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Evaluating the Predictive Power of the Energy-Related Uncertainty Index on Bitcoin Volatility

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Abstract: Uncertainty indices at low frequency have garnered increasing attention in financial research due to their significant impact on asset returns. This study delves into the emerging field of low-frequency uncertainty indices in financial research, focusing on the Energy-Related Uncertainty Index (EUI) and its implications for Bitcoin volatility modeling. Utilizing GARCH-MIDAS models, we compare Bitcoin's volatility under the influence of EUI against Bitcoin's realized volatility (RV), examining its predictive power across 28 countries. The results reveal two key findings: Firstly, integrating EUI into the GARCH-MIDAS model significantly enhances its capability to explain Bitcoin volatility, with the effectiveness differing across countries. EUI's impact on Bitcoin volatility is especially pronounced with approximately a one-year lag. Secondly, although there is no apparent leverage effect in Bitcoin returns, EUI exhibits an asymmetric influence on Bitcoin volatility, highlighting its essential role in volatility modeling. These findings hold significance for investors and policymakers, providing valuable insights to enhance risk management strategies in the volatile cryptocurrency markets.

Keywords: energy uncertainty; realized volatility; stochastic model; cryptocurrency market; risk management

1. Introduction

Digital assets have become a hot trend in the modern financial landscape, revolutionizing how we perceive and handle value. These assets, encompassing a wide range of forms such as digital art, music, and more prominently, cryptocurrencies, offer a new level of security, transparency, and accessibility (Wątorek et al., 2021). Cryptocurrencies are decentralized digital currencies that use blockchain technology to secure transactions, making them immune to traditional banking systems and central authorities (S. V. Jin, 2024). At the forefront of this revolution is Bitcoin, the first and most well-known cryptocurrency. Introduced in 2009 by an anonymous entity known as Satoshi Nakamoto, Bitcoin has paved the way for the development of numerous other cryptocurrencies and blockchain applications. Bitcoin operates on a peer-to-peer network (Howell et al., 2023), enabling users to send and receive payments without the need for intermediaries. Its limited supply of 21 million coins ensures scarcity, often likened to digital gold (Baker et al., 2016; Cevik et al., 2022). Bitcoin's influence has not only introduced a new era of financial innovation but also inspired the creation of an entire ecosystem of digital currencies, each offering unique features and applications. As digital assets continue to gain traction, Bitcoin remains a crucial cornerstone, symbolizing the transformative potential of blockchain technology in the global economy (Ferdous et al., 2021). Many investors are drawn to Bitcoin due to its potential for high returns. Its value has surged dramatically over the years, making early adopters significant profits. However, Bitcoin is also known for its extreme volatility. Prices can fluctuate wildly within short periods, posing substantial risks alongside the potential rewards (Rani et al., 2024). To navigate these fluctuations, investors pay close attention to Bitcoin's volatility. By analyzing market trends and using strategic trading methods, they aim to maximize their gains while mitigating the risks associated with Bitcoin's unpredictable nature. This dynamic has made Bitcoin both an exciting and challenging asset in the digital economy.

Among various economic indicators, low-frequency uncertainty factors have proven effective in predicting market volatility, including Bitcoin (Isah et al., 2024; Yu et al., 2024b). However, as the macroeconomic environment evolves, more low-frequency indices are being discovered and gaining attention. One such emerging indicator is energy-related uncertainty, which reflects fluctuations and instability in the energy markets (Dang et al., 2023a). Energy uncertainty can significantly impact Bitcoin, as energy consumption is integral to Bitcoin mining. This relationship suggests that changes in energy costs and availability might influence Bitcoin's value and volatility. Climate change exacerbates this uncertainty by causing more frequent and severe weather events, disrupting energy supply chains, and increasing costs. Despite its potential, the ability of energy-related uncertainty to predict Bitcoin's behavior remains underexplored. This research gap raises two questions: Can the EUI serve as a reliable predictor of Bitcoin volatility, and how does the EUI's predictive power vary across different countries? Investigating this relationship could provide deeper insights into Bitcoin's market dynamics and offer investors a new tool for navigating its inherent risks. By addressing this gap, future research can enhance our understanding of the factors driving Bitcoin's value and volatility in an increasingly complex economic landscape influenced by climate change.

