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ENERGY-RELATED UNCERTAINTY AND STOCK MARKET VOLATILITY: EVIDENCE FROM THE WEALTHIEST ECONOMIES IN THE WORLD THROUGH THE GARCH-MIDAS APPROACH

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This study aims to analyze the effect energy-related uncertainty has on the volatility of the stock markets of 18 developed and developing countries ranking among the wealthiest according to their GDP. The study focuses on understanding how EUI influences market dynamics and volatility patterns across different economies. Using the GARCH-MIDAS approach, this research examines stock market indices from January 2003 to October 2022. The analysis reveals that all stock market indices are influenced by EUI. Notably, the S&P-TSX index exhibits the lowest MIDAS weight, indicating that Canada's market volatility is the least affected by EUI. Conversely, the highest MIDAS component weights are observed in the markets of China and the United Kingdom. The EUI shows the greatest influence on the volatility of the Indian and Chinese markets, whereas its influence is minimal on the Brazilian and Canadian markets.

Keywords: energy uncertainty, realized volatility, risk management, GARCH-MIDAS

JEL Classification: C58, G32, K32, Q43

INTRODUCTION

The growth of global economies has helped nations to develop new infrastructures, reduce scarcity, and improve the living standards of their citizens. These high exploitation ratios raise serious environmental concerns, namely biodiversity loss, land degradation and increasing water and air pollution levels. Failure to achieve the sustainable society and pollution reduction goals envisioned by the United Nations Sustainable Development Goal can lead to enormous environmental shortfalls (Langnel & Amegavi, 2020; Alvarado, Ortiz, Jiménez, Ochoa-Jiménez & Tillaguango, 2021; Hussain, Mir, Usman, Ye & Mansoor, 2022). Therefore, states must develop new energy policies aligning with the world's changes and developments.

Energy policy encompasses strategies for energy consumption, production, and supply, serving as a crucial tool for governments to address energy

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challenges and economic development. Governments often adjust these policies in response to changing national and international conditions, leading to policy uncertainty. Recent examples include Germany, Austria, and Italy restarting coal-fired power plants despite committing to zero carbon targets, and the Netherlands lifting restrictions on coal plants to secure clean energy by 2030. Similarly, thanks to its energy policy, China has made significant progress in the energy market over the past 40 years. However, the clash of multiple objectives in the Chinese energy market may lead to uncertainty in energy policy by changing the scope of macro regulation in different periods (He & Xu, 2024).

Recent global turmoil, including political polarization, trade frictions, the COVID-19 pandemic, and the Russian-Ukrainian and Israeli-Palestinian conflicts, has heightened concerns about rising uncertainty. Researchers have begun to utilize various indices, such as the economic policy uncertainty index and the climate policy uncertainty index so as to assess different forms of uncertainty. In this context, the energy uncertainty index (EUI) has gained importance in financial markets, particularly amid fluctuations in global energy markets and deepening economic globalization. While many studies have analyzed the influence of specific energy prices, particularly crude oil, on financial markets, focusing solely on these prices limits a comprehensive understanding of the energy market. A holistic view can help regulators develop effective safeguards and provide traders with better insights into energy market risks. To address this, T. H. N. Dang, C. P. Nguyen, G. S. Lee, B. Q. Nguyen and T. T. Le (2023) introduced the EUI, which captures uncertainty in the energy market through various measures, including exports, imports, supply, demand, policies, and prices. Unlike traditional financial uncertainty proxies, the EUI is tailored to reflect energy market-related uncertainties, making it a better indicator of risks associated with oil and geopolitical crises.

According to the current value model of asset prices, market volatility is linked to the time-varying nature of cash flows and discount factors, suggesting a connection between uncertainty and asset market volatility regarding expected cash flows (Shiller, 1981; Bernanke, 1983). Economic conditions primarily influence expected cash flows and interest rates; thus, ambiguity about future macroeconomic circumstances can shift asset return volatility (Schwert, 1989). This research aims to explore the influence of EUI on stock market volatility in the world's wealthiest economies.

There are three primary motivations for this current research. Firstly, the EUI developed by T. H. N. Dang *et al* (2023) hinders economic action and outcomes at the national and sectoral levels. The connection between stock return volatility and the EUI becomes clearer, providing valuable insights for investors into portfolio selection and risk management. The findings are also significant for the policymakers focused on market volatility drivers and the stability of the global financial system. Daily volatility estimation is essential for accurately measuring fluctuations and generating out-of-sample high-frequency forecasts. This approach aids traders in making timely investment decisions and enhances the quality of daily forecasts related to the expected shortfall and value-at-risk estimates.

Volatility in equity returns, representing financial market uncertainty, poses a significant policy constraint that can negatively affect economic activities. Thus, the high-frequency forecastability of equity market uncertainty enables policymakers to use MIDAS-based models to predict low-frequency indicators, helping to avoid potential stagnation. Thirdly, the previous literature has generally emphasized the effects of the EUI on equity returns (Imbet, 2022; Li, Pei, Yang & Zhang, 2024; Kayani, Sheikh, Khalfaoui, Roubaud & Hammoudeh, 2024; Wang, Huang & Huang, 2024; Zhang, 2024), so the number of the studies measuring the response of stock return volatility (Salisu, Ogbonna, Gupta & Cepni, 2024b; Salisu, Ogbonna, Gupta & Bouri, 2024c) remains entirely restricted. In addition, to the best of our knowledge, research needs to be done in the world's wealthiest countries. Due to the foregoing points, this research study will contribute to the literature.

