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Energy-Related Uncertainty and International Stock Market Volatility

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Abstract

The aim of this paper is to predict the daily return volatility of 28 developed and developing stock markets based on the monthly metrics of corresponding country and global energy-related uncertainty indexes (EUIs) recently proposed in the literature. Using the generalized autoregressive conditional heteroscedasticity-mixed data sampling (GARCH-MIDAS) framework, the results show that country-specific and global EUIs have predictive powers for stock returns volatility for the in-sample periods, with increased levels of EUIs exhibiting the tendency to heighten volatility. This predictability also withstands various out-of-sample forecast horizons, implying that EUI is a statistically relevant predictor of stock returns volatility in the out-of-sample analysis. Moreover, the forecast precision of the GARCH-MIDAS model is improved by incorporating global EUIs relatively more than country-specific EUIs. Our findings are robust to the choice of EUI proxies and sample definition. They have important implications for investors and policymakers concerned with stability in the global financial system and economy.

JEL Codes: C32, C53, G15, G17, Q43

Keywords: Monthly energy-related uncertainty index; daily stock returns volatility; developed and developing economies; GARCH-MIDAS; predictions

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1. Introduction

The present value model of asset prices (Shiller, 1981a, b) shows that asset market volatility depends on the variability of cash flows and the discount factor. Therefore, time-variation in asset market volatility is linked to the evolving degree of uncertainty regarding future discount factors and expected cash flows (Bernanke, 1983). Since both interest rates and expected cash flows depend on the state (health) of the economy, it is plausible that a change in the level of uncertainty about future macroeconomic conditions would cause a proportional change in the volatility of asset returns (Schwert, 1989). Given this theoretical backdrop, the objective of this paper is to examine the predictive power of the country and global energy-related uncertainty indexes (EUIs) recently developed by Dang et al. (2023) reflecting both economic and energy-market-related uncertainties, for the return volatility of 28 developed and developing stock market indices.

This line of investigation emanates from two strands of recent empirical research on the in-sample and out-of-sample predictive abilities of economic uncertainty and the well-established oil-stock nexus (Degiannakis et al., 2018; Smyth and Narayan, 2018), specifically oil market-related uncertainty (see, for example, Liu and Zhang (2015), Feng et al. (2017), Dutta et al. (2020), Yu et al. (2021), Xiao et al. (2021), Gong et al. (2022), Qin and Bai (2022), Ghani and Ghani (2023), Li et al. (2023), and Salisu et al. (2023)). In light of this, our current paper can be considered an extension of these strands of research by bringing for the time the information content of economic and energy market uncertainties together,[1] realizing that oil prices are not necessarily a good proxy for energy prices (Kilian, 2008; Melichar, 2016; Cross and Nguyen, 2018), for forecasting the volatility of international stock indices. This link is understandable since the energy-related uncertainty has been shown by Dang et al. (2023) to hinder economic activity and output, not only at a country level but also at an industry level, thus it is likely to feed into the variability of discount factors and expected cash flows. Obviously, the predictive exercise we undertake in this paper should be of immense value to investors, given that accurate predictions of stock returns volatility carry widespread implications for portfolio selection, derivative pricing, and risk management (Poon and Granger, 2003; Rapach et al., 2008). It also matters for

[1] Previous studies indicate that uncertainty can be driven by the overall uncertainty in macroeconomic fundamentals and energy shocks (see, Jurado et al., 2015).

policymakers concerned with the factors affecting stock market volatility and thus the stability in the global financial system and economy.

To achieve our objective empirically, we use the generalized autoregressive conditional heteroscedasticity (GARCH) mixed data sampling (MIDAS) model, i.e., the GARCH-MIDAS model, originally developed by Engle et al. (2013).[2] Several reasons justify this choice. Firstly, the stock market data are at a daily frequency, whereas EUIs used as predictors are available only at a monthly frequency, and hence the modelling of volatility requires a MIDAS-based approach. This ensures that there is no loss of information by averaging the daily data to a lower frequency (Clements and Galvão, 2008), with the simultaneous use of the GARCH framework for modelling and forecasting. Secondly, the GARCH model is the most common method of modelling and forecasting financial series, ever since the seminal contribution of Bollerslev (1986) (as an extension of the ARCH model of Engle (1982)).[3] It accounts for various stylized facts of stock returns, notably volatility clustering, heavy tails in the return distribution, and autocorrelation of absolute returns. Thirdly, the GARCH-MIDAS model is justified by the argument that volatility has two different components, one pertaining to short-term fluctuations and the other to a long-term aspects, with the latter likely to be affected by slow-moving predictors, i.e., the energy-related uncertainty index in our case.

At this stage, we must emphasize that the decision to predict the daily volatility of stock index returns is not only due to the underlying statistical need to provide more accurate measures of volatility (Ghysels et al., 2019) but also because high-frequency (e.g. daily) predictions, particularly out-of-sample, are important for traders and investors making timely portfolio decisions, given that daily volatility forecast features prominently in the context of value-at-risk (VaR) and expected shortfall estimates (Ghysels and Valkanov, 2012). At the same time, being a measure of financial market uncertainty, the variability of stock returns is also a concern from a policy perspective, because it can impact economic activity negatively (Bloom, 2009; Ludvigson et al., 2021). Hence, high-frequency predictability of stock market uncertainty would help policymakers to nowcast the future path of low-frequency (e.g. monthly) real activity variables,

[2] A large amount of literature uses variants of the GARCH-MIDAS model to predict daily aggregate and industry-level international stock returns volatility, and the reader is referred to Salisu and Gupta (2021), Salisu et al. (2022, forthcoming a, b) and Segnon et al. (2023) for detailed reviews.
[3] See Bollerslev (2023) for an insightful discussion on the history of GARCH models.

using MIDAS-based models (Bańbura, 2011), and in the process, allow them to develop appropriate and early policy responses to prevent possible recessions.

Naturally, even though we consider in-sample predictions of stock returns volatility due to energy-related uncertainty, a real-time forecasting analysis specifically, besides being a well-established stronger test of predictability from an academic perspective (Campbell, 2008), should be of pertinent importance to investors and policy authorities in making their respective decisions optimally.

The main results show that both country-specific and global EUIs have the power to predict the volatility of stock index returns in the in-sample analysis, with increased levels of EUIs tending to heighten stock index volatility. Predictability is also significant for various out-of-sample forecast horizons. The forecast precision of the GARCH-MIDAS model improves when global EUIs are used compared to country-specific EUIs.

The rest of the paper is structured as follows: Section 2 provides an overview of the data, while Section 3 outlines the methodology. Section 4 presents the results, and Section 5 concludes the paper.