Motivated by the above, we utilize a generalized autoregressive conditional heteroskedasticity with mixed data sampling (GARCH-MIDAS) model to analyze Bitcoin volatility influenced by the EUI and realized volatility. Additionally, we extend our analysis to 28 countries with available EUI indices. This research reveals that Firstly, incorporating EUI into the GARCH-MIDAS model markedly improves its ability to explain Bitcoin volatility, with effectiveness varying by country. EUI's impact on Bitcoin volatility is particularly significant with around 12 lags. Secondly, although Bitcoin returns do not show a leverage effect, EUI has an asymmetric impact on volatility, emphasizing its vital role in volatility modeling. These findings are significant for investors and policymakers, offering valuable insights to improve risk management strategies in the highly volatile cryptocurrency markets.

This paper potentially contributes and innovates in the following three areas: First, it is the first to examine the impact of the newly released Energy-Related Uncertainty Index on Bitcoin volatility, shedding light on how external economic factors, especially energy market fluctuations, affect the cryptocurrency market. Second, by evaluating the predictive power of the EUI across 28 countries, the research provides a global perspective on the influence of energy-related uncertainties on Bitcoin volatility. This can guide policymakers in formulating region-specific regulations to stabilize their local cryptocurrency markets. Third, the findings assist policymakers and regulatory bodies in understanding the systemic risks associated with cryptocurrency markets, particularly in the context of energy consumption and sustainability. This knowledge can inform strategies to mitigate potential risks at the intersection of energy markets and digital currencies.

The remainder of this paper is designed as follows. Section 2 reviews the work in related literature. Sections 3 and 4 present the methodology and data, respectively. Section 5 discusses the empirical results. Section 6 concludes the findings.

2. Literature Review

2.1. Low-Frequency Macroeconomic Uncertainty

Since the global financial crisis, macroeconomic uncertainty has gained significant attention. Low-frequency predictors like Economic Policy Uncertainty (EPU), Trade Policy Uncertainty (TPU) by Baker et al. (2016b), Geopolitical Risk (GPR) by Caldara & Iacoviello (2022), Climate Policy Uncertainty (CPU) by Gavriilidis (2021b), and the World Uncertainty Index (WUI) by Ahir et al. (2022b) have been recognized for their effectiveness in forecasting market volatility, compensating for the limitations of high-frequency indicators. In existing literature, GARCH models are widely used for analyzing volatility. With GARCH-based models, scholars have demonstrated the predictive effectiveness of low-frequency predictors in the stock market (Asgharian et al., 2013; Li et al., 2023; Roudari et al., 2023) and futures market (Fang et al., 2023; Jia et al., 2023). Most research has focused on policy uncertainties including EPU and TPU. Notably, D. Jin & Yu (2023a) found that climate policy uncertainty significantly affects cryptocurrency price volatility, Xia et al. (2023) showed global EPU indices impact Bitcoin's long-term volatility, and Wang et al. (2023) examined the effects of fiscal and monetary policy uncertainty on Bitcoin volatility. To address gaps in energy finance research, this paper investigates the predictive effectiveness of the EUI on Bitcoin return volatility (Dang et al., 2023b). Previous studies have validated predictors like CPU (D. Jin & Yu, 2023b), GPR (Ferretti et al., 1989), and macro news surprises (Ch'ien et al., 2004) for cryptocurrency volatility. Scholars have also explored the impact of climate risk on the cryptocurrency environment (Zribi et al., 2023) and the relationship between Bitcoin and energy prices (Syuhada et al., 2022). However, the price of oil is not a good proxy for energy prices (Cross & Nguyen, 2018), and we need a more comprehensive predictor of energy uncertainty, where EUI fulfills it very well. The relationship between EUI as a new predictor and cryptocurrency volatility has not been validated, which prompts us to focus on whether EUI can provide a valid prediction for cryptocurrency volatility.

2.2. Energy Uncertainty and Cryptocurrency

Currently, much of the predictive research available on cryptocurrencies focuses on the relationship between digital currencies and economic policy uncertainty, as well as the diversification and hedging links between digital currencies and traditional financial assets. Given the massive consumption of cryptocurrencies, especially Bitcoin (Corbet et al., 2020), there are growing concerns about the ecological consequences of cryptocurrencies. In many studies, Bitcoins are viewed as assets rather than currencies due to their high volatility, it is also sensitive to other commodities in the market and other macroeconomic indicators (Dyhrberg, 2016; Yamada et al., 2013). On the other hand, with the development of clean energy sources and a clear policy direction toward sustainability, the issue of Bitcoin's consumption of energy may be resolved as a sustainable investment option for consumers, and demand changes (Lee et al., 2022).