The rest of the research paper is structured into the following sections: Section 2 summarizes the existing literature on the topic, Section 3 introduces the dataset and the methodology, Section 4 presents the empirical evidence and the last, section 5, concludes the paper and draws policy implications.

LITERATURE REVIEW

While many scholars have examined the influence of trade, geopolitical, and climate policy uncertainty on the global economy, the added complexity of energy-related uncertainty (EUI) and its interplay with other uncertainties presents the challenge that needs careful attention. As a result, economic stakeholders and policymakers have increasingly focused on the EUI as a vital concern for global financial conditions. This section summarizes the studies exploring the relationship between the EUI and macroeconomic factors and financial market indicators.

Among these research studies, M. Chiah, D. H. B. Phan, V. T. Tran and A. Zhong (2022) suggested that the value premium was significantly more pronounced when the EUI was high. T. H. N. Dang *et al* (2023) reported through VAR models that the EUI strongly responded to oil shocks, including sharp declines in oil prices and rises during the global financial crisis, the European debt crises, the COVID-19 pandemic, and the Russian invasion of Ukraine. Employing panel regression models, H. Ali, S. Kumar, M. Asim and W. Sajjad (2024) revealed a statistically significant inverse relationship between the EUI and institutional investment. X. He and C. Xu (2024) argued that EUI had a positive influence on energy efficiency using the basic panel regression analysis based on the panel data from provincial-level cities in China. M. Shahbaz, M. S. Meo, H. W. Kamran and M. S. ul Islam (2024) observed that the EUI positively affected CO2 emissions from the power generation and transport sectors, analyzed using a time-varying bootstrap rolling window causality test.

Applying the GARCH-MIDAS approach, A. A. Salisu, A. E. Ogbonna, R. Gupta and Q. Ji (2024a) found that country-specific EUIs significantly outperformed the benchmark for at least 14 currencies at short-, medium- and long-term forecast horizons. H. Xu, Y. Wang, J. Chen, H. Lin and P. Yu (2024) concluded that there was an asymmetric relationship between the EUI and Bitcoin volatility. X. Zhang and Q. Guo (2024) reported that positive or negative changes in the EUI contained information about oil price volatility. O. Usman, O. Ozkan, A. Koy and T. S. Adebayo (2024) employed quantile-on-quantile regression models to examine the impact of EUI shocks on US inflation and concluded that EUI shocks acted as cost-push shocks and raised inflation.

Several studies have explored the relationship between energy-related uncertainty index (EUI) and stock markets. J. F. Imbet (2022) found that EUI had a positive influence on stock returns on the NYSE AMEX and Nasdaq, as companies increased investments to hedge against future energy costs. U. Kayani *et al* (2024) reported that adverse global EUI shocks boosted stock returns in the consumer services, financials, healthcare, and industrial sectors, while positive shocks decreased returns in the materials and technology sectors. H. Li *et al* (2024) used the R^2 connectedness approach to show that the EUI uniquely influenced market shock transmission in G20 countries. Additionally, A. A. Salisu *et al* (2024b) demonstrated that the GARCH-MIDAS model incorporating the EUI outperformed the traditional GARCH-MIDAS realized volatility in 37 out of 50 US states. In a related study, A. A. Salisu *et al* (2024c) found that increases in both global and country-specific energy-related uncertainty indices (EUI) raised stock market return volatility in 28 developed and emerging economies. Y. Wang *et al* (2024) used an out-of-sample R^2 test to show that the EUI outperformed both global and US EUIs in predicting Chinese stock returns. Lastly, X. Zhang (2024) employed a supervised dimensionality reduction technique to argue that the country-specific EUI held predictive value for stock market returns in the US and China.

The literature review reveals that the EUI concept is either defined by individual indices, created within the framework of the sample of the study (Chiah *et al*, 2022; Imbet, 2022; He & Xu, 2024) or by the

EUI introduced by T. H. N. Dang *et al* (2023) (Ali *et al*, 2024; Kayani *et al*, 2024; Li *et al*, 2024; Salisu *et al*, 2024a; Salisu *et al*, 2024b; Salisu *et al*, 2024c; Shahbaz *et al*, 2024; Wang *et al*, 2024; Xu *et al*, 2024; Zhang, 2024; Zhang & Guo, 2024). Moreover, the evaluation of country-specific research in the relationship between the EUI and stock markets reveals that the research focus is on the US and China (Imbet, 2022; Kayani *et al*, 2024; Salisu *et al*, 2024b; Wang *et al*, 2024; Zhang, 2024), G20 countries (Li *et al*, 2024) and 28 developed and developing countries (the MSCI indices of countries) (Salisu *et al*, 2024c). These points highlight that the current research will contribute to the world of science.