2. Data and Preliminary Analyses

The dataset used in this study consists of the monthly Energy Uncertainty Index (EUI) and daily MSCI stock market index (in US dollars to avoid the influence of exchange rate fluctuations) of the corresponding 28 developed and developing countries.[4] Monthly data on EUI are sourced from Dang et al. (2023)[5], whereas daily MSCI stock data are downloaded from Refinitiv Datastream. The data cover the period of 1996:01-2022:10, although the data for Croatia, Russia and Vietnam start at 2002:05, 1996:12, and 2006:11, respectively, based on the availability of their stock prices. In other words, barring the cases of Croatia, Russia and Vietnam, the other twenty-five countries have 7,000 observations each, and therefore, the EUI data is aligned with the MSCI stock index data from which the log-returns and their volatility are calculated.

[4] The countries are Australia, Belgium, Brazil, Canada, Chile, China, Colombia, Croatia, Denmark, France, Germany, Greece, India, Ireland, Italy, Japan, Mexico, Netherlands, New Zealand, Pakistan, Russia, Singapore, South Korea, Spain, Sweden, the United Kingdom (UK), the United States (US) and Vietnam.

[5] The data is available for download from https://www.policyuncertainty.com/energy_uncertainty.html. Note that whenever there is a missing value for a particular month, especially towards the earlier part of the sample period, we interpolate the EUI data

Dang et al. (2023) construct monthly EUI indexes in three steps. Firstly, they construct an economic uncertainty index for each country, as in Ahir et al. (2022), by counting the frequency of terms such as "uncertain," "uncertainty," and "uncertainties" in each monthly country report of the Economist Intelligence Unit. They then divide that count by the number of words in the same report and normalize each resulting country-level index to a mean of 100 over time. In the second step, the authors take the same approach to construct an energy-related index for each country from the same source. For this purpose, they use the energy-related keywords listed in Table 1 of their paper, most of which align with Afkhami et al. (2017). Finally, in the third step, they compute the monthly country-level EUI values as the simple mean of the economic uncertainty and energy-related indexes. Dang et al. (2023) also compute the Global EUI series as the equal-weighted and GDP-weighted means of the country-specific EUI series.

Table 1, below, illustrates the preliminary statistics for EUI and stock index returns, including the mean, standard deviation, skewness and kurtosis. The standard deviation shows how clustered/dispersed the series are around their means. Skewness shows the direction of the movement/fluctuation (to either right–positive or left–negative), whereas kurtosis indicates the heaviness or thinness of the tail from what is known to be typical of a normal distribution. The EUI ranges between 15.68 and 29.18 for Singapore and France, respectively, suggesting that, on average, energy-related uncertainty in France is the highest compared to other countries. Considering stock index returns, Greece has the lowest mean of returns (-0.01) whereas the highest mean is reported for Denmark (0.05).

Table 1a: Summary Statistics

	EUI					Stock index returns				
Country	Mean	Std. Dev.	Skew.	Kurt.	Obs.	Mean	Std. Dev.	Skew.	Kurt.	Obs.
Australia	17.11	9.29	1.32	6.13	322	0.02	1.41	-0.57	11.47	7000
Belgium	22.37	12.61	1.30	5.51	322	0.01	1.41	-0.41	12.47	7000
Brazil	23.69	14.08	0.57	2.69	322	0.04	2.25	-0.02	11.17	7000
Canada	21.27	13.23	1.08	4.25	322	0.03	1.34	-0.60	15.02	7000
Chile	19.11	11.77	1.19	4.42	322	0.01	1.42	-0.18	15.63	7000
China	18.88	11.44	0.77	3.29	322	0.01	1.84	0.26	9.59	7000
Colombia	24.68	15.17	1.32	4.87	322	0.03	1.69	-0.21	18.72	7000
Croatia	23.31	14.60	1.50	6.40	322	0.01	1.29	-0.09	13.18	5326
Denmark	18.51	11.38	1.30	5.46	322	0.05	1.35	-0.18	8.97	7000
France	29.18	13.10	0.81	3.84	322	0.03	1.47	-0.02	10.53	7000
Germany	25.56	13.14	0.57	3.06	322	0.02	1.53	-0.04	9.16	7000
Greece	24.36	13.12	0.68	3.28	322	-0.01	2.27	-0.14	10.71	7000
India	19.34	14.65	1.35	4.52	322	0.04	1.61	0.01	12.43	7000
Ireland	26.14	14.55	1.03	4.65	322	0.01	1.65	-0.43	12.02	7000
Italy	23.40	11.41	0.73	3.66	322	0.01	1.61	-0.27	11.44	7000
Japan	21.29	11.38	1.22	5.41	322	0.01	1.36	0.16	8.03	7000
Mexico	28.79	14.65	0.89	3.93	322	0.04	1.70	-0.04	12.88	7000
Netherlands	23.41	11.69	0.60	3.60	322	0.03	1.44	-0.05	9.31	7000
New Zealand	20.15	11.49	1.10	4.51	322	0.01	1.36	-0.26	9.35	7000
Pakistan	22.56	14.01	1.55	6.34	322	0.00	1.72	-0.25	9.65	7000
Russia	22.18	11.94	1.07	4.92	322	0.02	3.14	-5.23	174.27	6571
Singapore	15.68	9.85	1.21	4.62	322	0.01	1.34	0.16	10.34	7000
South Korea	24.50	13.33	1.02	4.09	322	0.04	2.17	0.78	21.94	7000
Spain	24.21	12.84	0.80	3.67	322	0.02	1.60	-0.02	11.74	7000
Sweden	21.43	11.62	0.90	3.96	322	0.04	1.76	0.09	8.58	7000
UK	27.45	12.75	0.78	3.91	322	0.01	1.30	-0.14	13.69	7000
US	23.18	13.61	1.08	4.56	322	0.03	1.21	-0.22	12.98	7000
Vietnam	22.02	15.01	1.37	5.19	322	0.00	1.53	-0.13	4.88	4152
All	22.63	13.24	1.07	4.56	9016	0.02	1.68	-1.20	84.18	191049

Note: EUI denotes the energy uncertainty index, while Std. Dev., Skew., Kurt., and Obs. Means, standard deviation, skewness, kurtosis and observations, respectively. The stock returns series, on the other hand, is computed as [ln(S_{it}/S_{it-1})*100], where S_{it} is the i-th country's stock price at time t. The sample spans the period 1996:01 to 2022:10.