The price of Bitcoin has a positive relationship with energy consumption and carbon emissions, and a high Bitcoin price also increases Bitcoin's energy demand (Qin et al., 2023). Price movements of commodities in the energy sector have also had a positive impact on Bitcoin price movements (Meiryani et al., 2022). The Bitcoin market and crude oil prices also show significant two-way spillover effects (Okorie & Lin, 2020).

3. Methodology

Engle et al. (2013) expand on the GARCH model of Bollerslev (1986) by developing the GARCH-MIDAS (GM) model, which accommodates variations at different frequencies. To explore volatility dynamics asymmetry, Amendola et al. (2019) employ the Double Asymmetric GARCH-MIDAS (DAGM) model. This model integrates the asymmetric GJR-GARCH model by Glosten et al. (1993) to capture daily volatility dynamics (the first asymmetry) and incorporates a lower frequency variable that influences the slow-moving volatility level through the MIDAS component, introducing differential effects based on the variable's sign (the second asymmetry).

Following Amendola et al. (2019, 2020, 2021), this paper initially utilizes the GM and DAGM models to evaluate Bitcoin volatility under varying EUI conditions. The Bitcoin returns follow the process $r_{i,t} = \sqrt{\tau_t \times g_{i,t}}\varepsilon_{i,t}$, with $\varepsilon_{i,t}|\Phi_{i,t-1} \sim t_\nu(0,1)$ in which τ_t and $g_{i,t}$ indicate the long-term and short-term component of variance, respectively. In the GM and DAGM model, $g_{i,t}$ follows a unit-mean reverting GARCH(1,1) process specified by

$$g_{i,t} = (1-\alpha-\beta) + \alpha\frac{(r_{i-1,t})^2}{\tau_t} + \beta g_{i-1,t} \tag{1}$$

and a GJR-GARCH(1,1) process expressed as

$$g_{i,t} = (1 - \alpha - \gamma/2 - \beta) + \left(\alpha + \gamma \cdot \mathfrak{I}_{(r_{i-1,t}<0)}\right) \frac{(r_{i-1,t})^2}{\tau_t} + \beta g_{i-1,t} \tag{2}$$

with $\mathfrak{I}_{(\cdot)}$ is an indicator function. As is typical in a GM model, the short-run parameters are subject to the constraints: $\alpha > 0;\ \beta \geq 0;\ \alpha + \beta < 1$. In the DAGM model, the constraints are $\alpha > 0;\ \beta \geq 0;\ \gamma \geq 0;\ \alpha + \beta + \gamma/2 < 1$. Meanwhile, τ_t represents the long-term component of the local level of volatility, defined as

$$log(\tau_t) = m + \theta \sum_{j=1}^{K} \delta_j(\omega)\, X_{t-j} \tag{3}$$

$$log(\tau_t) = m + \theta^+ \sum_{k=1}^{K} \delta_k(\omega)^+\, X_{t-k} \mathfrak{I}_{(X_{t-k}\geq 0)} + \theta^- \sum_{k=1}^{K} \delta_k(\omega)^-\, X_{t-k} \mathfrak{I}_{(X_{t-k}<0)} \tag{4}$$

where m serves as the intercept, θ represents the general response to the EUI or RV, while θ^+ and θ^- account for the asymmetric responses to the one-sided filter. $\delta_j(\omega)$, $\delta_k(\omega)^+$ and $\delta_k(\omega)^-$ appropriately weight the past K realizations of the exogenous stationary predetermined variable, denoted X_{t-k}. Specifically, monthly realized volatility is calculated as $RV = \sqrt{\sum_{i=1}^{21} r_{i,t}^2}$. Throughout this work, the Beta function will be utilized as the weighting function for all the GM models, which is expressed as

$$\delta_k(\omega) = \frac{(k/K)^{\omega_1 - 1}(1 - k/K)^{\omega_2 - 1}}{\sum_{j=1}^{K} (j/K)^{\omega_1 - 1}(1 - j/K)^{\omega_2 - 1}} \tag{5}$$

with $\omega_1 = 1$, which allows for greater weighting of the most recent observations (following a monotonically decreasing weighting scheme). The Beta functions ensure that $\sum_{k=1}^{K} \delta_k(\omega_2) = 1$.

