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# Forecasting Market Fear: the roles of policy uncertainty and geopolitical Risk

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**ABSTRACT**

This paper examines the predictive power of Economic Policy Uncertainty (EPU) and Geopolitical Risk (GPR) indices on market fear, as reflected by implied volatility indices across various assets and regions. A GARCH-MIDAS model is employed to analyse how low-frequency economic policy and geopolitical risks affect high-frequency market fear indices, using realized volatility as a benchmark. The study incorporates global, U.S., and Russia-based EPU, alongside multiple GPR variants, to assess their influence on implied volatility across stocks, commodities, and IT equities. Our results show that GARCH-MIDAS models incorporating external uncertainty indices significantly outperform the conventional GARCH-MIDAS model based on realized volatility alone, with particularly strong performance observed for global and U.S. uncertainty measures across multiple forecast horizons. These results highlight the importance of monitoring external uncertainties to support pre-emptive policy measures and to guide investors in integrating such insights into risk assessment models for improved volatility management.

**KEYWORDS**

Economic policy uncertainty (EPU); geopolitical risk (GPR); implied volatility indices; GARCH-MIDAS model; market fear; forecasting

**JEL CLASSIFICATION**

C22; G12; G17; E44; F51

## I. Introduction

Global economic and geopolitical uncertainties have increasingly influenced financial markets. Stocks, commodities, and energy have been dramatically affected, causing regime shifts in their historical movements. The recent COVID-19 global health crisis impacted global financial markets more severely than the 2007–2009 global financial crisis (Olubusoye et al. 2021; Yaya et al. 2021; Ogbonna and Olubusoye 2022; Salisu, Ogbonna, and Oloko 2023; among others). Events causing price shifts include, among others, trade disputes, political instability, health crises, armed conflicts, and abrupt economic changes, all of which can lead to rapid market volatility (Chiang 2021). Implied volatility indices provide valuable insights into market sentiment and risk by measuring expected future market fluctuations. Often referred to as 'fear gauges', these indices reflect market anxiety, particularly as geopolitical and economic developments rapidly reshape the investment environment (T. Li et al. 2020; Yaya et al. 2021). They respond dynamically to perceived risks, making them highly sensitive to geopolitical events and economic changes that may not be immediately apparent in standard market analyses. With financial and commodity markets becoming increasingly interconnected through globalization and technology, understanding how external uncertainties impact these indices is crucial for market participants and policymakers to navigate instability and develop effective risk management strategies (Farag, Jeddi, and Kopp 2025; Ogbonna and Olubusoye 2022).

In recent years, interest in indices that measure Economic Policy Uncertainty (EPU) and Geopolitical Risk (GPR) has grown. These indices assess the shifting landscape of global and domestic risks by tracking changes in the volume of news articles that focus on adverse economic and geopolitical conditions (Caldara and Iacoviello 2022; Cunado et al. 2020; Salisu and Ogbonna 2022; Salisu et al. 2022). Economic policy uncertainty

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indices, for instance, monitor government policies that could affect economic growth, while geopolitical risk indices gauge the potential for conflict, warfare, and terrorism. Despite their predictive potential, limited research has examined on how accurately these uncertainty indices can forecast market-implied volatility across different asset classes and regions. Incorporating them into predictive models for various financial instruments remains an area with significant potential for further exploration.

The main objective of this study is to assess the predictive power of EPU and GPR indices on market fear, as measured by implied volatility indices for various assets and regions. Using a GARCH-MIDAS framework, the study aims to examine the impact of low-frequency economic policy and geopolitical risk measures on high-frequency implied volatility indices. This approach bridges the gap between low-frequency external uncertainties and high-frequency market responses, allowing us to capture the influence of long-term trends in economic policy and geopolitical conditions on daily implied volatility. The GARCH-MIDAS model offers a comprehensive framework that distinguishes between short- and long-term effects, providing a detailed understanding of how shifts in external uncertainty translate into changes in market sentiment. Ultimately, this research seeks to identify and quantify the mechanisms through which external economic and geopolitical conditions influence market behaviour, informing both investors and policymakers.

To address this objective, we ask: 'How do economic policy uncertainty and geopolitical risk indices affect the implied volatility of different market fear indices?' Specifically, we aim to discern the extent to which these uncertainty indices can explain variations in implied volatility indices representing different asset classes – including equities, commodities, and financial services – across various geographic regions. Additionally, this study investigates whether the predictive power of these indices varies across asset classes and regions by analysing how each fear index responds to shifts in global, U.S., and Russia-based policy uncertainty and geopolitical risk. Understanding these variations is crucial, as each asset class and region may exhibit distinct sensitivities to global and domestic events due to differing economic structures and market compositions.

Furthermore, this study seeks to uncover whether incorporating EPU and GPR indices into a predictive model can enhance the forecast accuracy of implied volatility changes. To this end, it examines the performance of the GARCH-MIDAS-X model compared to the traditional GARCH-MIDAS-RV model to determine the forecasting benefits of including EPU and GPR indices. The GARCH-MIDAS-X model incorporates low-frequency external variables, such as economic policy uncertainty and geopolitical risks, directly into the modelling process, offering a deeper understanding of how these external factors influence market behaviour. This approach differs from the traditional GARCH-MIDAS-RV model, which focuses solely on realized volatility without accounting for external uncertainties. By comparing the two models, the study aims to assess whether including economic and geopolitical factors improves the ability to predict changes in market fear indices. This comparison helps uncover the strengths and weaknesses of each approach and clarifies how incorporating uncertainty measures can lead to more accurate forecasts of market volatility. The results will provide investors and policymakers with insights into the utility of these indices and guide the development of more effective strategies to understand, anticipate, and manage market risks across different time frames.

This research contributes to existing literature by incorporating a comprehensive set of implied volatility indices with global uncertainty measures in a GARCH-MIDAS framework. By exploring the influence of these measures on a wide range of implied volatility indices, this study provides insights that are crucial for both risk management and policy formulation. The findings of this study have practical implications for developing strategies to hedge against market volatility driven by economic and geopolitical events.

The paper is structured as follows: Section II reviews literature on economic policy uncertainty, geopolitical risk, and their effects on market volatility. Section III outlines the data and methodology, detailing implied volatility indices, EPU, and GPR within the GARCH-MIDAS-X framework. Section IV presents empirical results, comparing the predictive performance of GARCH-MIDAS-X with the traditional GARCH-MIDAS-RV model. Section V concludes.