DATA SET AND METHODOLOGY

The data set and preliminary analysis

In this research study, the relationship between the EUI and stock market volatility is analyzed, focusing on 18 of the 25 wealthiest economies in the world according to the GDP weighted by purchasing power parity and their benchmark stock market data. The review covers the USA, China, Germany, Japan, India, United Kingdom, France, Brazil, Italy, Canada, Russia, Mexico, Australia, South Korea, Spain, Netherlands, Belgium and Sweden. The data on the stock markets consist of the daily data for the period between January 2003 and October 2022, while the index data on the EUI includes the monthly data for the same period. The data on the countries' energy-related uncertainties were obtained from *policyuncertainty.com*, and the data on the major stock indices were obtained from *investing.com*. The stock market return series with the formula $r_t = \ln(p_t) - \ln(p_{t-1})$ were obtained, and the series of changes in the EUI with the formula $EUC_t = \ln(Y_t) - \ln(Y_{t-1})$ were calculated. Tables 1 and 2 present the descriptive statistics of the stock market returns and the series of changes in the EUI, respectively.

Table 1 shows that the null hypothesis saying that the stock market return series are not normally distributed is accepted, based on the J-B statistics of all the variables. According to the standard deviation values of the variables, Russia has the highest deviation value, which strengthens this argument. The fact that the skewness values of all the series are negative means that there are more negative than positive returns in the series, and the series exhibit a left-weighted structure. Moreover, the kurtosis values of the return series are positive and far from 3, suggesting that the series exhibit a leptokurtic distribution.

Table 2 displays the descriptive statistics of the countries' EUIs. According to Table 2, Germany's EUI, Belgium's EUI and the Netherlands' EUI have the highest standard deviation among all the variables. Therefore, there is a significant variation in energy use in these countries. The kurtosis coefficients of all the variables indicate that the series have a pointed distribution, and the positive skewness values signal a positive asymmetry. The null hypothesis saying that not all EUI series are normally distributed based on the J-B statistic values is also accepted. This fact reflects occasional abnormal increases or decreases in energy use.

Additionally, the ARCH-LM test benefits the preliminary examination of whether the data are suitable for modelling with ARCH group models or not. Table 3 contains the heteroskedasticity status of the stock market indices returns. Since EUIs constitute the MIDAS component of the GARCH-MIDAS approach, no case of heteroskedasticity is examined.

The ARCH-LM-F statistics of the series presented in Table 3 are the proof of a very strong heteroskedasticity in all the return series, and the F test results are statistically significant. All the stock return series are suitable for modelling with the ARCH group. More precisely, the results reveal that the return variance varies over time, and that heteroskedasticity should be taken into consideration in financial models.

Moreover, the ARCH group models assume that the series are stationary and perform better in stationary series, for which reason the stationarity of the series is examined applying the ADF and PP unit root tests, and the results of the unit root tests are given in Table 4.

Table 1 The descriptive statistics of the stock market return series

Indices	Median	Std. Dev.	Skew	Kurt.	J-B Stat
Australia- S&P ASX 200R	0.000924	0.012315	-0.650239	11.64456	11224.14 (0.000)
Belgium- BEL 20R	0.000511	0.014601	-0.673863	13.64478	16909.38 (0.000)
Brazil- BOVESPAR	0.001044	0.020186	-0.491159	11.94317	11888.84 (0.000)
Canada- S&P TSXR	0.000868	0.012661	-1488431	28.53260	97051.38 (0.000)
China- Shanghai CompositeR	0.000385	0.017987	-0.347449	7.859676	35395.90 (0.000)
France- CAC 40R	0.000794	0.015992	-0.315777	11.88688	11658.27 (0.000)
Germany- DAXR	0.001003	0.016065	-0.281612	11.19076	99002.30 (0.000)
India- Nifty 50R	0.001221	0.016781	-0.295909	14.91002	20885.46 (0.000)
Italy- FTSE MIBR	0.000795	0.017972	-0.893351	15.02027	21690.38 (0.000)
Japan- Nikkei 225R	0.000697	0.016513	-0.456755	10.43208	82353.19 (0.000)
Mexico- S&P BMV IPCR	0.000898	0.014022	-0.390167	14.05117	18027.02 (0.000)
Netherlands- AEXR	0.000809	0.015392	-0.416854	12.67066	13838.10 (0.000)
Russia- MOEXR	0.001031	0.025035	-2.711112	52.54823	364900.2 (0.000)
South Korea- KOSPI CompositeR	0.000717	0.014977	-0.364287	11.21204	99828.65 (0.000)
Spain- IBEX35R	0.000769	0.016697	-0.618457	13.14377	15337.58 (0.000)
Sweden- OMX StockholmR	0.001209	0.014861	-0.464126	10.75073	89499.05 (0.000)
United Kingdom- FTSE 100R	0.000601	0.013323	-0.444395	14.03463	17999.97 (0.000)
United States- S&P 500R	0.001000	0.013784	-0.566982	14.87402	20897.10 (0.000)

Source: Authors

According to the ADF and PP unit root test results, all the series are stationary at the same level, for which reason the analyses continue with the level values of the series. As a result, due to the different data frequencies, the GARCH-MIDAS approach is preferred, which allows the analysis of the high- and low-frequency data in the same model.

Methodology - the GARCH-MIDAS approach

The GARCH-MIDAS model is the approach that allows the examination of the low- and high-frequency data together. In other words, the model allows combining data at different frequencies. The model consists of the MIDAS and GARCH components.