4. Data

Bitcoin data from September 30, 2017, to October 1, 2023, was acquired to coincide with the availability of the EUI. This timeframe encompasses significant events such as the US–China trade conflict, the COVID-19 epidemic, and the Ukraine-Russia military engagement. These events have had notable impacts on financial markets, offering a comprehensive perspective on the dynamic correlations within the studied market. To accommodate low-frequency uncertainty, monthly uncertainty data predating the Bitcoin dataset was obtained and realized volatility was calculated accordingly with a matching length. Monthly uncertainty factors were sourced from www.policyuncertainty.com. Further details regarding variables can be found in Table 1. All the daily data are converted into logarithmic percentage return series as $r_t = ln(P_t/P_{t-1}) \times 100$ and monthly data are converted into the difference in logarithms as $\Delta risk_t = ln(risk_t/risk_{t-1}) \times 100$.

The descriptive statistics in Table 2 for Bitcoin and energy–related uncertainty indices across 28 countries reveal significant impacts on Bitcoin volatility. Bitcoin shows high volatility with extreme maximum (147.418) and minimum (−84.883) values, a high standard deviation (5.490), significant skewness (4.180), and kurtosis (166.774), indicating frequent extreme price movements. The global energy uncertainty index also displays substantial variability, with a high standard deviation (58.208) and notable kurtosis (10.170). Country-specific impacts vary, with Russia and Canada showing significant volatility and high standard deviations, while Japan and Mexico exhibit consistent adverse effects with negative mean values and high negative skewness. The ADF test confirms the stationarity of these indices, and the L-B and ARCH tests indicate significant autocorrelation and heteroscedasticity. These findings underscore the critical influence of energy uncertainty on Bitcoin volatility, highlighting the need for investors to consider these factors in their strategies, as the effects vary considerably across different countries.

The correlation matrix in Figure 1 reveals varying degrees of relationships between the global energy uncertainty index (Globe) and country-specific indices. Notably, Russia (0.43) and China (0.20) exhibit strong positive correlations with the global index, indicating their energy uncertainties are significantly influenced by global trends. Brazil (0.19), Sweden (0.20), and the UK (0.16) also show moderate correlations. Conversely, countries like Australia (0.01), Belgium (0.02), and Canada (0.01) display weak correlations, suggesting more localized energy uncertainty influences. The US and UK exhibit moderate inter-country correlations, highlighting regional interconnectedness. Overall, the matrix underscores how global energy uncertainties impact certain key economies while others remain more insulated from these global dynamics.

Table 1. Summary of variables.

Variable	Abbr.	Market	Source
Bitcoin Closing Prices	BTC	Global Bitcoin market	www.investing.com
Bitcoin Realized Volatility	RV	Risk from Bitcoin volatility	Author calculations
Energy-Related Uncertainty	EUI	Risk from energy uncertainty	www.policyuncertainty.com

Table 2. Descriptive statistics.