The Russian market is the most unstable, with a standard deviation value of 3.14, while the US market is the most stable (with a 1.21 standard deviation value). Skewness is positive for all the countries' EUIs, whereas it is mixed for stock returns. Except for India, Japan, Singapore, South Korea and Sweden, the stock index returns of all countries are negatively skewed. The kurtosis statistic indicates that the distribution of EUI series and stock index reruns is leptokurtic, barring the EUI of Brazil. These outcomes suggest that the series are not normally distributed.

We test, in Table 1b, for the presence of heteroscedasticity and autocorrelation using an autoregressive conditional heteroscedasticity (ARCH) test and a Q-statistic with its squared form based on the Ljung-Box autocorrelation test. We find strong evidence of both conditional heteroscedasticity and autocorrelation in both variables across the sample countries. This supports our preference for the GARCH-MIDAS model to examine the predictive power of energy uncertainty for stock index returns volatility.

Table 1b: Conditional Heteroscedasticity and Autocorrelation Tests

Country	EUI									Stock Returns								
	ARCH (2)	ARCH (4)	ARCH (6)	Q(2)	Q(4)	Q(6)	$Q^2(2)$	$Q^2(4)$	$Q^2(6)$	ARCH (2)	ARCH (4)	ARCH (6)	Q(2)	Q(4)	Q(6)	$Q^2(2)$	$Q^2(4)$	$Q^2(6)$
Australia	19.2^a	9.6^a	6.36^a	6.35^b	10.7^b	16.8^b	31.1^a	31.1^a	31.2^a	1010^a	727.8^a	489.1^a	2.56	7.31	10.86^c	1826^a	371^a	4870^a
Belgium	3.83^b	2.58^b	2.55^b	6.47^b	28.5^a	32.39^a	7.9^b	11.3^b	15.5^b	244.6^a	151.3^a	163.6^a	0.25	5.45	11.13^c	527.7^a	836.3^a	1479^a
Brazil	4.46^b	6.81^a	4.85^a	10.9^a	31.8^a	40.4^a	0.09^a	-0.02^a	0.01^a	797.5^a	433.8^a	331.2^a	1.48	2.95	16.62^b	1619^a	2497^a	3382^a
Canada	7.12^a	4.25^a	2.84^b	6.37^b	24.5^a	28.60^a	16.4^a	21.95^a	22.2^a	601.2^a	446.6^a	357.3^a	6.89^b	19.5^a	57.63^a	1358^a	27645^a	4196^a
Chile	2.32	1.22	2.41^b	7.99^b	12.4^b	21.96^a	4.72^c	4.98	16.5^b	535.6^a	306.5^a	254.5^a	1.54	21.5^a	29.9^a	1090^a	1605^a	2213^a
China	25.50^a	13.19^a	8.74^a	16.1^a	25.8^a	35.62^a	38.7^a	38.84^a	39.1^a	462.5^a	277.4^a	197.5^a	1.36	4.11	26.97^a	1037^a	1633.8^a	2056^a
Colombia	14.92^a	10.35^a	8.91^a	8.51^b	15.6^a	16.00^b	27.6^a	44.31^a	64.6^a	631.2^a	361.4^a	336.3^a	11.8^a	16.7^a	23.34^a	1289^a	1913.6^a	2927^a
Croatia	30.86^a	15.33^a	10.47^a	16.0^a	19.4^a	28.49^a	66.0^a	73.60^a	82.6^a	310.2^a	171.5^a	120.4^a	6.34^b	18.1^a	22.91^a	706.7^a	985.86^a	1166
Denmark	4.12^b	4.27^a	2.93^a	8.45^b	22.6^a	28.0^a	9.05^b	19.78^a	20.7^a	336.3^a	259.3^a	266.4^a	5.5^c	17.3^a	34.56^a	726.5^a	1470.8^a	2560^a
France	3.22^b	1.59	1.11	13.3^a	16.9^a	17.95^a	7.18^b	7.47	7.86	216.0^a	227.5^a	179.2^a	2.39	17.6^a	38.69^a	462.2^a	1202.7^a	1762^a
Germany	2.43^c	1.26	1.60	8.56^b	9.25^c	12.1^c	5.04^c	5.39	10.22	187.1^a	209.7^a	158.2^a	0.85	5.01	16.61^b	393.7^a	1067.1^a	1488^a
Greece	12.15^a	7.66^a	5.52^a	29.5^a	35.3^a	38.47^a	28.1^a	30.33^a	35.4^a	178.5^a	119.1^a	93.5^a	0.46	9.0^c	13.44^b	396^a	660.6^a	902.8^a
India	5.52^a	3.57^a	2.42^b	15.3^a	18.6^a	18.98^a	5.01^c	5.06	5.70	182.4^a	119.9^a	106.2^a	0.12	4.51	30.56^a	409.4^a	663.3^a	1031^a
Ireland	18.92^a	10.22^a	7.08^a	39.8^a	47.8^a	51.7^a	38.9^a	46.7^a	47.4^a	281.2^a	221.5^a	252.2^a	3.05	12.9^b	36.86^a	622.7^a	1207.3^a	2378^a
Italy	4.24^b	4.72^a	3.58^a	9.87^a	19.9^a	20.61^a	9.14^b	22.89^a	28.1^a	129.8^a	145.7^a	105.8^a	0.004	8.96^c	22.70^a	287^a	762.2^a	992.0^a
Japan	2.00	7.16^a	4.94^a	1.12	21.9^a	27.6^a	4.43	31.63^a	38.5^a	314.6^a	210.6^a	146.9^a	10.7^a	12.7^b	21.06^a	660.6^a	1164.4^a	1448^a
Mexico	57.24^a	30.65^a	21.90^a	19.9^a	47.4^a	56.19^a	121^a	159.6^a	177^a	375.9^a	230.6^a	171.4^a	5.58^c	9.80^b	19.23^a	842.2^a	1263.6^a	1591^a
Netherlands	5.17^a	4.58^a	3.09^a	14.4^a	15.9^a	29.03^a	10.8^a	21.08^a	22.1^a	261.6^a	261.0^a	239.9^a	2.37	26.8^a	46.74^a	570.2^a	1430.9^a	2342^a
New Zealand	9.60^a	5.21^a	3.93^a	7.27^b	10.7^b	15.96^b	21.4^a	22.48^a	28^a	375.3^a	216.4^a	150.7^a	2.19	2.83	12.13^c	840.8^a	1240.9^a	1436^a
Pakistan	30.54^a	15.10^a	9.92^a	12.4^a	14.3^a	19.52^a	47.5^a	48.21^a	48.4^a	323.9^a	194.6^a	136.0^a	4.83^c	14.1^a	18.4^a	721^a	1122.7^a	1371^a
Russia	2.47^c	4.62^a	4.55^a	3.367	14.5^a	39.01^a	5.4^c	20.65^a	35.0^a	410.7^a	205.8^a	148.3^a	1.86	3.35	6.35	926.5^a	1030.3^a	1171^a
Singapore	0.43	0.40	1.15	2.07	9.06^c	18.88^a	1.16	2.02	6.99	562.4^a	342.9^a	235.2^a	4.49	5.3	12.05^c	1237^a	2103.2^a	2631^a
South Korea	9.13^a	6.36^a	6.86^a	6.03^b	14.5^a	18.4^a	19.3^a	32.4^a	62.4^a	285.7^a	253.8^a	247.2^a	0.52	38.9^a	60.89^a	612.0^a	1390.6^a	2413^a
Spain	13.62^a	6.67^a	4.83^a	27.2^a	32.5^a	33.8^a	31.8^a	35.7^a	36.6^a	142.2^a	161.9^a	120.2^a	1.13	11.8^b	18.43^a	311.8^a	854.08^a	1142^a
Sweden	27.46^a	22.83^a	15.0^a	24.4^a	31.9^a	38.6^a	56.3^a	114.7^a	126^a	209.3^a	189.5^a	163.2^a	10.8^a	13.7^a	30.56^a	462.5^a	1055.9^a	1646^a
UK	6.80^a	3.67^a	2.84^b	19.7^a	27.4^a	27.9^a	15.6^a	19.5^a	24.7^a	269.1^a	256.6^a	215.9^a	6.32^b	31.2^a	59.73^a	593.8^a	1439.1^a	2198^a
US	3.29^b	1.68	2.29^b	2.65	7.14	10.89^c	7.07^b	7.48	16^b	893.8^a	476.5^a	396.7^a	0.23	3.01	16.85^b	1743^a	2652.8^a	3953^a
Vietnam	8.89^a	4.58^a	3.05^a	11.0^a	15.3^a	23.57^a	19.8^a	20.28^a	20.7^a	363.9^a	213.8^a	149.3^a	0.05	14.7^a	18.56^a	814.8^a	1328.5^a	1704^a