Table 2 The descriptive statistics of the EUIs

EUI	Median	Std. Dev.	Skew.	Kurt.	J-B Stat
AUSTRALIA_EUI	-0.032899	0.629900	2.410080	13.03357	1223.576
BELGIUM_EUI	-0.013579	1.775903	11.47654	156.6938	238467.8
BRAZIL_EUI	-0.009946	0.512095	2.329233	12.46525	1099.011
CANADA_EUI	0.007923	0.882412	4.045437	30.63148	8185.991
CHINA_EUI	0.010431	0.941082	3.647672	23.61911	4723.903
FRANCE_EUI	-0.009946	0.512095	2.329233	12.46525	1099.011
GERMANY__EUI	-0.015919	1.137762	7.745261	84.21153	67498.28
INDIA_EUI	-0.005771	0.648815	1.514469	5.397004	147.3360
ITALY_EUI	0.005883	0.532913	1.828630	9.339375	528.9369
JAPAN_EUI	-0.027112	0.619586	1.736086	7.372009	307.8082
MEXICO_EUI	-0.020979	0.458390	1.520524	6.477787	210.7619
NETHER__EUI	0.007650	1.074568	5.812537	53.03923	26060.78
RUSSIA_EUI	-0.023487	0.485089	1.318556	5.178122	115.5234
S. KOREA_EUI	-0.009648	0.525511	1.958862	9.439631	561.0720
SPAIN_EUI	-0.019628	0.753895	2.620134	13.38654	1336.488
SWEDEN_EUI	-0.020971	0.803585	2.531535	11.82132	1021.572
UK__EUI	0.007358	0.410758	1.300376	5.642251	135.7359
USA_EUI	-0.009914	0.685486	1.891441	8.630056	454.3263

Source: Authors

The short-term component follows the standard GARCH process, whereas the long-term component incorporates the low-frequency variables through the MIDAS approach (Wu, Mei & Ding, 2022).

The MIDAS component includes the low-frequency data. The model analyzes the effect of the low-frequency data on the volatility of the high-frequency data. The GARCH component is the first stage of this two-component model. For the returns with a constant conditional mean and conditional volatility, the model is specified as expressed in Equation 1:

$$r_{i,t} = \mu + \sqrt{\tau_t \times g_{i,t}} \times \varepsilon_{i,t}, \forall\, i = 1, \ldots.. N_t \quad (1)$$

and

$$\varepsilon_{i,t} \big| \phi_{i-1,t} \sim N(0,1) \quad (2)$$

where $\phi_{i-1,t}$ denotes the information available on the day *i-1* of the period *t*. The second item on the right-hand side of Equation (1), the conditional variance part, is decomposed into two parts. The first component is the short-term component $g_{i,t}$ with a higher frequency, assumed to follow the traditional GARCH(1,1) process. The second component is the long-term volatility captured by *i* in the rolling window framework. The conditional variance is stated in Equation 3:

$$g_{i,t} = (1 - \alpha - \beta) + \alpha \frac{(r_{i-1,t} - \mu)^2}{\tau_i} + \beta g_{i-1,t} \quad (3)$$

The parameter μ in Equation 3 is the unconditional mean return, α and β being the ARCH and GARCH terms, where $\alpha > 0$, $\beta \geq$ and $\alpha + \beta < 1$ are required. τ_i is defined as the realized volatility adjusted following the MIDAS regression, expressed as in Equation 4 (Asgharian, Hou & Javed, 2013):

Table 3 The ARCH-LM test results

Variables	ARCH-LM F Test
United States- S&P 500R	487.4448***
China- Shanghai CompositeR	57.34925***
Germany- DAXR	273.1774***
Japan-Nikkei 225R	296.5299***
India-Nifty 50R	91.50384***
United Kingdom-FTSE 100R	553.0609***
France-CAC 40R	355.6342***
Brazil-BOVESPAR	493.8389***
Italy-FTSE MIBR	314.5327***
Canada-S&P TSXR	636.8492***
Russia-MOEXR	360.6114***
Mexico-S&P BMV IPCR	49.11086***
Australia-S&P ASX 200R	482.2495***
South Korea-KOSPI CompositeR	184.9784***
Spain-IBEX35R	316.1572***
Netherlands-AEXR	324.7613***
Belgium-BEL 20R	241.1024***
Sweden-OMX StockholmR	230.1203***

Source: Authors

$$\tau_i = m + \theta \sum_{k=1}^{K} \varphi_k(w_1, w_2) RV_{t-k}$$
$$RV_t = \sum_{i=1}^{N_t} r_{i,t}^2 \tag{4}$$

where K is the number of the volatility-smoothed periods. This equation can be further modified to include economic variables along with RV in order to examine the effect of the variables on the long-term return variance, as in Equation 5:

$$\tau_t = m + \theta_1 \sum_{k=1}^{K} \varphi_k(w_1, w_2) RV_{t-k} + \theta_2 \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{t-k}^{l} + \theta_3 \sum_{k=1}^{K} \varphi_k(w_1, w_2) X_{t-k}^{v} \tag{5}$$

where X^{l}_{t-k} indicates the level of the macroeconomic variable and X^{v}_{t-k} refers to the variance of the macroeconomic variable, i.e. the variance of the low-frequency data. As a result, the total conditional variance is shown in Equation 6:

$$\sigma_{it}^2 = \tau_t \cdot g_{i,t} \tag{6}$$

The beta lag polynomial describes the weighting scheme used in the equations 4 and 5, as in Equation (7):

$$\varphi_k(w) = \frac{(\frac{k}{K})^{w_1-1}(1-\frac{k}{K})^{w_2-1}}{\sum_{j=!}^{K} \left(\frac{j}{K}\right)^{w_1-1} (1-\frac{j}{K})^{w_2-1}} \tag{7}$$

In the empirical implementation of this research, the constraint w=1 is used, which implies that the weights are monotonically decreasing. However, R. F. Engle, E. Ghysels and B. Sohn (2013) estimate the GARCH-MIDAS model using the maximum likelihood estimation and construct the heteroskedasticity and autocorrelation consistent (HAC) standard errors.