	Mean	Max.	Min.	Std. Dev.	Skew.	Kurt.	J–B	ADF	L–B	ARCH
BTC	0.212	147.418	−84.883	5.490	4.180	166.774	4562412.273***	−18.587***	328.774***	691.411***
Global	0.127	332.541	−316.743	58.208	−0.156	10.170	1384.776***	−7.757***	243.382***	71.664***
Australia	−0.597	160.335	−195.833	52.173	−0.174	1.197	17.280***	−7.932***	61.853***	68.198***
Belgium	−0.421	325.180	−279.864	61.758	0.131	4.471	223.202***	−6.158***	163.339***	35.413**
Brazil	0.377	157.556	−216.763	53.643	0.032	0.807	7.291**	−5.911***	64.725***	36.411**
Canada	0.528	220.265	−308.007	63.826	−0.418	2.811	95.688***	−7.862***	102.177***	88.372***
Chile	0.448	131.445	−133.973	49.060	0.108	0.154	0.782	−6.948***	56.049***	23.075
China	0.292	213.216	−218.401	65.909	−0.042	0.880	8.700**	−6.903***	108.098***	60.346***
Colombia	−0.013	430.321	−616.083	69.003	−1.147	33.845	12801.890***	−8.191***	70.644***	70.175***
Croatia	0.284	226.133	−210.998	63.759	−0.019	1.299	18.778***	−6.961***	113.733***	62.044***
Denmark	0.186	271.852	−588.473	73.887	−1.714	14.988	2629.933***	−6.464***	105.275***	17.316
France	−0.237	151.452	−190.480	45.747	−0.088	2.277	58.041***	−6.561***	95.692***	48.276***
Germany	0.156	267.698	−253.838	53.809	0.425	3.849	172.866***	−5.232***	55.154***	71.620***
Greece	1.179	297.623	−145.004	52.515	0.550	3.130	122.502***	−6.551***	63.680***	9.273
India	−0.193	233.547	−205.509	55.628	0.119	1.239	17.691***	−6.594***	41.838***	20.270
Ireland	0.367	290.296	−220.820	49.463	0.251	5.426	330.307***	−5.520***	70.330***	25.522
Italy	0.511	144.424	−139.490	45.736	0.049	0.078	0.173	−6.145***	54.609***	18.420
Japan	−1.426	158.386	−359.801	55.330	−0.807	5.901	416.370***	−5.319***	49.771***	8.865
Mexico	−2.082	119.704	−414.505	47.433	−2.438	20.422	4904.155***	−5.825***	67.431***	3.272
Netherlands	−0.148	251.143	−246.965	57.632	0.115	2.751	84.806***	−6.961***	117.390***	92.479***
New Zealand	−0.608	234.065	−159.828	59.592	0.217	0.635	6.587**	−6.983***	80.044***	36.529**
Pakistan	−0.188	277.614	−171.027	56.438	0.310	2.537	75.891***	−6.144***	59.088***	46.819***
Russia	1.139	578.280	−195.844	57.729	3.602	36.145	15111.670***	−6.229***	76.538***	4.163
Singapore	−0.719	214.677	−177.772	60.479	0.251	0.382	4.431	−7.247***	59.862***	26.317
South Korea	−1.014	140.376	−258.829	45.749	−0.552	3.708	166.497***	−6.636***	49.492***	11.381
Spain	0.074	181.219	−180.968	54.842	0.117	0.686	5.945**	−6.570***	95.712***	48.758***
Sweden	0.033	180.397	−231.733	55.520	−0.083	1.866	39.025***	−6.668***	102.668***	59.837***
UK	−0.481	107.600	−113.405	37.451	−0.112	0.433	2.639	−6.805***	57.525***	12.678
US	0.082	353.591	−383.996	62.630	−0.211	7.977	709.817***	−7.058***	57.192***	69.277***
Vietnam	−0.509	276.616	−203.814	71.228	0.331	0.960	15.127***	−6.720***	107.115***	20.968

Notes: *** and ** denote statistical significance at 1% and 5% levels, respectively. J-B (Jarque-Bera Test) tests for normality based on skewness and kurtosis, ADF (Augmented Dickey-Fuller Test) checks for stationarity in a time series, L-B (Ljung-Box Test) detects autocorrelation in time series data, and ARCH identifies the presence of heteroscedasticity.

Figure 1. Correlation heatmap among EUIs.

5. Empirical Results

5.1. Bitcoin Volatility Under Global EUI

The estimated results from the GM models in Table 3, comparing realized volatility and the energy uncertainty index as external regressors across different lag periods (K=6,12,18), provide key insights into Bitcoin volatility prediction. The γ parameter is not significant in any of the models, indicating no apparent leverage effect, meaning negative return shocks do not asymmetrically affect future volatility. The α and β parameters are highly significant across all models, underscoring the strong explanatory power and persistence of volatility in Bitcoin markets. Notably, the θ parameters for EUI shocks indicate potential asymmetries. In the energy uncertainty index models, the θ parameter for negative shocks is significant and negative across all lag periods, suggesting that increased energy uncertainty correlates with decreased Bitcoin volatility, potentially reflecting Bitcoin's role as a hedge during energy market disruptions. Model evaluation metrics, including AIC, BIC, and log-likelihood, consistently favor models using the energy uncertainty index, with the best performance observed at a lag period of 12, approximately one year. Figure 2 further substantiates this finding. Lower AIC and BIC values, along with higher log-likelihood values, indicate superior model fit and predictive accuracy, underscoring the effectiveness of the energy uncertainty index in capturing Bitcoin volatility dynamics within the GM framework.