## II. Review of literature

Threats from terrorism, tensions between states, and wars are all considered geopolitical risks (GPR) (Caldara and Iacoviello 2022). Such extreme risks shape market dynamics by altering future expectations (Liu et al. 2019). Researchers have explored the relationship between GPR, economic uncertainty, and various financial instruments – bonds, stocks, currencies, the US dollar, bank credit, and cryptocurrencies like Bitcoin (Al Mamun et al. 2020; Bouri, Hussain Shahzad, and Roubaud 2020; Ogbonna and Olubusoye 2022; Olubusoye et al. 2021; Salisu, Ogbonna, and Oloko 2023, 2024). GPR's impact on commodities markets has also been examined (Baur and Smales 2020; Chiang 2022; Demir and Danisman 2021; J. Huang et al. 2021; Salisu et al. 2022). Recent studies apply time-series methods to assess GPR indices' effects on returns and volatility across conventional stock markets, global Islamic equity and bond markets, and major defence companies' stocks (Caldara and Iacoviello 2022; Salisu et al. 2022).

Demir and Danisman (2021) found economic uncertainty significantly reduces bank lending, especially business loans. Bilgin et al. (2020) show World Uncertainty Index (WUI) negatively affects conventional bank loan growth, but not Islamic banks. Bouri, Hussain Shahzad, and Roubaud (2020) and Hu and Gong (2019), using Economic Policy Uncertainty (EPU), also report a negative impact on bank lending.. While GPR and EPU effects on individual and Islamic bank credit have been studied (Hu and Gong 2019; Bouri, Hussain Shahzad, and Roubaud 2020; Demir and Danisman 2021), their broader impact across different asset classes remains underexplored. Asset responses to GPR may vary and merit further investigation.

### *Economic uncertainty and stocks*

The Economic Policy Uncertainty (EPU) index developed by S. Baker et al. (2016) has garnered significant scholarly interest. Numerous studies assess how fluctuations in economic policy uncertainty affect stock returns, reaching varied conclusions on the relationship's significance and effectiveness.

Various analytical methods have been used to examine the link between EPU and financial fundamentals.. Caggiano, Castelnuovo, and Figueres (2017) and Bekiros, Gupta, and Kyei (2016) explore the effect of US EPU on its unemployment and stock market. S. Baker et al. (2016) also develop a Trade Policy Uncertainty (TPU) index, focusing on its relation to China's macroeconomic conditions. In contrast, Y. Huang and Luk (2020) construct an EPU index using Chinese local newspapers, excluding those directly controlled by the CPC Central Committee.

Growing literature explores EPU's impact in specific national contexts. Kang, Lee, and Ratti (2014) and Gulen and Ion (2016) find a strong negative correlation between firm-level investment decisions and rising uncertainty. Another research strand investigates EPU's predictive capacity: Karnizova and Li (2014) show that a newspaper-based EPU index can predict future US recessions, while Liu et al. (2019) demonstrate its ability to forecast stock market volatility.

Bekiros, Gupta, and Kyei (2016) and Liu et al. (2019) both highlight the EPU index's predictive power for stock market volatility. However, Bekiros, Gupta, and Kyei (2016) find no predictability in terms of stock returns, indicating causal predictability exists only for volatility.

### *Geopolitical risk and stocks*

Another group of studies has examined how geopolitical events, including terror attacks, affect the ability to forecast changes in volatility and returns in the financial markets (Salisu et al. 2022). Numerous geopolitical risk measures have been used in studies. The ground-breaking study was carried out by Bouras et al. (2019) using a panel-GARCH technique to investigate the effects of global and country-specific Geopolitical Risk (GPR) on the volatility and returns of 18 developing stock markets.

Bouri, Hammoud, and Kassm (2023) investigate the impact of oil volatility and geopolitical risk on GCC stock sectors from February 2010 to June 2022. They find that oil volatility impacts returns and volatility more than geopolitical risk, especially in Consumer Discretionary and Staples sectors. Both factors positively affect returns and volatility during bull markets, with a stronger impact on volatility. Additionally, oil volatility's impact on sector volatility increased slightly during the COVID-19 outbreak and is more significant in bull markets. These insights are crucial for understanding how oil volatility and geopolitical risk influence different sectors, particularly under varying market conditions.

Ichev and Marinč (2018) demonstrate that stock markets react rapidly to outbreaks of serious diseases such as Ebola, SARS, and MERS, underscoring the sensitivity of financial markets to health crises. This finding is echoed by Engelhardt et al. (2020), who note that stock markets are significantly affected by the COVID-19 pandemic, reinforcing the vulnerability of these markets to pandemics. This highlights the changes in investor behaviour under high uncertainty, emphasizing the need for strategic investment decisions during such periods.

## Geopolitical risk with oil and other commodities

Chiang (2022) shows that gold prices are sensitive to economic uncertainty, especially during inflation, downturns, currency depreciation, and crises. Studies by Beckmann, Czudaj, and Pilbeam (2015) and Batten, Ciner, and Lucey (2014) find that gold typically rises with inflation, making it a valuable hedge. Gold is also favoured in economic downturns. Chiang (2022), Jones and Sackley (2016), Li and Lucey (2017), and Raza et al. (2018) report a positive correlation between economic policy uncertainty (EPU) and gold prices. Baur and Smales (2020), Chiang (2021), and Li and Lucey (2017) identify gold as a hedge against geopolitical risk (GPR). S. R. Baker et al. (2020) attribute a COVID-19-related gold price surge to investor flight to safety. Chkili (2017) also highlights gold as a safe haven and buffer during volatility in Islamic stock markets.

Due to low price elasticity and strategic importance, oil is highly sensitive to GPR. Major geopolitical events—e.g. the Gulf War (1990), 9/11 (2001), Iraq War (2003), London bombings (2005), and Arab Spring (2011) – have caused sharp oil price swings. GPR includes risks from wars, terrorism, conflicts, and international tensions (Caldara and Iacoviello, 2022). Crude oil is essential to national economies and linked to security (Mo et al. 2019). Monge, Gil-Alana, and Pérez de Gracia (2017) analysed oil price changes across six post-WWII geopolitical events. Zhang et al. (2009) used dummy variables to assess crude oil volatility during the Iraq (2003) and Persian Gulf (1991) wars. Toft, Duero, and Bieliauskas (2010) emphasize terrorism's threat to energy security. Cunado et al. (2020) find GPR has negative, time-varying effects on oil returns due to reduced global demand. Sharif, Aloui, and Yarovaya (2020) note temporal and horizon-based differences in GPR – oil shock correlations.

Omar, Wisniewski, and Nolte (2017), using event study methods, found global crises positively impacted oil market returns, suggesting oil as a potential safe haven during global tensions. Similarly, Ramiah et al. (2018) show that terror acts raise uncertainty in both stock and commodity markets. The GPR index aids forecasting oil futures volatility, as shown by Bouoiyour et al. (2019), Demirer et al. (2018), Liu et al. (2019), and Mei et al. (2020). Mei et al. (2020) find a strong link between short-term oil volatility and GPR, making it a useful forecasting tool. GPR influences oil prices via supply, demand, economic activity, investor sentiment, market movements, and asset correlations. Ulussever et al. (2023) used machine learning and econometrics to study global factors affecting food prices, finding that Multi-layer Perceptron outperforms traditional models. Kılıç Depren et al. (2022) support this and note that COVID-19 adversely impacted model accuracy.