RESULTS AND DISCUSSION

The parameters of the GARCH model are significant for all the variables and reveal volatility persistence in the stock market return series. In addition, the MIDAS parameters are also significant for all the variables. Separate models are constructed for each variable and the parameter estimates for all the models are given in Table 5.

The parameter μ in Table 5 represents the average return, the parameter α reflects the short-term shocks and the parameter β indicates the long-term shocks. Furthermore, the GARCH model condition is $\alpha + \beta < 1$. The MIDAS parameters are θ, ω and m. Secondly, in estimating the GARCH-MIDAS model, m in the equation τ_t, which is the long-run component of total volatility, represents the initial value of the log-likelihood function. ω indicates the weight required for the MIDAS regression, and θ shows the total effect the low-frequency variable has on the volatility of the

Table 4 The unit root test results

Stock Market Variables	ADF		PP		EUI Variables	ADF		PP	
United States-S&P 500R	t-stat	-65.7062 (0.000)	t-stat	-65.9334 (0.000)	USA	t-stat	-14.4277 (0.000)	t-stat	-21.22396 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.4581	1% level	-3.457984
China-Shanghai CompositeR	t-stat	-58.8534 (0.000)	t-stat	-58.8725 (0.000)	China	t-stat	-11.0169 (0.000)	t-stat	-20.30462 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.4581	1% level	-3.457984
Germany-DAXR	t-stat	-59.1051 (0.000)	t-stat	-59.16 (0.000)	Germany	t-stat	-16.9883 (0.000)	t-stat	-17.08122 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Japan-Nikkei 225R	t-stat	-59.8494 (0.000)	t-stat	-59.9208 (0.000)	Japan	t-stat	-20.8883 (0.000)	t-stat	-26.53216 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
India-Nifty 50R	t-stat	-58.6481 (0.000)	t-stat	-58.6674 (0.000)	India	t-stat	-15.3271 (0.000)	t-stat	-23.67243 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.4581	1% level	-3.457984
United Kingdom-FTSE 100R	t-stat	-46.0307 (0.000)	t-stat	-62.1113 (0.000)	UK	t-stat	-23.7453 (0.000)	t-stat	-27.71046 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
France-CAC 40R	t-stat	-45.092 (0.000)	t-stat	-61.0011 (0.000)	France	t-stat	-22.7023 (0.000)	t-stat	-22.78833 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Brazil-BOVESPAR	t-stat	-61.3442 (0.000)	t-stat	-61.3759 (0.000)	Brazil	t-stat	-22.7023 (0.000)	t-stat	-22.78833 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Italy-FTSE MIBR	t-stat	-61.2807 (0.000)	t-stat	-61.3023 (0.000)	Italy	t-stat	-22.6937 (0.000)	t-stat	-24.41467 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Canada-S&P TSXR	t-stat	-61.1039 (0.000)	t-stat	-61.1699 (0.000)	Canada	t-stat	-71.5633 (0.000)	t-stat	-18.2151 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45823	1% level	-3.457984
Russia-MOEXR	t-stat	-44.1351 (0.000)	t-stat	-58.2605 (0.000)	Russia	t-stat	-16.9038 (0.000)	t-stat	-24.33895 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.4581	1% level	-3.457984
Mexico-S&P BMV IPCR	t-stat	-44.6862 (0.000)	t-stat	-55.9337 (0.000)	Mexico	t-stat	-16.2038 (0.000)	t-stat	-24.60454 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.4581	1% level	-3.457984
Australia-S&P ASX 200R	t-stat	-61.3892 (0.000)	t-stat	-61.4533 (0.000)	Australia	t-stat	-21.4626 (0.000)	t-stat	-22.46272 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
South Korea-KOSPI CompositeR	t-stat	-56.8221 (0.000)	t-stat	-56.7699 (0.000)	South Korea	t-stat	-20.6698 (0.000)	t-stat	-25.47752 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Spain-IBEX35R	t-stat	-44.1133 (0.000)	t-stat	-59.0318 (0.000)	Spain	t-stat	-22.1984 (0.000)	t-stat	-22.68461 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Netherlands-AEXR	t-stat	-43.7076 (0.000)	t-stat	-58.2936 (0.000)	Netherlands	t-stat	-19.3992 (0.000)	t-stat	-19.0053 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Belgium-BEL 20R	t-stat	-56.7179 (0.000)	t-stat	-56.7197 (0.000)	Belgium	t-stat	-17.0084 (0.000)	t-stat	-17.02712 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984
Sweden-OMX StockholmR	t-stat	-60.684 (0.000)	t-stat	-60.8141 (0.000)	Sweden	t-stat	-22.1993 (0.000)	t-stat	-21.48863 (0.000)
	1% level	-3.43202	1% level	-3.43202		1% level	-3.45798	1% level	-3.457984

The values in parentheses represent the p-value. Furthermore, "X has a unit root" is the null hypothesis.