We then proceed with further analysis using the DAGM model. The estimated results for the DAGM models in Table 4, comparing realized volatility and the energy uncertainty index as external regressors across the same lag periods, provide more detailed insights into the asymmetric impacts of positive and negative shocks. The α parameter is highly significant at the 1% level across all models, indicating robust explanatory power, with slightly higher values in the realized volatility models. The γ parameter is insignificant, suggesting no substantial leverage effect, meaning shocks do not asymmetrically affect future volatility, consistent with GM models. The β parameter is highly significant across all models, underscoring the persistent nature of Bitcoin volatility. Notably, the parameters for positive and negative shocks θ^+ and θ^- reveal different impacts of positive and negative shocks from EUI and RV, namely asymmetries. Specifically, under EUI, θ^- shows significant negative values across all lag periods, indicating that negative energy uncertainty significantly reduces Bitcoin volatility. The parameters ω_2^+ and ω_2^- for both positive and negative shocks are highly significant, emphasizing the importance of asymmetry in external regressors. Furthermore, model evaluation metrics, including AIC, BIC, and log-likelihood, favor the energy uncertainty index models, particularly at a lag period of 12. This finding is further validated by Figure 3. These metrics suggest superior model fit and predictive accuracy, highlighting the effectiveness of the DAGM model, especially with energy uncertainty as an external regressor, in capturing the complex dynamics of Bitcoin volatility.

Table 3. Estimated results for GARCH-MIDAS models.

	GM–RV			**GM–EUI**		
	K=6	**K=12**	**K=18**	**K=6**	**K=12**	**K=18**
α	0.170***	0.173***	0.173***	0.166***	0.166***	0.168***
	(0.019)	(0.020)	(0.020)	(0.018)	(0.019)	(0.019)
γ	−0.004	−0.006	−0.006	0.002	0.002	0.002
	(0.024)	(0.025)	(0.025)	(0.026)	(0.026)	(0.026)
β	0.827***	0.825***	0.825***	0.832***	0.832***	0.830***
	(0.021)	(0.022)	(0.022)	(0.021)	(0.021)	(0.021)
m	4.363***	4.227***	4.226***	5.763***	6.154***	6.075***
	(0.364)	(0.446)	(0.455)	(0.641)	(0.588)	(0.554)
θ	0.194	0.962**	0.962*	−2.164**	−6.318***	−5.492***
	(0.136)	(0.429)	(0.506)	(0.900)	(1.177)	(0.935)
ω_2	1.014***	1.011***	1.011***	1.001***	1.229***	1.982***
	(0.280)	(0.312)	(0.279)	(0.365)	(0.289)	(0.450)
ν	3.214***	3.205***	3.205***	3.156***	3.154***	3.146***
	(0.117)	(0.122)	(0.118)	(0.116)	(0.117)	(0.116)
AIC	16228.19	16223.93	16227.97	15882.15	15878.14	15880.89
BIC	16272.12	16267.86	16271.90	15925.95	15921.95	15924.70
LL	−8107.09	−8104.96	−8106.98	−7934.07	−7932.07	−7933.45

Notes: The standard deviations are reported in parentheses. ***, **, and * denote statistical significance at 1%, 5%, and 10% levels, respectively.