## Geopolitical risks, economic policy uncertainty, and environmental outcomes

The interplay between geopolitical risks, economic policy uncertainty (EPU), and environmental outcomes is complex. Jiatong et al. (2023) and (Jiatong et al. 2023b) find that renewable energy consumption (REC) reduces carbon emissions, while EPU, geopolitical risk, and economic growth contribute to increasing emissions. This indicates that while renewable energy can mitigate environmental damage, uncertainties in economic policies and geopolitical stability can exacerbate carbon emissions. Z. Wang and Sibt-E-Ali further reveal that geopolitical risk negatively affects investment in renewable energy infrastructure, highlighting the challenges in fostering sustainable energy development amidst geopolitical tensions. H. Li et al. (2023) reinforce these findings, showing that while geopolitical risk and renewable energy sources help lessen the ecological footprint, EPU and the use of non-renewable energy increase it.

The relationship between geopolitical risk, economic uncertainty, and various financial instruments such as bonds, stocks, currencies, bank credit, and cryptocurrencies has been studied extensively (Al Mamun et al. 2020; Bouri, Hussain Shahzad, and Roubaud 2020; Ogbonna and Olubusoye 2022; Olubusoye et al. 2021; Salisu et al. 2024; Salisu, Ogbonna, and Oloko 2023). Similarly, the impact of Renewable Energy Investments (Z. Wang and Sibt-E-Ali 2024) and Environmental Outcomes (Jiatong et al. 2023; 2023, Hua Li et al. 2024) has been investigated. However, there is a gap in understanding how these indices predict implied volatility across different asset classes and regions using advanced models like GARCH-MIDAS.

This study addresses this gap by examining the predictive power of Economic Policy Uncertainty (EPU) and Geopolitical Risk (GPR) indices on market-implied volatility across various asset classes and regions. Limited research has explored the accuracy of these indices in forecasting implied volatility. Utilizing a GARCH-MIDAS framework, this study captures the impact of low-frequency economic and geopolitical uncertainties on high-frequency market dynamics, bridging the gap between long-term trends and daily market responses. It investigates the extent to which EPU and GPR indices explain variations in implied volatility for equities, commodities, and financial services across different regions. Additionally, the study compares the forecasting performance of the GARCH-MIDAS-X model, which incorporates these indices, with the traditional GARCH-MIDAS-RV model.

## III. Methods

Datasets analysed are implied volatility of stocks, commodities and other assets, computed by the Chicago Board Options Exchange (CBOE).[1] These are obtained from the online economic database of St Louis Federal Reserve Bank at https://fred.stlouisfed.org. The included variables are based on data availability and are grouped and described in Table 1. Also, EPUs and GPRs datasets are obtained from the EPU website at https://www.policyuncertainty.com/. We have included, in addition to the Global EPU, the US and Russia EPU due to the ongoing Russia–Ukraine war. We have also considered both the geopolitical risk (GPRT) and geopolitical threat (GPRA) in addition to the overall geopolitical risk (GPR) index (see Caldara and Iacoviello, 2022).

The implied volatility indices are of daily frequency, with different starts dates, with the earliest starting from 2 January 1997 to 29 February 2024, while the GPR and the EPU indices are only available in monthly frequency. The inclusion of GARCH structure in the model allows transforming the daily frequency into a stable/stationary equivalence often referred to as the price difference or log-returns. For example, in the case of VIX, its log-returns are obtained as,

$$\Delta VIX_t = \log\left(\frac{VIX_t}{VIX_{t-1}}\right) \tag{1}$$

where $\Delta VIX_t$ is the log daily change in implied volatility, $VIX_t$ is the current day implied volatility, and $VIX_{t-1}$ is the previous day's index value of the implied volatility. The variable description is presented in Table 1. Table 2 presents summary statistics and preliminary analyses for various market-implied volatility measures and different external uncertainty indicators (both global and its variants for the US and Russia). Daily changes in market-implied volatility are predominantly negative, with the exception of OVX, which exhibits positive changes on average. Among these measures, OVX and VXEEM demonstrate the highest and lowest variability, respectively. Most of the changes in market-implied volatility display positive skewness and

[1]Implied volatility (otherwise referred to as market fear index) is computed on current market prices of tradable financial assets or options with the pre-knowledge that the asset has all available information, that is, market efficiency. Implied volatility reflects market sentiment and expectations of market participants (see Pathak and Deb 2020).

**Table 1.** Variable definitions.

| Group | Variable | Acronym | Definition |
|---|---|---|---|
| **Fear Indices** | | | |
| Global | Global | VIX | This CBOE fear gauge index is obtained from Standards & Poors 500 stock index. It tracks the overall stock market performance in the United States and has been know widely accepted as the global market fear gauge index. |
| US Stocks | DJIA | VXD | It renders the expected 30-day volatility of DJIA stock index returns. |
| | Nasdaq-100 | VXN | It renders the expected 30-day volatility of NASDAQ-100 stock index returns. |
| | Russell 2000 | RVX | It renders market expectations of near-term small cap equity market volatility of Russell 2000 stock index option prices |
| Emerging markets | Emerging markets | VXEEM | It gives the expected 30-day volatility of MSCI Emerging Market index returns. |
| Commodities | Oil | OVX | It gives as estimate of the expected 30-day volatility of crude oil as priced by the United States Oil Fund (USO) |
| | Gold | GVZ | It renders an estimate of the expected 30-day volatility of returns on the SPDR Gold Shares ETF (GLD) |
| IT stocks | Apple Equity | VXAPL | It gives the estimate of the expected 30-day volatility of Apple stock. Apple is one of five highly active equity in US stocks which is a technology equity. |
| | Amazon Equity | VXAZN | It estimates the expected 30-day volatility of Amazon stock returns. Amazon is one of five highly active equity in US stocks which is a technology equity. |
| | Google Equity | VXGOG | It estimates the expected 30-day volatility of Google stock returns. Goggle is one of five highly active equity in US stocks which is a technology equity. |
| Financial services | Goldman Sachs | VXGS | It measures the expected volatility of the respective individual equities on Goldman Sachs stock market. It is one of five highly active equity in US stocks. |
| **Economic policy uncertainty and Geopolitical risk** | | | |
| Economic policy uncertainties | Global EPU | GEPU | This index is a GDP-weighted average of EPUs of the 21 countries listed: Australia, Brazil, Canada, Chile, China, Colombia, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, the Netherlands, Russia, South Korea, Spain, Sweden, the United Kingdom, and the United States. |
| | USA EPU | USEPU | This is the United States EPU index. The computation of most country EPU relies on the approach used in obtaining US EPU. |
| | Russia EPU | REPU | Economic policy uncertainty for Russia is majorly based on a Russian daily newspaper for economic and political news. |
| Geopolitical risks | Geo-Political Risk | GPR | The index is calculated by counting the number of articles that relate to adverse geopolitical events in each newspaper for each month based on keywords below for both GPRT and GPRA. |
| | Geo-Political Risk Threat | GPRT | This index includes words relating to War Threats, Peace Threats, Military Buildups, Nuclear Threats and Terror Threats. |
| | Geo-Political Acts | GPRA | The Geopolitical Acts (GPRA) index includes relating to: Beginning of War, Escalation of War, and Terror Acts. |

leptokurtosis, contributing to the non-normality of the series, as evidenced by statistically significant Jarque-Bera Statistics. Due to differing start and end dates, the number of observations varies across the daily series. Monthly uncertainty measures, including GEPU, GPR, GPRA, GPRT, RUSEPU, and USEPU, also exhibit positive skewness, leptokurtosis, and non-normal distributions. All series, including market-implied volatility changes and uncertainty measures, display evidence of conditional heteroscedasticity and autocorrelation. The presence of conditional heteroscedasticity suggests the suitability of a GARCH-type model, while the mixed data frequency nature of the employed data calls for the adoption of a MIDAS framework. Thus, the GARCH-MIDAS model framework is deemed appropriate.