Source: Authors

high-frequency variable. The positive and statistically significant θ parameter means that the independent variable will cause high volatility on the dependent variable in the long run.

The USA-S&P 500 index model indicates that both short- and long-term volatility values are statistically significant, suggesting persistent volatility with a mean reversion. The θ parameter shows that the EUI significantly affects long-term volatility. Additionally, the constant term parameter (ω) is significant, confirming the importance of the S&P 500's volatility level. The positive and significant parameter m indicates that the short-term fluctuations in the EUI may influence long-term volatility trends.

All the parameters for the China-Shanghai Composite index are statistically significant. While the mean return (μ) is positive, it is relatively low, indicating modest daily returns. Both short- and long-term shocks significantly affect current volatility, confirming volatility persistence. Overall, changes in the EUI significantly influence volatility both in the short run and in the long run, thus indicating high persistence in the volatility of the Chinese market.

The model parameters of the DAX index are statistically significant. Based on the GARCH parameter results in the DAX series, it can be concluded that previous volatility is effective on current volatility, and volatility is clustering in the series. In addition, the EUI also affects the volatility of the DAX series. According to the parameter θ, long-term changes in the EUI can increase the volatility of DAX. According to the results, volatility persistence is also high in this index, and the EUI significantly increases the overall volatility level of the DAX index. This result suggests that the EUI significantly influences DAX.

The short- and long-term volatility values of the Japan-Nikkei 225 are statistically significant, from which point of view it can be assumed that volatility in the Nikkei 225 is permanent. According to the MIDAS parameters, the EUI significantly influences the Nikkei 225 volatility. Therefore, long-term changes in the EUI may increase the volatility of the Nikkei 225 index.

According to the model parameters of Nifty50, all the parameters are statistically significant, so it can be concluded that the short-term shocks are significant in the volatility of the index, there is volatility persistence in the index, and long-term changes in the EUI are effective in the volatility of the Nifty 50 based on the MIDAS parameters. The evidence from the model suggests that volatility persistence in the Nifty50 is significantly high.

The analysis results for the FTSE100 show that all the parameters of the model are statistically significant. Moreover, the GARCH parameters prove that the short-term shocks affect the volatility of the index and that the volatility of the previous periods exerts a significant influence on current volatility. According to the parameter θ, the hypothesis saying that long-term changes in the EUI affect the FTSE volatility is accepted.

For the CAC40, all the parameters of the model are statistically significant. The positive mean return indicates that daily returns are generally positive. The sum of the α and β values is less than 1, confirming the stability of the GARCH model. The results show that both short- and long-term shocks exert an influence on volatility with significant persistence. The notable θ parameter suggests that the EUI raises volatility in the long run, affecting the CAC40 both in the short run and in the long run. Overall, the EUI significantly increases the volatility of the index.

The BOVESPA model shows that the ω parameter is not statistically significant, thus indicating that the volatility level of the series is not essential. However, the GARCH parameters reveal that the short-term shocks significantly affect volatility, and past volatility exerts a strong influence on current volatility. The significance of the θ parameter indicates that the EUI affects BOVESPA, though the influence appears to be relatively limited compared to the other markets.

According to the results of the FTSE-MIB model, the short-term shocks have an influence on volatility and past volatility has an influence on current volatility. In addition, volatility persistence is present in the series, and the daily average return of the index is positive. However, the MIDAS parameters show that