Note: The reported figures are F-statistics for the ARCH test and Ljung–Box Q-statistics for the autocorrelation test, considered at three lag lengths (k = 2, 4, and 6). The null of no conditional heteroscedasticity and serial correlation are tested for ARCH and autocorrelation tests, respectively. Statistical significance of tests at 1%, 5%, and 10% levels, denoted by a, b, and c, respectively, indicates the rejection of the null hypotheses.

3. Methodology

We employ the mixed data sampling (MIDAS) technique to maintain and reflect the authenticity of our dataset combining monthly with daily series. Specifically, we adopt a GARCH-MIDAS approach, which has the ability to connect high-frequency data (in our case, daily stock returns) with lower-frequency data, such as monthly EUIs within a single model framework. This allows us to investigate the impact of EUI on stock returns volatility directly, thus avoiding information loss associated with data aggregation and potential biases introduced by data disaggregation through various techniques.

By including all variables in the model at their natural frequencies, the GARCH-MIDAS model ensures that we fully leverage the information contained in the original data, leading to more accurate estimation results. Previous research in the field empirically demonstrates the superiority of the MIDAS-based model framework compared to the competing models that require variables to be synchronized to a uniform frequency (as discussed in detail in Salisu and Gupta (2021), Salisu et al. (2022a, b, 2023, forthcoming a, b), and Segnon et al. (2024)).

The GARCH-MIDAS model specification for the stock returns on $i^{\{th\}}$ day in the $t^{\{th\}}$ month is given as:

$$r_{i,t} = \nu + \sqrt{\mu_t \times \tau_{i,t}} \times \varepsilon_{i,t}, \qquad \forall i = 1,2,...,N_t \tag{1}$$

$$\varepsilon_{i,t} \mid \varsigma_{i-1,t} \sim N(0,1) \tag{2}$$

Equation (1) specifies daily stock returns $(r_{i,t})$ as a function of an unconditional mean (ν) of stock returns, a conditional variance $\left(\sqrt{\mu_t \times \tau_{i,t}}\right)$ and the error term, $\varepsilon_{i,t}$. The subscript (i,t) is used to distinguish between daily and monthly frequencies, respectively, with N_t indicating the number of days in month t. The conditional variance, $\sqrt{\mu_t \times \tau_{i,t}}$, comprises two components, a short-term component denoted by $(\tau_{i,t})$ and a long-term component denoted by (μ_t). The error term, $\varepsilon_{i,t}$, in Equation (2), follows a Gaussian distribution and $\varsigma_{i-1,t}$ is the information set available up to the $(i-1)^{th}$ day of month t.

The short-run component $\tau_{i,t}$ of the conditional variance is defined as:

$$\tau_{i,t} = (1-\lambda-\gamma) + \lambda \frac{(r_{i-1,t}-\nu)^2}{\mu_t} + \gamma\tau_{i-1,t} \tag{3}$$

where λ and γ denote the ARCH and GARCH terms, respectively, that are constrained to be non-negative, with values that sum up to less than unity. Additionally, the monthly energy uncertainty index is transformed into a daily frequency, a process that is done without any loss of generality (for detailed technical explanations, refer to Engle et al. (2013)). As part of this transformation, the days in a month t are adjusted without explicit tracking. Equations (4) and (5) subsequently define the daily long-term component (μ_i) for realized volatility and the exogenous factor, respectively:

$$\mu_i = m + \varphi \sum_{k=1}^{K} \theta_k(\omega_1, \omega_2) RV_{i-k} \tag{4}$$

$$\mu_i = m + \varphi \sum_{k=1}^{K} \theta_k(\omega_1, \omega_2) X_{i-k} \tag{5}$$

where m represents the long-run intercept and φ denotes the coefficient associated with the predictor, which can be either the realized volatility of stock returns or an exogenous factor (energy uncertainty index). We explore four variants of the long-term component in the GARCH-MIDAS model, with the distinguishing factor among the contending models being our choice of predictor(s). These variants incorporate the following predictors: (i) realized volatility (RV), which defines the conventional GARCH-MIDAS model and serves as a benchmark in this study; (ii) RV and country-specific EUI; (iii) RV and global EUI (equally weighted); and (iv) RV and global EUI (GDP weighted). In the variants where exogenous predictors are combined with RV, principal components analysis (PCA) is employed to merge them into a single factor. Notably, the current study incorporates the principal component factor within the rolling window framework rather than the PCA method itself.