Ghysels et al. (2019) integrated the GARCH process of Bollerslev (1986) into the Mixed Data Sampling (MIDAS) regression of Engle, Ghysels, and Sohn (2013) in order to determine the long-term effects of low-frequency explanatory variables, such as economic indicators, on high-frequency market volatilities. Thus, the resulting GARCH-MIDAS-X[2] model, with exogenous variable X allows one to determine the impact of the exogenous variable on the conditional volatility series of the high-frequency dataset.

The GARCH-MIDAS-RV model takes into account a return series $r_{i,t}$ of an implied volatility (market fear) on day $i$ at time , which follows the process

$$r_{i,t} = \mu + \sqrt{\tau_t h_{i,t}}\varepsilon_{i,t};\ \forall i = 1,\ldots,N_t;\ \ \varepsilon_{i,t}|_{i-1,t(0,1)} \tag{2}$$

where $N_t$ denotes the number of days in the time t; $_{i-1,t}$ denotes the available information set up to day $(i-1)$ of time $t$. From (2), $h_{i,t}$ and $\tau_t$, respectively, define the variance into a short-run component, as these change at every time $t$. The conditional variance is given as,

[2]Several empirical studies exist in the literature on the application of the GACH-MIDAS framework to assess the nexus of different market volatilities and uncertainty measures as predictors (see Ayinde et al. 2023; Yaya et al., 2022a; 2022b among others).

**Table 2.** Summary analysis and preliminary analyses.

| | Mean | Coefficient of Variation | Skewness | Kurtosis | Jarque-Bera | Nobs | *ARCH*(5) | *ARCH*(10) | *Q*(5) | *Q*(10) | $Q^2(5)$ | $Q^2(10)$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Daily Frequency** | | | | | | | | | | | | |
| GVZ | −1.56E–02 | 3.45E + 04 | 0.92 | 10.48 | 9.50E + 03*** | 3838 | 75.36*** | 38.03*** | 38.095*** | 52.407*** | 488.43*** | 512.46*** |
| OVX | 1.44E–04 | 3.93E + 06 | 1.62 | 28.96 | 1.17E + 05*** | 4096 | 40.68*** | 53.57*** | 23.105*** | 29.687*** | 249.6*** | 595.8*** |
| RVX | −1.28E–03 | 4.51E + 05 | 0.81 | 7.90 | 5.43E + 03*** | 4905 | 108.81*** | 57.69*** | 24.464*** | 43.851*** | 772.12*** | 936.81*** |
| VIX | −7.03E–03 | 9.85E + 04 | 0.94 | 9.06 | 1.12E + 04*** | 6659 | 57.74*** | 32.46*** | 54.228*** | 89.544*** | 393.07*** | 495.01*** |
| VXAPL | −1.89E–02 | 3.65E + 04 | −0.34 | 8.46 | 4.22E + 03*** | 3353 | 9.85*** | 7.55*** | 22.594*** | 38.255*** | 60.368*** | 105.05*** |
| VXAZN | −8.74E–03 | 8.39E + 04 | −2.49 | 31.86 | 1.20E + 05*** | 3353 | 3.51*** | 1.96** | 0.814 | 5.5901 | 18.114*** | 20.403** |
| VXD | −8.34E–03 | 9.04E + 04 | 0.59 | 92.96 | 2.18E + 06*** | 6467 | 486.96*** | 244.56*** | 50.593*** | 88.97*** | 1459*** | 1477.4*** |
| VXEEM | −2.78E–02 | 2.77E + 04 | 0.15 | 30.38 | 9.87E + 04*** | 3160 | 186.82*** | 93.44*** | 27.708*** | 37.93*** | 610.54*** | 614.19*** |
| VXGOG | −4.99E–03 | 1.53E + 05 | −1.15 | 12.24 | 1.27E + 04*** | 3353 | 6.25*** | 3.14*** | 10.053* | 12.424 | 33.764*** | 34.33*** |
| VXGS | −1.88E–02 | 3.37E + 04 | 0.63 | 7.37 | 2.89E + 03*** | 3353 | 93.26*** | 50.15*** | 9.768* | 17.061* | 731.86*** | 967.34*** |
| VXN | −2.06E–02 | 2.93E + 04 | 0.74 | 8.43 | 7.43E + 03*** | 5631 | 83.76*** | 44.76*** | 39.722*** | 66.457*** | 582.3*** | 704.09*** |
| **Monthly Frequency** | | | | | | | | | | | | |
| GEPU | 1.41E + 02 | 5.33E + 01 | 1.116 | 3.637 | 7.32E + 01*** | 326 | 5.09*** | 3.58*** | 26.452*** | 33.386*** | 33.854*** | 49.328*** |
| GPR | 1.01E + 02 | 5.04E + 01 | 4.192 | 29.270 | 1.03E + 04*** | 326 | 0.5 | 0.25 | 11.495** | 13.704 | 2.7374 | 2.8292 |
| GPRA | 1.03E + 02 | 7.98E + 01 | 5.536 | 46.120 | 2.69E + 04*** | 326 | 0.31 | 0.15 | 17.039*** | 18.214* | 1.7 | 1.7523 |
| GPRT | 1.02E + 02 | 4.37E + 01 | 2.851 | 15.706 | 2.63E + 03*** | 326 | 8.80*** | 4.34*** | 3.0116 | 6.6738 | 47.737*** | 48.371*** |
| RUSEPU | 1.78E + 02 | 8.81E + 01 | 1.838 | 6.809 | 3.81E + 02*** | 326 | 12.57*** | 6.14*** | 58.682*** | 75.348*** | 71.844*** | 77.986*** |
| USEPU | 1.34E + 02 | 4.75E + 01 | 1.932 | 9.216 | 7.27E + 02*** | 326 | 9.83*** | 5.25*** | 21.055*** | 30.509*** | 71.39*** | 74.052*** |