Table 5 The GARCH-MIDAS results

Variable	μ	α	β	ϑ	ω	m	LLF	AIC	BIC
United States-S&P 500R	0.00089279 [4.872] 1.1048e-06***	0.14161 [12.746] 0.0000***	0.81743 [65.05] 0.0000***	0.11712 [8.8054] 0.0000***	2.9735 [3.0566] 0.00223***	0.010874 [14.781] 0.0000***	9228.81	-18445.6	-18408.6
China-Shanghai CompositeR	0.00042097 [1.6703] 0.094869*	0.076468 [11.684] 0.0000***	0.88487 [64.168] 0.0000***	0.18332 [20.159] 0.0000***	11.001 [3.6271] 0.0000***	0.0094538 [11.045] 0.0000***	8178.38	-16344.8	-16307.8
Germany-DAXR	0.0009949 [4.6313] 3.6344e-06***	0.13124 [9.7179] 0.0000***	0.81503 [41.273] 0.0000***	0.12875 [8.3413] 0.0000***	13.871 [2.4604] 0.013879**	0.012394 [16.731] 0.0000***	8598.06	-17184.1	-17147.1
Japan-Nikkei 225R	0.00082304 [3.4334] 0.00059615***	0.13319 [11.786] 0.0000***	0.79736 [50.737] 0.0000***	0.13072 [10.443] 0.0000***	9.9903 [3.2537] 0.0011392***	0.013166 [18.564] 0.0000***	8341.75	-16671.5	-16634.5
India-Nifty 50R	0.0011098 [4.8371] 1.3178e-06***	0.11192 [10.606] 0.0000***	0.80422 [45.459] 0.0000***	0.19671 [28.51] 0.0000***	2.2644 [7.3328] 0.0000***	0.006234 [7.6713] 0.0000***	8492.67	-16973.3	-16936.3
United Kingdom-FTSE 100R	0.00041605 [2.2482] 0.024566**	0.15262 [11.074] 0.0000***	0.7562 [36.143] 0.0000***	0.14937 [14.831] 0.0000***	11.16 [4.6755] 2.9331e-0***	0.0088146 [18.359] 0.0000***	9176.82	-18341.6	-18304.6
France-CAC 40R	0.00076944 [3.3901] 0.000698***	0.14584 [10.615] 0.0000***	0.80082 [39.39] 0.0000***	0.13298 [8.4817] 0.0000***	9.7257 [2.4346] 0.014911**	0.01248 [14.082] 0.0000***	8587.96	-17163.9	-17126.9
Brazil-BOVESPAR	0.00085433 [2.8125] 0.0049166***	0.10082 [10.492] 0.0000***	0.84301 [50.385] 0.0000***	0.070816 [3.2537] 0.0011***	3.516 [1.207] 0.22743	0.017687 [19.248] 0.0000***	7839.84	-15667.7	-15630.7
Italy-FTSE MIBR	0.00066559 [2.6603] 0.007807***	0.14641 [13.755] 0.0000***	0.82375 [62.308] 0.0000***	0.1647 [9.9301] 0.0000***	1.7394 [2.7615] 0.005753***	0.014131 [9.9749] 0.0000***	8130.23	-16248.5	-16211.5
Canada-S&P TSXR	0.0004983 [3.1365] 0.00171***	0.12253 [15.558] 0.0000***	0.85057 [90.544] 0.0000***	0.090865 [7.0278] 0.0000***	1.0493 [2.7378] 0.0061851***	0.010529 [16.432] 0.0000***	9613.28	-19214.6	-19177.5
Russia-MOEXR	0.0011737 [4.672] 2.9837e-06***	0.17361 [25.637] 0.0000***	0.75998 [62.634] 0.0000***	0.15119 [19.378] 0.0000***	7.5746 [5.4563] 0.0000***	0.014461 [22.13] 0.0000***	7956.24	-15900.5	-15863.5
Mexico-S&P BMV IPCR	0.00046836 [2.3493] 0.018809***	0.077206 [13.62] 0.0000***	0.90428 [123.31] 0.0000***	0.12834 [6.8406] 0.0000***	1.0673 [2.7679] 0.0056416***	0.011935 [12.816] 0.0000***	8901.09	-17790.2	-17753.2
Australia-S&P ASX 200R	0.00050528 [2.7114] 0.0067011***	0.091311 [10.341] 0.0000***	0.86268 [49.509] 0.0000***	0.11701 [6.7632] 0.0000***	7.9339 [2.2043] 0.027506**	0.0097832 [15.369] 0.0000***	9244.93	-18477.9	-18440.9
South Korea-KOSPI CompositeR	0.00044484 [2.1825] 0.029074**	0.10758 [9.3657] 0.0000***	0.81563 [43.172] 0.0000***	0.16898 [21.6] 0.0000***	5.8372 [7.5964] 0.0000***	0.007604 [14.718] 0.0000***	8956.52	-17901	-17864
Spain-IBEX35R	0.00047398 [2.0172] 0.043672**	0.15508 [12.525] 0.0000***	0.78378 [45.066] 0.0000***	0.1463 [11.823] 0.0000***	9.1872 [2.7563] 0.0058456***	0.012747 [15.397] 0.0000***	8359.16	-16706.3	-16669.3
Netherlands-AEXR	0.00074787 [3.6885] 0.000225***	0.1414 [10.266], 0.0000***	0.78277 [35.85] 0.0000***	0.15603 [15.427] 0.0000***	10.132 [4.6529] 3.2738e-0***	0.0098868 [19.007] 0.0000***	8829.04	-17646.1	-17609.1
Belgium-BEL 20R	0.00061243 [2.8765] 0.0040217***	0.13904 [11.795] 0.0000***	0.79707 [47.155] 0.0000***	0.13242 [11.936] 0.0000***	9.2432 [2.6714] 0.0075531***	0.011054 [19.711] 0.0000***	8846.6	-17681.2	-17644.2
Sweden-OMX StockholmR	0.00086688 [4.2592] 2.0519e-05***	0.1145 [11.245] 0.0000***	0.84755 [51.019] 0.0000***	0.11098 [4.9104] 0.0000***	10.237 [1.6365] 0.10000*	0.012473 [11.92] 0.0000***	8785.4	-17558.8	-17521.8

[ ] represents t-statistic and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Source: Authors

the EUI has an influence on the volatility of the FTSE-MIBR.

The S&P-TSX model results indicate that all the parameters are significant. The short-term shocks and the volatility of the previous period in the series affect current volatility. According to the parameter θ, the influence of the EUI on the volatility of the S&P-TSX is statistically significant. Therefore, the long-term movements in the EUI are among the factors with the potential to cause volatility in the S&P-TSX.

As for the Russia-MOEX, the short-term shocks are also significant in the context of volatility. Moreover, according to the MIDAS parameters, the EUI has an influence on the volatility of the Russian financial markets. Therefore, an increase in the EUI is likely to lead to an increase in the volatility of the Russian MOEX index.

The model for the Mexico-S&P-BMV-IPC shows that all the parameters are statistically significant and the short-term shocks and past volatility are perceived to influence current volatility in this index, accompanied by volatility continuity. The results of the MIDAS parameters prove that the effect of the EUI on the volatility of the Mexican markets is positive and significant, i.e. an increase in the EUI may cause volatility in the Mexican financial markets.