In Equations (4) and (5), the beta polynomial weights $\theta_k(w_1, w_2) \geq 0,\quad k = 1,\ldots,K$ are subject to the constraint that the weights must add up to one. This constraint is essential for identifying the model's parameters. Similarly, the secular component of the MIDAS weights undergoes a filtering process using a span of thirty-six MIDAS months, which has been determined as the optimal lag for our model specification.

We opt for a one-parameter beta polynomial, which offers greater flexibility in the beta weighting scheme (Colacito et al., 2011). This weighting scheme allows us to transform a two-parameter beta weighting function $\left[\theta_k\left(w_1, w_2\right)=\frac{\left[k/(K+1)\right]^{w_1-1}\times\left[1-k/(K+1)\right]^{w_2-1}}{\sum_{j=1}^{K}\left[j/(K+1)\right]^{w_1-1}\times\left[1-j/(K+1)\right]^{w_2-1}}\right]$ into a one-parameter beta weighting function $\left[\theta_k(w)=\frac{\left[1-k/(K+1)\right]^{w-1}}{\sum_{j=1}^{K}\left[1-j/(K+1)\right]^{w-1}}\right]$ by setting w_1 to one and defining $w=w_2$, which ensures that the weighting function exhibits a monotonically decreasing pattern, as suggested by Engle et al. (2013). Here, the weights (θ_k) are constrained to be positive and add up to one $\left(\sum_{k=1}^{K}\theta_k=1\right)$. Additionally, the parameter (w) is constrained to be greater than one $(w>1)$, ensuring that larger weights are assigned to more recent lag observations compared to distant observation lags. Consequently, we assess the statistical significance of the slope parameter, φ, to determine the in-sample predictability of the incorporated predictors; given that a significant estimate suggests predictability of the related predictor for stock returns volatility.

Given our interest in the out-of-sample forecast performances of the four contending GARCH-MIDAS model variants, we use the modified Diebold-Mariano (Harvey et al., 1997) test, which is an extension of the conventional Diebold and Mariano (1995) test for comparing paired models. The modified DM statistic DM^* is defined as follows:

$$DM^*=\left(\sqrt{\frac{T+1-2h+T^{-1}h(h-1)}{T}}\right)DM \tag{6}$$

where T is the length of the out-of-sample periods of the forecast errors; h is the forecast horizon; $DM=\bar{d}/\sqrt{V(d)/T}\sim N(0,1)$ defines the conventional DM test, where $\bar{d}=1/T\sum_{t=1}^{T}d_t$ is the mean loss differential $d_t\equiv g(\varepsilon_{it})-g(\varepsilon_{jt})$ obtained as the difference between loss functions $g(\varepsilon_{it})$ and $g(\varepsilon_{jt})$ of the forecast errors (ε_{it}) and (ε_{jt}), respectively, from the contending models; and $V(d_t)$ is the unconditional variance of the loss differential d_t. We therefore test the null hypothesis that asserts equality in the forecast precisions of the contending paired models $(H_0: d=0)$, against an alternative hypothesis $(H_0: d\neq 0)$. A rejection of the null hypothesis would imply that the forecast precisions of the contending paired models are statistically distinct, and the sign of the DM* statistic informs the preferred model. A negative DM* statistic indicates a preference for our predictive GARCH-MIDAS-EUI model over the conventional GARCH-MIDAS-RV model, whereas a positive DM* statistic indicates the opposite. Our out-of-sample forecast evaluation is conducted using 75% of the full sample data, under three forecast horizons: 20-, 60-, and 120-days ahead forecasts.

4. Empirical results and discussion

We present our main results along the lines of in-sample predictability of EUI for stock returns volatility and out-of-sample forecast evaluation of paired GARCH-MIDAS models. We consider three benchmarks in this study. Firstly, for comparison between the GARCH-MIDAS models that incorporate EUI (country-specific or global (equally- or GDP-weighted)) and the conventional GARCH-MIDAS-RV model, the latter model is considered our benchmark model. Secondly, for the comparison between the GARCH-MIDAS-[global-EUI] model and the GARCH-MIDAS-[country-specific-EUI] model, the GARCH-MIDAS-[country-specific-EUI] model is the benchmark. Thirdly, the GARCH-MIDAS-[global-EUI (GDP-weighted)] is considered the benchmark for the comparison between the GARCH-MIDAS-[global-EUI (equally-weighted)] model and the GARCH-MIDAS-[global-EUI (GDP-weighted)] model.

For the predictability, we only present the GARCH-MIDAS slope coefficient (φ), for each country considered, as an indicator of in-sample predictability. In addition, we ascertain that the predictability extends beyond the in-sample period. We thus assess the out-of-sample forecast performance of the GARCH-MIDAS variants' prediction of stock returns volatility using the modified Diebold and Mariano (Harvey et al., 1997) test, as presented in Table 3. This is done at three forecast horizons, 20-day ahead, 60-day ahead and 120-day ahead, to establish whether incorporating the exogenous energy uncertainty index provides additional information to improve the forecast accuracy of the modelled stock returns volatility.

Table 2 presents the in-sample predictability results for the stock returns volatility over the considered sample periods for twenty-eight countries. It contains the MIDAS slope coefficient (φ) associated with the realized volatility and the incorporated exogenous factors, which indicates the position of predictability of stock returns volatility due to RV (column 2), country-specific EUI (column 3), global EUI equally-weighted (column 4) and global EUI GDP-weighted (column 5).

We find that the stock returns volatility responds positively to its own uncertainty, which is indicative of the tendency for own market uncertainty to heighten volatility in the stock market.

While the statistical significance of the MIDAS slope coefficient (φ) reflects whether or not the EUI has predictive potential for stock returns volatility, the sign of the slope coefficient indicates the direction of the impact of the former on the latter. There is a large proportion of evidence of significantly positive estimates of φ across the EUI variants (country-specific EUI (in 100% of the significant cases), global EUI equally weighted (in approximately 86.4% of the significant cases), and global EUI GDP-weighted (in approximately 90.5% of the significant cases)) incorporated into the GARCH-MIDAS model. This finding generally aligns with our theoretical expectations discussed in the introduction, indicating that uncertainty about the future macroeconomic fundamentals, including energy-related uncertainties, can drive the volatility of stock index returns. In this regard, it is well-known that uncertainty can be driven by the overall uncertainty in macroeconomic conditions and energy shocks (Jurado et al., 2015). However, we also observe cases of significantly negative slope coefficients (in the cases of China under the global EUI equally weighted, and in both variants of the global EUIs for Greece and the UK), which could be a result of less trading in the risky asset (stock) following heightened uncertainty. But in general, the energy uncertainty index has in-sample-based predictive potential for the volatility of stock index returns in most cases.

