean | 0.00567 | 4.512 | 4.6925 | 2.154 | 16.22 | 4.90 | 7.23 | 4.16 | 7.24 | 1.44 | 4.63 | 2.18 |
| Std. dev. | 0.010 | 0.3841 | 0.1970 | 0.304 | 0.371 | 0.73 | 0.145 | 0.373 | 0.27 | 0.96 | 0.173 | 0.29 |
| Skewness | −0.047 | 0.54 | 0.9016 | 0.710 | −0.79 | −0.85 | 0.614 | −0.54 | −0.625 | −0.88 | 2.27 | −0.019 |
| Kurtosis | 9.23 | 2.773 | 2.7122 | 1.609 | 1.88 | 4.827 | 2.39 | 3.27 | 2.49 | 4.37 | 0.060 | 1.60 |
| Jarque-Bera | 4168.*** | 30.262** | 361.8*** | 10.23*** | 6.64** | 32.56*** | 212*** | 141.3*** | 9.48*** | 26.30*** | 2.821** | 9.26*** |
| Q(5) | 61.65*** | 139*** | 12925*** | 540*** | 552*** | 55.13*** | 13353*** | 13356*** | 410*** | 92.71*** | 534*** | 553*** |
| Q(22) | 84.42*** | 262*** | 55976*** | 953*** | 1611*** | 126.37*** | 55963*** | 55799*** | 1139*** | 159*** | 144*** | 677*** |
| ADF | −20.55*** | −10.43*** | −10.31* | −3.81** | −19.17*** | −22.98*** | −18.42*** | −2.34* | −14.31*** | −3.92*** | −10.24* | −30.1*** |

Note: This Table presents descriptive statistics of all variables; stock-r is returns of kse100 index for Pakistan, economic policy uncertainty index-x1, exchange rate-x2, long-run interest rate-x3, money supply (M2)- x4, foreign direct investment (FDI)-$x_{5,}$ oil prices-x6, gold-prices-x7, remittance-x8, industrial production-x9, consumer price index-x10, short term interest rate (x11). We used log values of all variables for the sample period of Aug 2010 to Dec 2020. The observations include all variables (Obs), mean, standard deviation (Std.dev), skewness (skew), and kurtosis (Kurt) Jarque-Bera and serial correlation at the 5th and 22nd levels. All variables are normally distributed, according to the Jarque and Bera (1987) test, and the ADF test to test stationary. All variables are stationary ***, ***, ** and * at the 1%, 5% and 10% significance levels, respectively.

**Table 3**
In-sample estimation results.

| Parameters | x1 | x2 | x3 | x 4 | x5 | x 6 | x 7 | x 8 | x 9 | x 10 | x 11 |
|---|---|---|---|---|---|---|---|---|---|---|---|
| $\mu$ | 0.017 | 0.0180*** | 0.037 | 0.025*** | 0.012 | 0.023*** | 0.017*** | 0.016* | 0.012* | 0.033** | 0.016** |
| $\alpha$ | 0.047** | 0.083*** | 0.0130*** | 0.079*** | 0.083 | 0.013*** | 0.010* | 0.011 | 0.012 | 0.011* | 0.012** |
| $\beta$ | 0.0271* | 0.032*** | 0.096** | 0.035*** | 0.035 | 0.030*** | 0.035* | 0.043 | 0.036 | 0.030 | 0.038*** |
| $\theta$ | −3.912 | −2.054*** | −0.605 | −4.28*** | −2.56 | −0.921*** | −2.61** | −1.64** | −1.44*** | 0.341* | 0.082 |
| $\omega_1$ | 0.086*** | 0.090*** | 0.091*** | 0.091*** | 0.090*** | 0.093*** | 0.091*** | 0.093*** | 0.093*** | 0.092* | 0.091*** |
| $\omega_2$ | 0.0195*** | 0.0129*** | 0.019*** | 0.0151*** | 0.0162*** | 0.0192*** | 0.012*** | 0.010*** | 0.015*** | 0.018 | 0.019*** |

Note: This Table contains model parameters values with respective significance levels. All parameter values for related variables x1 to x11 mentioned in (Table 1). In our sample estimation, parameters are significant at the ***1%, ** 5% and * 10% significance levels.