The figures in the table are the summary statistics (mean, coefficient of variation, skewness, kurtosis, Jarque–Bera test for normality and number of observations) and some preliminary formal tests for presence of conditional heteroscedasticity (ARCH) and autocorrelation (Ljung-Box) at specified lags. We report the F-statistics for the ARCH test and Ljung – Box Q-statistics for the autocorrelation test, with significance levels at 1%, 5%, and 10% levels, denoted respectively as ***, **, and *.

$$\sigma_{i,t} = \tau_t h_{i,t} \tag{3}$$

where $h_{i,t}$, the conditional variance dynamics of the short-run component, has a GARCH (1,1) process,

$$h_{i,t} = (1 - a - b) + a\frac{\left(r_{i-1,t} - \mu_i\right)^2}{\tau_t} + bh_{i-1,t} \tag{4}$$

where $a > 0$ and $b > 0$, $a + b < 1$ to ascertain the covariance stationary conditional variance series realizations, and $\tau_t$ is the smoothed realized volatility in the MIDAS regression given as,

$$log(\tau_t) = \delta + \theta\sum_{l=1}^{L}\varphi_l(w_1, w_2)RV_{t-l} \tag{5}$$

where $w_1$ and $w_2$ denotes the weights, and by restricting $w_1 = 1$, one is left with $w_2$ of which its size dictates the speed of decay of the weighing scheme function $\varphi_l(w_1, w_2)$ as in Conrad, Loch, and Ritter (2014); To approximate the monthly realized volatility, $RV_t = \sqrt{\sum_{i=1}^{N_t} r_{i,t}^2}$ and $N = 22$, and $L$ denotes the lag number at which a smoothed realized volatility $(RV)$ is achieved.

The long-run constant term in the model is denoted by the parameter $\delta$, and the slope coefficient, θ, indicates how the response variable is affected by the sum of the weighted effects of realized volatilities when there are no explanatory variables (Yaya et al. 2022). To put it briefly, this parameter θ quantifies how predictable the low-frequency exogenous variables are able to drive the daily implied volatility returns (see Asgharian, Hou, and Javed 2013), that is it determines its impact on its conditional variance series. By including the exogenous variables (EPU or GPR), we investigate the impact of the economic variables on the long-run conditional variance series of market fear indices. Thus, we modify (4) as,

$$log(\tau_t) = \delta + \theta\sum_{l=1}^{L}\varphi_l(w_1, w_2)X_{t-l}^{Q} \tag{6}$$

where $X_{t-l}^{Q}$ denotes the monthly EPU or GPR index, and the weighting scheme in (5) and (6) is given by a Beta lag polynomial,

$$\varphi_l(w_1, w_2) = \frac{\left(\frac{l}{L}\right)^{w_1-1}\left(1 - \frac{l}{L}\right)^{w_2-1}}{\sum_{j=1}^{l}\left(\frac{j}{L}\right)^{w_1-1}\left(1 - \frac{j}{L}\right)^{w_2-1}}, l = 1, \ldots, L \tag{7}$$

The restricted form of the beta weighing scheme's parameter space is therefore $\Phi = \{\mu, \alpha, \beta, \theta, w_1, w_2, \delta\}$, where the market fear return's fixed $RV$

has been filtered by the GARCH-MIDAS model with $RV$, which estimates the long-run variance and the effect of the RV effect driven by $\theta$. In the meantime, the parameter space is still given as above since $RV$ is now replaced by EPU or GPR, resulting to GARCH-MIDAS-X model, where $X$ is the exogenous economic variable.

As applied in Salisu et al. (2022), we evaluate the forecasts of the GARCH-MIDAS predictive model, i.e. GARCH-MIDAS-X, with those of the traditional GARCH-MIDAS specifications that incorporate the realized volatility (GARCH-MIDAS-RV model), in order to assess the out-of-sample forecast performance. In a rolling window setup, the out-of-sample forecast performance is assessed for four forecast horizons, say when $h = 10, 30, 60, 180$, which correspond to short- and long-run predictability. Since there is no nesting of the competing models, this study utilizes the modified Diebold and Mariano (1995) (DM) test according to Harvey, Leybourne, and Newbold (1997), which computes the $p$-value and deals with the problem under the assumption of zero covariance at 'unobserved' lags to formally determine whether the forecast errors related to the competing models differ significantly. The DM is defined as:

$$DM = \frac{D}{\sqrt{\frac{V(d_t)}{T}}}(0,1) \quad (8)$$

where $D = \frac{1}{T}\sum_{t=1}^{T} d_t$ denotes the average loss differential $d_t \equiv l(\varepsilon_{xt}) - l(\varepsilon_{rvt})$; $l(\varepsilon_{xt})$ and $l(\varepsilon_{rvt})$, respectively, represent the forecast errors loss functions of the GARCH-MIDAS-X and GARCH-MIDAS-RV models; and $V(d_t)$ is the unconditional variance of the loss differential $d_t$.

The modified DM test statistic as per Harvey, Leybourne, and Newbold (1997) is defined as:

$$DM^* = \left(\sqrt{\frac{T + 1 - 2h + T^{-1}h(h-1)}{T}}\right) DM \quad (9)$$

where DM* denotes the modified DM statistic. The null hypothesis, $H_0$: $E(d_t) = 0$, of equal accuracy of the two forecast series is tested against the alternative, $H_a$: $E(d_t) \neq 0$, that the proposed model, GARCH-MIDAS-X model has a better forecast than GARCH-MIDAS-RV model (benchmark model). A statistically significant negative statistic suggests the adoption of the GARCH-MIDAS-X model, whereas a positive and significant test statistic leads to the selection of the GARCH-MIDAS-RV model, according to Harvey, Leybourne, and Newbold (1997) modified DM test. However, in the event that the test statistic is not significant – that is, if the null hypothesis is not rejected – it is presumed that the forecasting abilities of the two models are similar.

## IV. Empirical results

This section presents the main and extended results of our investigation into the predictability of market fears by external uncertainty. In Section 4.1, we report the primary findings using paired GARCH-MIDAS models: we first assess in-sample predictability by examining the MIDAS slope coefficients for market fears and then evaluate out-of-sample forecast accuracy via the modified Diebold and Mariano test across various forecast horizons. In Section 4.2, we extend the analysis by incorporating alternative uncertainty proxies – such as Twitter-based economic policy uncertainty – and by applying the framework to country-level and sectoral indices.

### *Main estimation results*

This study presents the main results of the in-sample predictability of external uncertainty for market fears and evaluate the out-of-sample forecast accuracy of paired GARCH-MIDAS models. The conventional GARCH-MIDAS-RV model serves as our benchmark for comparison with GARCH-MIDAS models incorporating single, each of the six different external uncertainty measures (both global and from the US and Russia).

The study begins by presenting the in-sample predictability indicator, focusing on the GARCH-MIDAS slope coefficient for each market fear (see results in Table 3). This study also investigates whether the predictability extends beyond the in-sample period by assessing the out-of-sample forecast performance using the modified Diebold and Mariano test (Harvey, Leybourne, and Newbold 1997), as detailed in Table 3. This study considers forecast horizons of 20, 60, and 120 days ahead to determine if including each external uncertainty index as a predictor enhances the forecast accuracy of the market fears model.