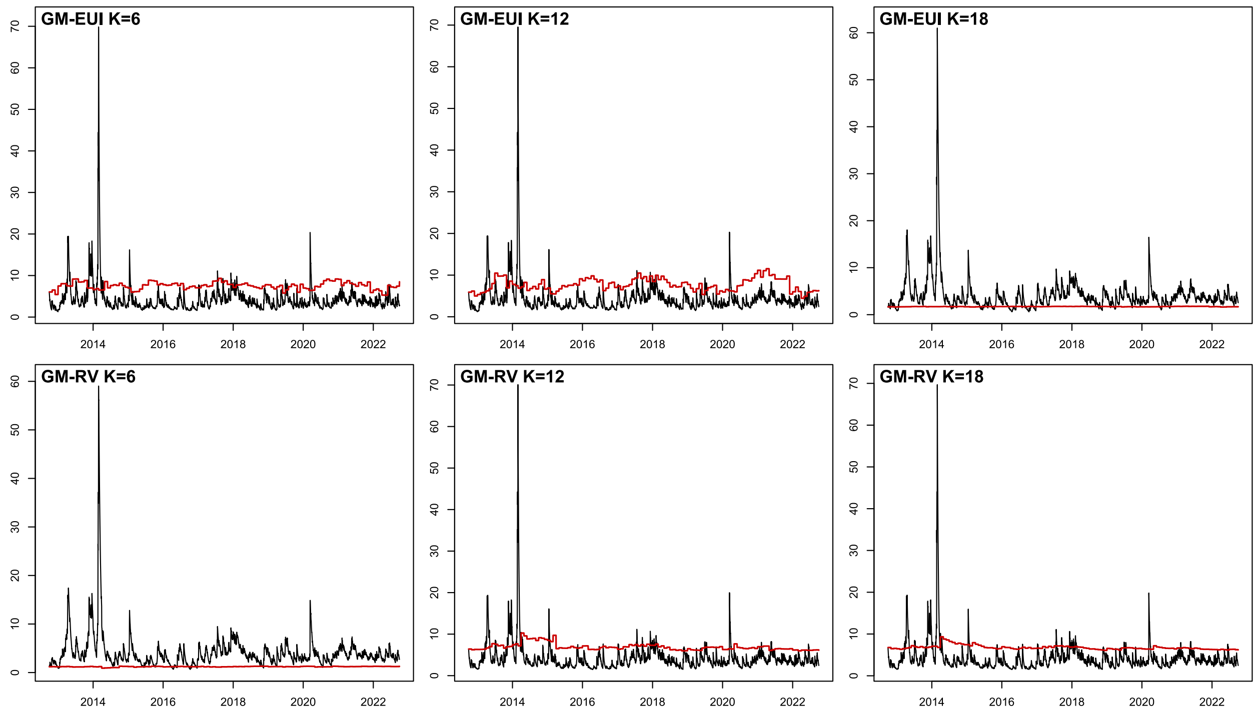

Figure 2. Short- and long-term volatility estimated by GM models.

Table 4. Estimated results for double asymmetry GARCH-MIDAS models.

	DAGM–RV			DAGM–EUI		
	K=6	K=12	K=18	K=6	K=12	K=18
α	0.180***	0.193***	0.193***	0.172***	0.186***	0.187***
	(0.019)	(0.020)	(0.020)	(0.020)	(0.030)	(0.022)
γ	−0.011	−0.019	−0.018	−0.001	−0.010	−0.012
	(0.027)	(0.030)	(0.030)	(0.030)	(0.048)	(0.027)
β	0.824***	0.815***	0.815***	0.828***	0.818***	0.817***
	(0.018)	(0.019)	(0.019)	(0.021)	(0.022)	(0.023)
m	7.202***	7.621***	7.398***	5.402***	4.109	2.335***
	(0.661)	(0.568)	(0.926)	(0.738)	(2.646)	(0.706)
θ^{+}	−0.110	1.528***	1.509***	−0.791*	−2.806*	0.823*
	(0.082)	(0.490)	(0.494)	(0.435)	(1.484)	(0.474)
ω_2^{+}	1.023***	1.022***	1.020***	1.001*	1.001**	3.992***
	(0.165)	(0.160)	(0.162)	(0.544)	(0.398)	(1.103)
θ^{-}	6.727***	11.527***	11.476***	−9.388***	−31.066***	−38.147***
	(0.946)	(0.883)	(0.390)	(0.445)	(4.213)	(0.470)
ω_2^{-}	1.614***	1.833***	1.829***	1.222***	1.145***	1.475***
	(0.002)	(0.282)	(0.246)	(0.266)	(0.111)	(0.121)
ν	3.099***	3.023***	3.025***	3.104***	3.021***	3.040***
	(0.105)	(0.099)	(0.099)	(0.109)	(0.107)	(0.100)
AIC	16222.69	16202.33	16202.75	16212.44	16190.73	16202.43
BIC	16279.17	16258.81	16259.23	16268.92	16247.21	16258.91
LL	−8102.35	−8092.16	−8092.37	−8097.22	−8086.36	−8092.21

Notes: See notes in Table 3.