**Table 4**
Out of sample estimations $R^2$ test results.

| Models | $R^2$oos | MSPE | $p$ values |
|---|---|---|---|
| GM-x1 | 2.3139 | 1.8049 | 0.0355** |
| GM-x2 | 2.3238 | 1.6643 | 0.0480** |
| GM-x3 | −1.8622 | 0.7705 | 0.2205 |
| GM-x4 | 1.9301 | 1.4789 | 0.0696* |
| GM-x5 | 2.3244 | 1.7723 | 0.0382** |
| GM-x6 | 3.9718 | 1.5818 | 0.0568* |
| GM-x7 | 1.9051 | 1.6362 | 0.0509* |
| GM-x8 | 2.3864 | 1.8890 | 0.0294** |
| GM-x9 | 2.2697 | 1.7922 | 0.0366** |
| GM-x10 | 2.2842 | 1.7627 | 0.0390** |
| GM-x11 | 1.7446 | 1.4705 | 0.0707* |
| GM-Mean | 2.3901 | 1.6834 | 0.0462** |
| GM-Median | 2.3963 | 1.7737 | 0.0381** |
| GM- Trimmed mean | 2.3020 | 1.7341 | 0.0415** |
| GM-DMSPE-1 | 2.4898 | 1.7420 | 0.0408** |
| GM-DMSPE(0.9) | 2.3568 | 1.8121 | 0.0350** |

Note: This table presents out of sample $R^2$ test results for all variables (x1 to x11), and five combination forecast results include GARCH-MIDAS mean, median, trimmed mean combinations and discount mean square prediction error 1 and DMSPE 2. The first column presents the model with the variables GARCH-MIDAS –EPU (x1) and so on; all variable names are given in Table 1. Furthermore, in columns 2–4, we represent R square values and their respective mean square prediction error (MSPE) and $p$ values. The statistical significance of $R^2$oos is based on the $p$-value proposed by Clark and West (2007) MSFE adjusted statistics. The $R^2$oos positive value indicates that the extended model has a lower MSFE than the benchmark model, which shows better accuracy. Furthermore, the significance levels for the rejection of the null hypothesis are presented as 1% ***, 5%** and 10%*, respectively.

$$\O_{i,t-1}^{-1} = \sum_{s=p+1}^{t} \theta^{t-s}\left(r_s - \widehat{r_{k,s}}\right) \tag{9}$$

where $\theta$ is the discount factor and $p$ is the actual sample period. By following Rapach et al. (2010), we use two values of $\theta$, which are 0 and 0.9 in our study. Our results are robust in combination forecasting. All combination models' $R_{oos}^2$ values are positive, higher than zero and significant. These results identify that models with combination forecast outperform then benchmark models. Also, the combining forecast information for all macroeconomic variables and uncertainty index is useful for volatility forecasting. All findings with individual and combination models are presented in Table 4.

## 7. Conclusion

This research examines the forecasting ability of macroeconomic variables and economic policy uncertainty index (EPU) for Pakistan stock market volatility. The macroeconomic variables include exchange rate, long-run interest rate, money supply (M2), short-term interest rate, remittances, consumer prices index (proxy for inflation), foreign direct investment, industrial production, global oil prices, and gold prices. We use the GARCH-MIDAS model for forecasting short-and long-run volatility. In our empirical analysis, we find some notable results. First, we find economic policy uncertainty index information is useful for Pakistan stock market volatility prediction. Second, we find global indicators oil prices are more powerful predictor of Pakistan market volatility. Moreover, all macroeconomic variables are effective indicators of Pakistan stock market volatility except long run interest rate. In addition, the combination information for all macroeconomic variables is also useful for forecasting volatility. These findings are in line with the literature (Asgharian et al., 2013; Liu & Pan, 2020). However, the abovementioned studies are not directly involved in forecasting Pakistan's stock market volatility. In addition, we did not find consistent findings in a longer period, such as two months and three months. Overall, results indicate that macroeconomic variables are significant predictors of stock market volatility in Pakistan. Therefore, the government and policymakers should consider these factors in policymaking and stock market volatility estimation.

## 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.

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