Having established the predictability of EUI for stock returns volatility, we subject the contending GARCH-MIDAS models to forecast evaluation using the modified Diebold and Mariano test. We test whether the GARCH-MIDAS variants incorporating each of the EUIs outperform the GARCH-MIDAS-RV model (see result in Table 3). Significantly negative DM* statistics imply that the GARCH-MIDAS-EUI (country-specific and global variants) model is preferred over the GARCH-MIDAS-RV model; significantly positive DM* indicates a preference for the benchmark GARCH-MIDAS-RV model; while non-significance indicates that the compared models are markedly different from one another. There is a large proportion of outperformance in favour of the GARCH-MIDAS-EUI, regardless of the variant of EUI being considered. There are cases of higher number of significant negative DM* statistics across the models with EUIs than significant positive DM* statistics. These results transcend the EUI proxies and indicate the statistical relevance of the incorporated EUI. In other words, EUI is confirmed to be a good predictor of stock returns volatility across the 28 countries considered.

Table 2: In-Sample Predictability Results

	Realized Volatility	Country-Specific EUI	Global EUI (Equally Weighted)	Global EUI (GDP Weighted)
Australia	0.0288*** [0.0028]	0.1274*** [0.0424]	0.1556*** [0.0447]	0.1375*** [0.0479]
Belgium	0.0290*** [0.0026]	0.1534*** [0.0413]	0.2000*** [0.0401]	0.2046*** [0.0397]
Brazil	0.0220*** [0.0026]	0.0422*** [0.0153]	0.0551*** [0.0146]	0.0555*** [0.0146]
Canada	0.0404*** [0.0021]	-0.0432 [0.0662]	-0.0666 [0.0662]	-0.0625 [0.0530]
Chile	0.0229*** [0.0033]	0.2206*** [0.0462]	0.2184*** [0.0455]	-0.0446 [0.0555]
China	0.0315*** [0.0026]	-0.0392 [0.0343]	-0.0255** [0.0127]	-0.0351 [0.0444]
Colombia	0.0266*** [0.0026]	0.2382*** [0.0245]	0.2525*** [0.0241]	0.2448*** [0.0254]
Croatia	0.0262*** [0.0016]	0.4205*** [0.0325]	0.4191*** [0.0332]	0.3856*** [0.0320]
Denmark	0.0265*** [0.0029]	0.1775*** [0.0409]	0.2074*** [0.0397]	0.2064*** [0.0393]
France	0.0303*** [0.0032]	0.1841*** [0.0442]	0.2585*** [0.0371]	0.2735*** [0.0369]
Germany	0.0241*** [0.0038]	-0.0262 [0.0415]	0.1449*** [0.0494]	0.1589*** [0.0468]
Greece	0.0407*** [0.0022]	0.1386*** [0.0084]	-0.0932*** [0.0337]	-0.0839*** [0.0323]
India	0.0270*** [0.0029]	0.1542*** [0.0324]	0.1736*** [0.0325]	0.1576*** [0.0312]
Ireland	0.0287*** [0.0029]	0.1785*** [0.0184]	0.1912*** [0.0176]	0.1952*** [0.0193]
Italy	0.0327*** [0.0031]	0.2764*** [0.0356]	-0.0400 [0.0370]	0.3009*** [0.0329]
Japan	0.0285*** [0.0031]	0.1640** [0.0720]	0.2774*** [0.0815]	0.3187*** [0.0696]
Mexico	0.0297*** [0.0023]	0.0322 [0.0428]	0.1173*** [0.0353]	0.1279*** [0.0301]
Netherlands	0.0319*** [0.0031]	0.1569*** [0.0530]	-0.028** [0.0133]	0.2347*** [0.0449]
New Zealand	0.0319*** [0.0026]	0.1070 [0.0731]	0.1269 [0.0841]	-0.0123 [0.0138]
Pakistan	0.0275*** [0.0030]	0.2565*** [0.0357]	0.3043*** [0.0361]	0.2674*** [0.0332]
Russia	0.0299*** [0.0031]	0.0786*** [0.0090]	0.0797*** [0.0089]	0.0822*** [0.0087]
Singapore	0.0323*** [0.0030]	0.1018 [0.0767]	-0.0379 [0.0328]	-0.0675 [0.0423]
Korea	0.0235*** [0.0026]	-0.0500 [0.0628]	-0.0663 [0.0502]	-0.0393 [0.0322]
Spain	0.0296*** [0.0029]	0.1971*** [0.0302]	0.2184*** [0.0296]	0.233*** [0.0282]
Sweden	0.0342*** [0.0026]	-0.0235 [0.0551]	-0.028 [0.0293]	-0.0243 [0.0166]
UK	0.0301*** [0.0026]	0.1983*** [0.0444]	-0.0322** [0.0138]	-0.0333*** [0.0128]
USA	0.0263*** [0.0025]	0.1452*** [0.0444]	0.1731*** [0.0446]	0.2121*** [0.0436]
Vietnam	0.0178*** [0.0043]	0.3479*** [0.0839]	0.379*** [0.0875]	0.2841*** [0.0608]
No. of sig. cases	***28***	***20***	***22***	***21***
No. of sig. +ve	***28***	***20***	***19***	***19***
% of sig. +ve	***100%***	***100%***	***86.4%***	***90.5%***

Note: The figures in each cell are the estimated slope coefficients with their corresponding standard error in square brackets and the statistical significance at 1%, 5% and 10% denoted by ***, ** and *, respectively.