Table 3 displays the in-sample predictability results for market fears across the eleven indexes. It includes the MIDAS slope coefficient associated with realized volatility and each of the six incorporated exogenous factors (GEPU, GPR, GPRA, GPRT, RUSEPU, and USEPU). These estimated coefficients indicate the predictability of market fears due to RV (column 2) and each external uncertainty index (columns 3–8). We observe that markets generally respond positively to their own uncertainty, indicating that increased market uncertainty heightens market fears.

While the significance level of the MIDAS slope coefficient indicates the predictive potential of uncertainty indexes for market fears, the coefficient's sign reveals the direction of their impact. Across the majority of cases, uncertainty indexes exhibit a negative relationship with market fears, and consistently so, across all six indexes. This suggests that market fears decrease when external uncertainties increase. Notably, when heightened uncertainty originates from sources outside the market, implied volatility changes associated with the markets tend to decrease, indicating each market's resilience to external uncertainty. Furthermore, the assessment of our predictive models' out-of-sample performances is conducted to establish that the observed predictability exceeds the in-sample period.

After establishing the predictability of external uncertainty for market fears, we proceed to evaluate the contending GARCH-MIDAS models through out-of-sample forecast assessment using the modified Diebold and Mariano test. This study examines whether GARCH-MIDAS variants incorporating each uncertainty index outperform the RV version (refer to Table 4 for the results). A significantly negative DM* statistic indicates that the precision of GARCH-MIDAS models incorporating each uncertainty index (including global variants and those based on the US and Russia) surpasses that of the GARCH-MIDAS-RV model. Conversely, a significantly positive DM* suggests a preference for the benchmark GARCH-MIDAS-RV model, while non-significance indicates no marked difference in precision between compared GARCH-MIDAS models. The majority of outperformance is observed in favour of GARCH-MIDAS-uncertainty, irrespective of the external uncertainty index variant. There is a higher occurrence of significantly negative DM* statistics across

**Table 3.** In-sample predictability.

| | Realized Volatility | Global Economic Policy Uncertainty | Geo-Political Risk | Geo-Political Risk (Attack) | Geo-Political Risk (Threat) | Russia Economic Policy Uncertainty | US Economic Policy Uncertainty |
|---|---|---|---|---|---|---|---|
| GVZ | −0.014 | −0.163*** | −0.170*** | −0.170*** | −0.172*** | −0.172*** | −0.160*** |
| | [0.012] | [0.023] | [0.025] | [0.025] | [0.025] | [0.023] | [0.023] |
| OVX | 0.02*** | −0.07*** | −0.070*** | −0.070*** | −0.070*** | −0.070*** | −0.07*** |
| | [0.001] | [0.006] | [0.007] | [0.007] | [0.007] | [0.006] | [0.006] |
| RVX | 0.005 | −0.104*** | −0.112*** | −0.069*** | −0.110*** | −0.087*** | −0.116*** |
| | [0.004] | [0.012] | [0.012] | [0.013] | [0.012] | [0.011] | [0.013] |
| VIX | 0.036*** | −0.109*** | −0.107*** | −0.107*** | −0.107*** | −0.143*** | −0.118*** |
| | [0.002] | [0.011] | [0.011] | [0.011] | [0.011] | [0.016] | [0.011] |
| VXAPL | −0.011 | −0.076*** | −0.075*** | −0.080*** | −0.072*** | −0.145*** | −0.144*** |
| | [0.007] | [0.011] | [0.011] | [0.011] | [0.011] | [0.013] | [0.013] |
| VXAZN | 0.03*** | −0.09*** | −0.100*** | −0.050*** | −0.095*** | −0.086*** | −0.094*** |
| | [0.001] | [0.003] | [0.004] | [0.003] | [0.004] | [0.003] | [0.004] |
| VXD | 0.026*** | −0.031*** | 0.007*** | −0.028*** | −0.026*** | −0.039*** | −0.045*** |
| | [0.002] | [0.003] | [0.001] | [0.003] | [0.003] | [0.004] | [0.004] |
| VXEEM | 0.018*** | −0.012*** | −0.012*** | −0.012*** | −0.012*** | −0.012*** | −0.012*** |
| | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] | [0.001] |
| VXGOG | 0.011*** | −0.142*** | −0.140*** | −0.081*** | −0.139*** | −0.145*** | −0.143*** |
| | [0.003] | [0.007] | [0.007] | [0.006] | [0.007] | [0.007] | [0.007] |
| VXGS | 0.021*** | −0.103*** | −0.084*** | −0.083*** | −0.084*** | 0.008*** | 0.008*** |
| | [0.003] | [0.015] | [0.015] | [0.015] | [0.015] | [0.001] | [0.001] |
| VXN | 0.027*** | −0.156*** | −0.150*** | −0.149*** | −0.153*** | −0.144*** | −0.150*** |
| | [0.002] | [0.016] | [0.016] | [0.016] | [0.016] | [0.016] | [0.016] |

The figures in each cell on the table are the estimated slope coefficient with their corresponding standard errors in square brackets and the significance levels at 1%, 5%, and 10% denoted by ***, ** and *, respectively.

models with external uncertainty indexes compared to significantly positive DM* statistics. These results hold across various external uncertainty proxies, underscoring the statistical relevance of incorporated uncertainty indexes. In essence, external uncertainty (including GEPU, GPR, GPRA, GPRT, RUSEPU, and USEPU) is confirmed as a good predictor of market fears across the 11 markets analysed.

## Additional results

Here, we consider variants of another important proxy for economic policy uncertainty – the Twitter-based economic policy uncertainty (TEU). This is informed by the perception that it could provide useful insights beyond those offered by traditional variants. Additionally, we extend the analysis to consider country-level (Canada, France, Germany, Italy, Japan, the UK, and the US) and sectoral indices (Energy, Financials, Industrials, Consumer Discretionary, Semiconductors, Oil & Gas, Metals & Mining, Transportation, Healthcare Equipment, and Home Builders) to establish robustness.

To harmonize the bases of comparison for the competing models during the in-sample and out-of-sample periods, we constrain the data for the extended analysis to the period for which the Twitter-based EPU variants are available (1 June 2011 to 28 April 2023). As in the main estimation, we assess in-sample predictability and out-of-sample forecast performance at 20-, 60-, and 120-day ahead forecast horizons using the modified Diebold-Mariano statistic.