A fact can be established that all the parameters are meaningful in the Australia-S&P ASX 200 index, as is the case for all the other markets. Based on the GARCH parameters, it is possible to infer that the short-term shocks affect the volatility of this market and past volatility also affects current volatility. According to the θ parameter, the effect of the EUI on the relevant market volatility is both positive and significant.

According to the model parameters for South Korea's KOSPI Composite Index, the daily average return is positive and significant, as is the case for all the other markets. Additionally, according to the GARCH parameters, the short-term shocks have an influence on the volatility of this market. In addition, past volatility also affects current volatility. The MIDAS parameters imply that the weighting of the MIDAS model is substantial enough to enable that an increase in the EUI may lead to an increase in the volatility of the South Korean financial markets.

Spain's IBEX35 results demonstrate that the uncertainty of the energy market is practical regarding market volatility. In addition, the short-term shocks and past volatility in the GARCH component parameters are adequate for current volatility.

The model parameters of the Netherlands' AEX index reveal that all the parameters are statistically significant. According to the GARCH parameters, both short-term shocks and past volatility are perceived to have an influence on current volatility. The EUI positively and significantly affects the volatility of the AEX index, based on which an increase in the EUI may cause an increase in the volatility of the AEX.

All the parameters are significant in the GARCH-MIDAS model of the Belgium BEL20 index, which shows a significant influence of the short-term shocks and past volatility on current volatility. According to the parameters of the EUI, an increase in the EUI may cause an increase in the volatility of the BEL20 index.

The Sweden OMX index is the last variable included in the analysis. The parameters of the model derived using this index are also statistically significant. The GARCH parameters prove that the short-term shocks affect volatility. In addition, past volatility in the series affects current volatility. The fact that the MIDAS parameters are positive and significant implies that the EUI influences the volatility of the OMX index and increasing uncertainty will increase volatility.

Comparatively, the Canada-S&P TSX model performs best according to the AIC and BIC criteria, but it also has the lowest MIDAS weight. In contrast, the Chinese and UK indices exhibit high MIDAS component weights, indicating significant long-term volatility effects. The EUI exerts the greatest effect on the volatility of the Indian and Chinese markets, while its impact is least pronounced in the Brazilian and Canadian markets. Among the GARCH components, the Chinese and German markets show the highest volatility persistence, whereas the UK and Russian markets show lower persistence.

Overall, the analysis indicates that EUIs significantly influence stock market volatility. Increased energy-related uncertainty may lead to the risk-averse investors exiting the market, causing sudden price fluctuations and undermining investors' confidence. This decline may affect market stability and firms' profitability, potentially leading to crises. Therefore, investors should adopt proactive investment strategies, anticipate market changes and adjust their portfolios accordingly. Incorporating the EUI as a forecasting factor and implementing risk management strategies, such as insurance and stop-loss orders, can help minimize potential losses.

CONCLUSION

This research study investigates the influence of energy-related uncertainty on stock market volatilities in 18 of the 25 wealthiest countries, using the GARCH-MIDAS technique due to the differing frequencies of the EUI (monthly) and stock market data (daily). The analysis shows that all the model parameters are statistically positive and significant across all the countries, indicating that the EUI positively affects market volatilities. These findings align with the previous studies of J. F. Imbet (2022) and U. Kayani *et al* (2024).

When examined on a market-by-market basis, the Chinese and German stock markets are most influenced by the EUI, probably due to China's significant role in global energy production and consumption. The EUI may cause fluctuations in energy prices (e.g. oil and natural gas prices), which may increase production costs and reduce companies' profits, thus simultaneously leading to lower stock indices and heightened volatility. The EUI may also encourage China to boost investments in renewable energy, positively influencing the stock performance of renewable companies, thus having both negative and positive implications for the Chinese stock markets. A similar scenario applies to Germany, where the EUI may increase production costs in the energy-intensive sectors, such as the automotive and chemicals sectors, potentially harming companies' profits and stock prices. Interestingly, Brazil and Canada are least exposed to the influence of the EUI on stock market volatility, which is notably due to their differences - as the market of a developed economy, the Canadian market is less influenced by external factors, whereas the Brazilian emerging market faces high volatility and political risks. The minimal effect of the EUI on Brazil's market is surprising, suggesting further research in this topic is warranted. Additionally, while the Toronto Stock Exchange includes strong energy sector companies, the research results differ from the expectations with respect to the EUI's influence. Future studies should explore these dynamics so as to provide valuable insights for financial researchers and investors in these markets.

The results suggest that high-frequency stock market uncertainty forecasts based on the EUI can help policymakers to predict low-frequency economic activity in real time through MIDAS models. This approach allows for the development of early warning systems to mitigate regional recessions. Additionally, integrating broader energy market uncertainties into risk management and investment strategies can benefit investors, particularly in the energy sector. Individual investors and portfolio managers can optimize asset allocations and hedging strategies based on enhanced EUI-based forecasts, potentially increasing risk-adjusted returns. However, it is important to note that analyzing stock market volatility with a single constraint may not provide a complete economic interpretation, which highlights the limitations of this research study. Nevertheless, from the investor's perspective, monitoring the EUI can serve as a valuable forecasting factor. Investors should take into consideration the EUI when considering external factors for portfolio optimization. Overall, this research study demonstrates the influence of the EUI on stock market volatility, analyzing it across different frequencies without data transformation, still preserving information integrity.

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