Table 3: Modified Diebold and Mariano Results (Realized Volatility-based Model is the Benchmark)

Country	Country-Specific EUI Versus Realized Volatility			Global EUI [Equally weighted] Versus Realized Volatility			Global EUI [GDP-Weighted] Versus Realized Volatility		
	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
Australia	-3.8189***	-3.8681***	-3.7761***	-4.3398***	-4.514***	-4.4615***	-4.0657***	-4.2459***	-4.2204***
Belgium	-3.0021***	-2.9311***	-2.9527***	-3.4844***	-3.4015***	-3.4683***	-4.6952***	-4.589***	-4.5928***
Brazil	0.2706	0.2189	0.1589	-1.7203*	-1.812*	-1.9499*	-2.0455**	-2.1681**	-2.3024**
Canada	-4.4806***	-4.5123***	-4.5258***	-5.46***	-5.4928***	-5.484***	-5.36***	-5.3878***	-5.3863***
Chile	-0.4688	-0.397	-0.3692	-3.9012***	-3.9859***	-4.0105***	-4.0673***	-4.1969***	-4.2569***
China	3.7739***	3.5059***	3.785***	1.534	1.2946	1.7055*	3.8575***	3.6241***	3.9228***
Colombia	-2.2697**	-2.1382**	-2.0224**	-2.0014**	-1.8715*	-1.7619*	-2.8024***	-2.6778***	-2.5718**
Croatia	15.7697***	15.5646***	15.1417***	14.8766***	14.7822***	14.5864***	17.0725***	16.9961***	16.7803***
Denmark	3.8735***	3.8484***	4.1298***	2.1399**	2.062**	1.9764**	-6.0395***	-5.9801***	-5.7171***
France	-3.6376***	-3.6442***	-3.6253***	-4.9213***	-5.0403***	-5.0109***	-5.2535***	-5.2394***	-5.2148***
Germany	0.6461	0.4928	0.2197	-2.353**	-2.5373**	-2.595***	-0.8219	-0.9379	-1.1711
Greece	15.0789***	13.829***	11.9155***	-10.8958***	-10.226***	-8.8165***	-11.3296***	-10.561***	-9.2469***
India	3.4059***	3.5522***	3.4156***	2.5121**	2.5496**	2.2311**	3.3304***	3.3179***	3.015***
Ireland	-0.5109	-0.3496	-0.1838	-3.8104***	-3.6333***	-3.7777***	-9.5783***	-9.4115***	-9.1821***
Italy	-4.8108***	-4.7442***	-4.7111***	-5.8095***	-5.7704***	-5.8943***	-8.6643***	-8.5871***	-8.5023***
Japan	16.0455***	15.6532***	15.6383***	18.2356***	18.0361***	18.8894***	22.1675***	22.0812***	22.0707***
Mexico	0.8857	0.8746	0.6822	1.1659	1.0408	0.8823	2.2561**	2.1488**	1.8863*
Netherlands	6.1367***	6.0997***	6.0107***	6.75***	6.6543***	6.2944***	4.2937***	4.2012***	4.0152***
New Zealand	1.6256	1.5226	1.6937*	1.7319*	1.5764	1.6917*	2.4996**	2.2938**	2.4295**
Pakistan	15.1148***	14.9748***	14.5887***	-2.3945**	-2.211**	-2.3028**	-2.4631**	-2.3617**	-2.3144**
Russia	-1.7218*	-1.7172*	-1.7241*	-1.7314*	-1.7199*	-1.7281*	-1.7664*	-1.7558*	-1.7594*
Singapore	-0.6376	-0.9739	-1.0423	-3.2388***	-3.478***	-3.4336***	-2.8706***	-3.0547***	-3.0001***
Korea	24.1643***	23.6036***	22.6459***	16.5102***	15.8783***	15.0113***	19.0165***	18.3984***	17.4294***
Spain	-3.9086***	-3.8815***	-3.8937***	-5.3948***	-5.4783***	-5.4117***	-4.8085***	-4.8856***	-4.8877***
Sweden	3.4655***	3.1094***	2.8475***	-0.3846	-0.7706	-0.8077	0.508	0.1402	0.0185
UK	-3.8449***	-3.814***	-3.8253***	-5.4954***	-5.6223***	-5.6313***	-4.8717***	-5.0027***	-5.0683***
USA	-3.4334***	-3.4401***	-3.4673***	-4.7305***	-4.759***	-4.7683***	-4.5107***	-4.5333***	-4.5572***
Vietnam	-3.9747***	-3.1608***	-2.5324**	-9.6889***	-8.8261***	-8.2422***	-9.5734***	-8.6969***	-8.1857***

Note: The modified Diebold and Mariano (DM*) test statistics compare each GARCH-MIDAS-EUI-based model with the GARCH-MIDAS-RV (benchmark) model. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. Significantly negative DM* statistics imply that the GARCH-MIDAS-EUI (country-specific and global variants) model is preferred over the GARCH-MIDAS-RV model; significantly positive DM* indicates a preference for the benchmark GARCH-MIDAS-RV model; while non-significance indicates that the compared models are markedly different from one another.

Similarly, the global EUI variants are compared with the country-specific EUI, as shown in Table 4, using the GARCH-MIDAS model incorporating an exogenous predictor, country-specific EUI, as the benchmark model in the global–country–specific pair. There is overwhelming evidence of outperformance of the global over the country-specific variant of EUI. The global EUI variants seem statistically more informative, improving the GARCH-MIDAS model's forecast precision more than the country-specific variant (see results in columns 2–7 of Table 4). Also, the equally-weighted and GDP-weighted global EUI-based model pairs are examined in columns 8–10, with the latter GARCH-MIDAS model serving as the benchmark. The results show that the equal-weighted EUI outperforms the GDP-weighted global EUI. Summarily, the predictability holds beyond the in-sample to out-of-sample at various forecast horizons. Our findings are robust to the choice of the EUI variant and the forecast horizon.

Taken together, our analysis highlights the importance of energy uncertainty for stock returns volatility, reflecting the responsiveness of the volatility of stock index returns in both developed and developing economies to uncertainty in the (global) energy market covering both economic and energy-market-related features. This finding nicely complements Megaritis et al. (2021) who argue that macroeconomic uncertainty has the ability to predict stock volatility. Uncertainty factors can trigger irrational trading and accentuate market fluctuations (Gong et al., 2022). Extreme shocks can trigger violent fluctuations in stock returns (Wang et al., 2020), pushing market participants to focus more on global stock market dynamics, especially large stock returns, possibly triggering herding activity, which can lead to a synchronized impact of uncertainty on international stock markets.