Across the market fear indices, country-level, and sectoral indices, the forecast precision of the exogenous-variable-based GARCH-MIDAS models (using traditional and Twitter-based EPU metrics and GPR variants) is compared with that of the conventional GARCH-MIDAS-RV

**Table 4.** Modified Diebold and Mariano Test Result.

| Variables | Horizons | Global Economic Policy Uncertainty | Geo-Political Risk | Geo-Political Risk (Attack) | Geo-Political Risk (Threat) | Russia Economic Policy Uncertainty | US Economic Policy Uncertainty |
|---|---|---|---|---|---|---|---|
| GVZ | $h = 20$ | −7.676*** | −10.336*** | 0.850 | −9.643*** | −11.977*** | −11.634*** |
| | $h = 60$ | −7.051*** | −9.640*** | 0.773 | −8.964*** | −11.249*** | −10.906*** |
| | $h = 120$ | −6.751*** | −9.408*** | 1.627 | −8.711*** | −11.023*** | −10.638*** |
| OVX | $h = 20$ | −8.898*** | −9.267*** | −13.359*** | −8.625*** | −9.983*** | −14.170*** |
| | $h = 60$ | −8.766*** | −9.140*** | −13.231*** | −8.498*** | −9.852*** | −14.039*** |
| | $h = 120$ | −8.592*** | −8.978*** | −13.030*** | −8.339*** | −9.666*** | −13.810*** |
| RVX | $h = 20$ | −3.656*** | 3.878*** | 3.808*** | 3.896*** | −4.597*** | −3.195*** |
| | $h = 60$ | −3.943*** | 3.442*** | 3.370*** | 3.460*** | −4.879*** | −3.491*** |
| | $h = 120$ | −4.740*** | 2.579** | 2.498** | 2.598** | −5.655*** | −4.307*** |
| VIX | $h = 20$ | −6.530*** | −12.164*** | −12.077*** | −12.233*** | −12.946*** | −12.342*** |
| | $h = 60$ | −6.623*** | −11.919*** | −11.834*** | −11.987*** | −12.680*** | −12.088*** |
| | $h = 120$ | −6.651*** | −11.398*** | −11.316*** | −11.464*** | −12.132*** | −11.558*** |
| VXAPL | $h = 20$ | −17.700*** | −17.874*** | −18.944*** | −17.555*** | −9.357*** | −18.422*** |
| | $h = 60$ | −18.275*** | −18.377*** | −19.035*** | −18.201*** | −9.921*** | −18.675*** |
| | $h = 120$ | −17.256*** | −17.364*** | −18.068*** | −17.178*** | −9.996*** | −17.682*** |
| VXAZN | $h = 20$ | −14.456*** | −14.391*** | −14.370*** | −14.413*** | −21.504*** | −14.459*** |
| | $h = 60$ | −13.846*** | −13.802*** | −13.784*** | −13.822*** | −20.715*** | −13.840*** |
| | $h = 120$ | −13.419*** | −13.385*** | −13.365*** | −13.408*** | −19.840*** | −13.400*** |
| VXD | $h = 20$ | 9.613*** | 10.282*** | 9.947*** | 10.319*** | 11.063*** | 10.452*** |
| | $h = 60$ | 9.627*** | 10.297*** | 9.962*** | 10.333*** | 11.074*** | 10.466*** |
| | $h = 120$ | 9.642*** | 10.314*** | 9.979*** | 10.351*** | 11.091*** | 10.482*** |
| VXEEM | $h = 20$ | 8.619*** | 8.611*** | 8.611*** | 8.609*** | 8.564*** | 8.618*** |
| | $h = 60$ | 8.599*** | 8.592*** | 8.594*** | 8.590*** | 8.473*** | 8.598*** |
| | $h = 120$ | 8.615*** | 8.609*** | 8.610*** | 8.607*** | 8.461*** | 8.614*** |
| VXGOG | $h = 20$ | 9.710*** | −4.886*** | −5.397*** | −5.124*** | −2.100** | 9.848*** |
| | $h = 60$ | 9.286*** | −4.322*** | −5.164*** | −4.329*** | −1.588 | 9.442*** |
| | $h = 120$ | 5.667*** | −6.072*** | −8.536*** | −4.561*** | −3.146*** | 5.915*** |
| VXGS | $h = 20$ | −15.400*** | −15.119*** | −15.142*** | −15.763*** | −9.633*** | −15.298*** |
| | $h = 60$ | −16.045*** | −15.708*** | −15.713*** | −16.444*** | −9.488*** | −15.908*** |
| | $h = 120$ | −16.359*** | −16.209*** | −16.258*** | −16.665*** | −10.425*** | −16.291*** |
| VXN | $h = 20$ | −10.248*** | −10.037*** | −9.997*** | −10.057*** | −10.399*** | −10.221*** |
| | $h = 60$ | −10.161*** | −9.937*** | −9.893*** | −9.958*** | −10.314*** | −10.133*** |
| | $h = 120$ | −9.349*** | −9.107*** | −9.065*** | −9.126*** | −9.516*** | −9.311*** |
| ***Proportion of Significantly Negative DM**** | | **72.73%** | **72.73%** | **63.64%** | **72.73%** | **81.82%** | **72.73%** |

The figures in each cell are the modified Diebold and Mariano statistics with ***, **, and * indicating statistical significance at 1%, 5%, and 10%, respectively. The significant negative estimates imply the outperformance of the external uncertainty-based GARCH-MIDAS model over the realized volatility (RV)-based variant, while significant positive estimates denote the outperformance of the latter over the former.

(benchmark) model. Subsequently, the Twitter-based EPU variants are compared against the global EPU-based GARCH-MIDAS model as the benchmark.

As in the main estimation results, realized volatility consistently exerts a strong positive influence on most of the market fear indices, as well as country and sectoral stock volatilities. Economic policy uncertainty – particularly global and US-specific metrics – and geopolitical risk variants exhibit negative coefficients across most market fear indices (see Table A1 in the appendix), suggesting that rising geopolitical tensions may paradoxically reduce market volatility, possibly due to hedging mechanisms or anticipatory investor behaviour. This finding is consistent with the main estimation results.

Regarding the Twitter-based EPUs (TEU_1–TEU_4), we find these proxies further enrich volatility predictability, with only differences in magnitude when compared to the global and US EPUs, while still maintaining significant negative relationships. The observed differences in magnitude could be attributed to mixed signals arising from tweet virality and volume adjustments. Essentially, the nature of predictability for the Twitter-based EPU in market fear indices may not be sensitive to the specific TEU variant used.

In the country-level analysis (see Table A2 in the appendix), we find a heterogeneous impact of uncertainty measures on volatility indices. While the US and UK show strong positive predictability from global EPU and geopolitical risks, Germany and France exhibit mixed effects, with geopolitical uncertainty at times stabilizing volatility. Japan presents an anomaly, where rising geopolitical and policy uncertainty corresponds with reduced volatility, possibly reflecting the presence of policy interventions.

From the results in Table A3 in the appendix, sectoral indices respond differently to uncertainty. Financials, industrials, and semiconductors exhibit heightened volatility under rising EPU and TEU measures, whereas the energy and oil & gas sectors react negatively to geopolitical risks, suggesting sectoral resilience. The relationship between sectoral indices and uncertainty is sensitive to the specific sector considered.