Table 4: Out-of-Sample Forecast Evaluation using Modified Diebold and Mariano Results (Comparison among the EUI-based Models)

Country	Global EUI (Equally weighted) Versus Country-Specific EUI			Global EUI (GDP-Weighted) Versus Country-Specific EUI			Global EUI [Equally Weighted] Versus Global EUI [GDP-Weighted]		
	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$	$h = 20$	$h = 60$	$h = 120$
Australia	-4.5221***	-5.1087***	-5.2306***	-3.4656***	-3.9314***	-4.0869***	0.8797	1.0663	1.2742
Belgium	-2.3329**	-2.2757**	-2.5674**	-8.5748***	-8.4032***	-8.2852***	17.2323***	16.917***	16.1669***
Brazil	-4.4743***	-4.5624***	-4.736***	-4.8392***	-4.9915***	-5.1499***	5.277***	5.7876***	5.8178***
Canada	-5.8411***	-5.8642***	-5.8065***	-5.4064***	-5.4149***	-5.3795***	-3.9362***	-4.1607***	-3.8482***
Chile	-5.5292***	-5.7304***	-5.7966***	-5.1933***	-5.416***	-5.5162***	3.5988***	3.806***	3.9409***
China	-4.0226***	-4.0559***	-3.6104***	0.8768	0.9092	1.0426	-7.2524***	-7.3156***	-6.891***
Colombia	4.7614***	4.7468***	4.6586***	-7.8737***	-8.0959***	-8.3587***	10.1841***	10.359***	10.5137***
Croatia	3.9074***	4.4073***	5.449***	1.042	1.651*	2.688***	2.5261**	2.418**	2.3825**
Denmark	-4.0573***	-4.1628***	-4.9495***	-16.5491***	-16.4667***	-16.4008***	25.984***	25.6002***	24.8096***
France	-5.3993***	-5.6588***	-5.6267***	-8.4188***	-8.3459***	-8.3152***	-2.3933**	-2.7248***	-2.6988***
Germany	-4.4899***	-4.6554***	-4.5073***	-6.0093***	-5.9421***	-5.9178***	-3.3193***	-3.5207***	-3.3645***
Greece	-17.1942***	-16.068***	-14.4622***	-17.2037***	-16.0738***	-14.4395***	3.1072***	2.1656**	3.6005***
India	-0.6201	-0.8182	-1.3586	1.5141	1.2214	0.7555	-8.5997***	-8.1443***	-8.292***
Ireland	-3.6478***	-3.6357***	-3.9833***	-10.1799***	-10.188***	-10.1046***	18.1895***	18.2462***	17.6107***
Italy	-4.9346***	-4.9918***	-5.4444***	-10.6618***	-10.6187***	-10.4865***	15.5971***	15.4133***	14.6546***
Japan	10.9271***	10.3098***	10.9338***	19.2723***	18.7701***	18.1818***	0.4829	-0.2013	0.7005
Mexico	0.7962	0.5081	0.5733	4.5033***	4.1933***	3.9433***	-6.1558***	-6.2785***	-5.7396***
Netherlands	2.1357**	2.0477**	1.5393	-2.0888**	-2.1698**	-2.3563**	12.4487***	12.4268***	11.7305***
New Zealand	0.7905	0.2611	-0.3601	3.9918***	3.516***	3.3413***	-4.2266***	-3.9349***	-4.0525***
Pakistan	-24.2808***	-23.8957***	-23.4812***	-25.0655***	-24.7659***	-24.1813***	0.7513	1.0478	0.5273
Russia	-1.7496*	-1.4555	-1.5244	-2.5433**	-2.4013**	-2.3348**	2.9079***	2.9362***	2.755***
Singapore	-5.7554***	-5.7911***	-5.6138***	-4.7792***	-4.7256***	-4.5442***	-1.6417	-1.9379*	-2.0227**
Korea	-4.0854***	-4.2527***	-4.2053***	-2.8982***	-3.0567***	-3.1336***	-8.7034***	-8.8754***	-8.3528***
Spain	-6.1026***	-6.3498***	-6.1803***	-4.8958***	-5.1635***	-5.1456***	-8.5586***	-8.669***	-8.1158***
Sweden	-4.0484***	-4.3422***	-4.1551***	-2.7784***	-3.035***	-2.9682***	-5.2109***	-5.3942***	-4.9885***
UK	-5.3888***	-5.6914***	-5.6946***	-4.3644***	-4.7037***	-4.8274***	-6.4138***	-6.403***	-6.0277***
USA	-5.3361***	-5.3933***	-5.3671***	-4.81***	-4.8523***	-4.8616***	-2.8665***	-2.9659***	-2.697***
Vietnam	-21.4084***	-20.9602***	-20.932***	-21.0444***	-20.5681***	-20.9713***	-1.7971*	-1.9629**	-0.7949

Note: The figures in Columns 2–4 and Columns 5–7 are the DM* statistics that compare the GARCH-MIDAS model that is respectively based on global EUI (equally-weighted) and global EUI (GDP-Weighted) with the GARCH-MIDAS that is based on country-specific EUI (benchmark) model. Columns 8–10 are the DM* statistics that compare the GARCH-MIDAS model that is based on global EUI (equally-weighted) with the GARCH-MIDAS model that is based on global EUI (GDP-Weighted), where the latter is the benchmark. ***, ** and * denote statistical significance at the 1%, 5% and 10% levels, respectively. For Columns 2–7, significantly negative DM* statistics imply that the GARCH-MIDAS model based on the global EUI variants is preferred over the GARCH-MIDAS-RV model based on country-specific EUI; significantly positive DM* indicates a preference for the benchmark GARCH-MIDAS model with country-specific EUI; while non-significance indicates that the compared models are markedly different from one another. For Columns 8–10, significantly negative DM* statistics imply that the GARCH-MIDAS based on the global EUI (equally-weighted) variants is preferred over the GARCH-MIDAS model with global EUI (GDP-weighted), while significantly positive DM* indicates the converse.

5. Conclusion

In this paper, we forecast the volatility of daily stock index returns for 28 developed and developing countries based on monthly country-specific and global energy-related uncertainty indexes (EUIs) using the GARCH-MIDAS framework over the period January 1996 to December 2022. We find that the uncertainty indexes related to energy, both the country-specific and global variants, possess the potential to forecast the volatility of stock returns for the in-sample periods. Higher levels of energy uncertainty indexes tend to correspond with increased volatility in stock returns. This in-sample predictability withstands various out-of-sample forecast horizons. Additionally, when comparing the predictive power and effectiveness of uncertainty indexes, the performance of the GARCH-MIDAS model that integrates global energy uncertainty indexes is superior relative to that integrating the country-specific metrics. Importantly, our findings are robust to the choice of EUI proxies and sample definition.

Based on our findings, we can conclude that investors should monitor the comparative roles of country-specific versus global energy-related uncertainty indexes while making their stock portfolio decisions, with relatively more emphasis on the latter, perhaps not surprisingly in line with an integrated global world system. With stock market volatility also capturing financial uncertainties, policymakers should be aware of the relative roles of macroeconomic and energy market uncertainties, both locally and worldwide, in formulating policy measures to prevent possible recessionary impacts and ensure economic stability.

As part of future research, looking at other asset markets, especially the exchange rate market, would be interesting, given the importance of the historical energy-exchange rate relationship (Salisu et al., 2021).

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