Forecast evaluation using the modified Diebold–Mariano test (see Tables A4–A6 in the appendix) highlights the superior predictive power of external uncertainty-based GARCH-MIDAS models for selected indices, particularly those linked to geopolitical and policy uncertainty, over the GARCH-MIDAS-RV model. This conclusion is drawn from the observation that the Twitter (TEU_2 and TEU_4)-based GARCH-MIDAS models underperformed compared to the GARCH-MIDAS-GEPU model and were, at best, equally effective in the case of TEU_1 and TEU_3 in forecasting market fears.

For country-level (with the exception of TEU_4) and sectoral volatilities, the Twitter-based EPU GARCH-MIDAS models underperformed relative to the GARCH-MIDAS-GEPU model. This underscores the superiority of the global EPU variants. Nonetheless, the Twitter-based variants offer additional insights that could help capture investor sentiment.

Our findings reinforce the importance of incorporating diverse uncertainty metrics into volatility forecasting models, offering valuable implications for risk management and policy formulation.

## V. Discussion

The results of our study indicate that incorporating external uncertainty measures into volatility forecasting models enhances their predictive power for market fear. This finding invites a closer examination of the underlying channels by which policy uncertainty and geopolitical risks impact market fear.

First, both economic policy uncertainty (EPU) and geopolitical risks (GPR) are likely to affect market fear through their influence on investor sentiment and risk perceptions. Empirical evidence in the literature suggests that heightened EPU tends to increase market participants' uncertainty about future economic outcomes. For example, Athari (2021) shows that higher global EPU is associated with lower bank profitability in Ukraine, indicating that uncertainty raises risk premia and alters investment behaviour. Similarly, increased geopolitical risk may signal instability beyond domestic borders, reinforcing investor concerns and contributing to higher market volatility. Such uncertainty can lead investors to delay or reduce investment, thereby amplifying market fear.

Second, uncertainty can impact financial decision-making at the firm level, which in turn affects broader market outcomes. Studies investigating the impact of EPU on corporate capital structure (e.g. Athari et al., 2022; Athari and Bahreini 2023; S. Baker et al. 2016; Pástor and Veronesi 2013; Julio, B., and Yook, Y. 2012) have found that higher uncertainty reduces firms' propensity to take on debt. This response is consistent with the notion that firms, when faced with policy-related uncertainty, prefer internal financing and become more risk averse. The resultant reduction in investment and credit supply can further contribute to negative market sentiment and increased market fear. In this context, market fear may be understood as a reflection not only of expected price volatility but also of underlying shifts in corporate behaviour that signal broader economic uncertainty.

Third, the transmission mechanism of uncertainty is also observable in macroeconomic variables. For instance, the study on Japan by Athari (2021) demonstrates that EPU has a leading role in explaining inflation fluctuations. The findings suggest that when policymakers' actions are perceived as uncertain, inflation dynamics become more volatile, which may feed into market fear by destabilizing expectations regarding economic stability and monetary policy. Although our study focuses on market fear, the parallel between macroeconomic uncertainty and investor sentiment underscores the multi-layered effects of policy uncertainty.

Overall, the channels identified in the literature indicate that both policy uncertainty and geopolitical risks adversely affect market stability. Their impact is transmitted via several routes: directly by increasing the volatility expectations and risk premiums demanded by investors; indirectly by altering firm-level decisions such as capital structure and investment, which then feed into broader market sentiment; and finally through macroeconomic variables such as inflation, which serve as an additional signal of economic uncertainty.

Our findings, when interpreted alongside these previous studies, reinforce the view that external uncertainty – whether stemming from economic policy or geopolitical events – plays an important role in shaping market fear. Policymakers and market participants should be aware of these channels, as efforts to reduce uncertainty may help stabilize both firm behaviour and market sentiment. Future research may further clarify these mechanisms by jointly modelling firm-level responses and macroeconomic indicators to disentangle their combined effects on market fear.

## VI. Conclusion

This paper explores the impact of external uncertainties on market fears across various asset classes by integrating economic policy and geopolitical risk indices into a GARCH-MIDAS model framework. Our objective is to assess the predictive potential of these indices, including the global, US, and Russian economic policy uncertainties, as well as several geopolitical risk variants, on implied volatility indices derived from diverse markets such as stocks, commodities, and IT equities. By incorporating high-frequency implied volatility data sourced from CBOE and low-frequency uncertainty indices, this study aims to establish a comprehensive understanding of how these external uncertainties influence the conditional variance of market fear indices. Through comparative analysis against traditional models, this study addresses key research questions surrounding the predictive capabilities of external uncertainties using a mixed-frequency data approach, providing valuable insights into their role in shaping financial market volatilities.

Our results reveal the significant predictive power of external uncertainty measures for market fears across various implied volatility indices, including equities, commodities, and specific stock sectors. Specifically, this study finds that market fears generally decrease in response to rising external uncertainties, suggesting resilience in the face of global economic policy and geopolitical risks. The GARCH-MIDAS-X model incorporating indices such as GEPU, GPR, GPRA, GPRT, RUSEPU, and USEPU consistently outperformed the traditional GARCH-MIDAS-RV model, as evidenced by significantly negative Diebold and Mariano statistics across forecast horizons of 20, 60, and 120 days.

Our results also highlight that markets often respond positively to their own uncertainty, with realized volatility remaining a crucial predictor of future volatility. Notably, OVX and VXEEM showed the highest and lowest variability, respectively, while all indices exhibited positive skewness and leptokurtosis, reinforcing the non-normality of these series. Additionally, the in-sample analysis confirms that external uncertainty indices tend to have a negative and statistically significant relationship with most fear indices, with their incorporation into GARCH-MIDAS models markedly enhancing forecast accuracy across various indices and horizons. Similar feats are observed for country and sectoral volatility indices in terms of the assessed nexus, while Twitter-based EPU may offer some sentiment-based insights to modelling market fears, its out-of-sample predictive performance compares less with the global EPU. Overall, the GARCH-MIDAS-X framework emerges as a robust tool for understanding and forecasting market fears in response to diverse external uncertainty factors.

The results of our study suggest several important policy implications, particularly for financial market regulators, policymakers, and investors. Given the significant predictive power of external uncertainty indices like GEPU, GPR, GPRA, GPRT, RUSEPU, and USEPU on market fears, policymakers should closely monitor these global and national risk factors to better anticipate market volatility and implement pre-emptive stabilization measures. Financial regulators might consider developing early-warning systems based on the GARCH-MIDAS-X framework to detect potential spikes in implied volatility, enabling more timely interventions to maintain market stability. Additionally, incorporating geopolitical and economic policy uncertainty indices into their risk assessment strategies can help institutional investors and portfolio managers manage risk exposures more effectively. Moreover, the negative relationship between external uncertainty and market fears highlights the importance of transparent communication and coordinated international policies to mitigate fears during times of heightened uncertainty, ultimately fostering more resilient and less volatile global markets.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

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