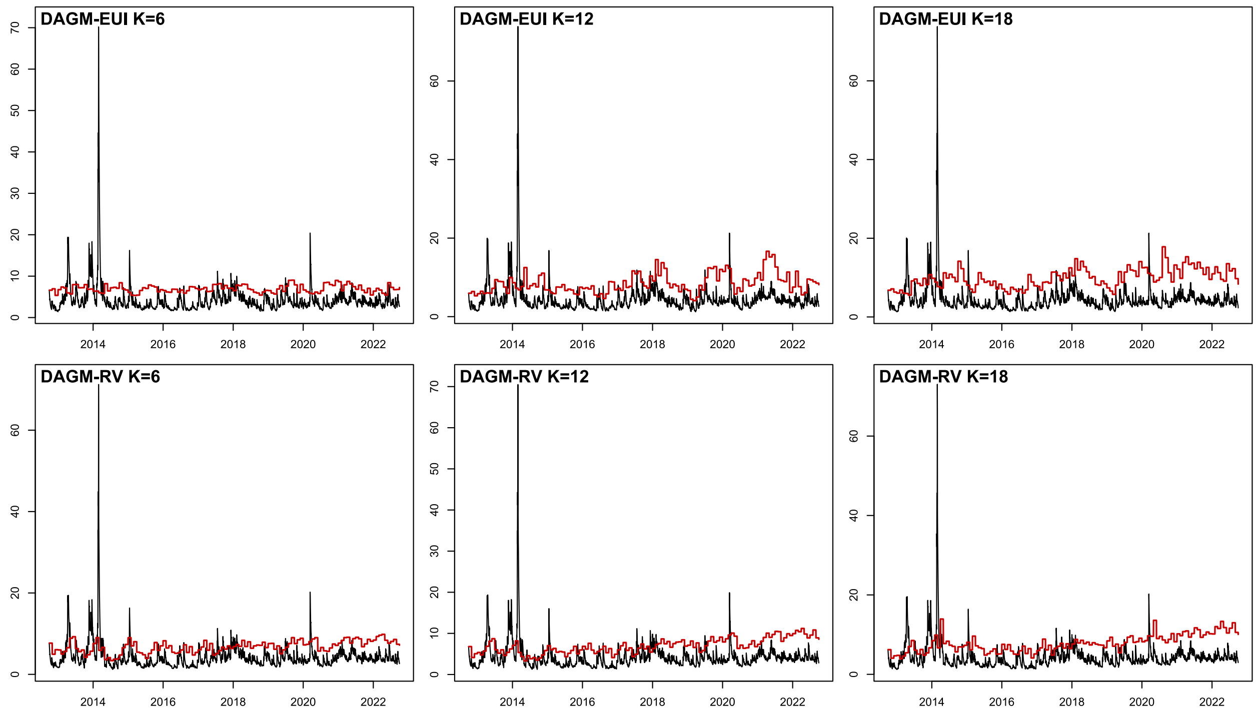

Figure 3. Short- and long-term volatility estimated by DAGM models.

5.2. Bitcoin Volatility Under Country EUI

According to the empirical results presented in Tables 3 and 4, when the lag length K=12 is used, the values of AIC and BIC are generally lower, indicating a superior model fit. Consequently, in this section, we have selected K=12 to estimate the country-specific impact of the energy uncertainty index. Additionally, given the absence of any leverage effect, we have employed the standard GARCH model. Table 5 displays the results of the GM model estimations for the energy uncertainty index across 28 countries, revealing significant variations in model performance and effectiveness. The evaluation of model quality using AIC, BIC, and log-likelihood metrics indicates that the incorporation of the energy uncertainty index enhances the predictive accuracy for Bitcoin volatility across diverse geopolitical contexts. Countries such as Belgium, France, and Greece exhibit particularly robust model performance, characterized by notably lower AIC and BIC values and higher log-likelihood values relative to other countries. This suggests that the energy uncertainty index serves as a more effective predictor of Bitcoin volatility in these regions. Conversely, countries like China and Vietnam demonstrate different dynamics, with relatively higher AIC and BIC values, indicating less improvement in predictive accuracy. These findings underscore the varying impact of energy uncertainty on Bitcoin volatility across different countries. In conclusion, the energy uncertainty index significantly enhances the GM model's ability to predict Bitcoin volatility, particularly in specific countries, underscoring its importance as an external regressor in volatility modeling.

Table 5. Estimated results for GARCH-MIDAS models with EUI in 28 countries.

	Australia	**Belgium**	**Brazil**	**Canada**	**Chile**	**China**	**Colombia**	**Croatia**	**Denmark**	**France**	**Germany**	**Greece**	**India**	**Ireland**
α	0.196***	0.185***	0.181***	0.180***	0.179***	0.178***	0.180***	0.177***	0.182***	0.183***	0.181***	0.176***	0.180***	0.178***
	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)	(0.021)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)
β	0.803***	0.813***	0.818***	0.819***	0.820***	0.821***	0.819***	0.822***	0.817***	0.816***	0.818***	0.823***	0.819***	0.820***
	(0.023)	(0.023)	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)	(0.022)	(0.022)	(0.022)	(0.021)	(0.022)	(0.021)
m	6.211***	6.320***	6.063***	6.130***	6.041***	5.460***	6.014***	6.033***	6.185***	6.198***	5.955***	6.149***	5.841***	5.851***
	(0.536)	(0.597)	(0.810)	(0.597)	(0.609)	(0.610)	(0.488)	(0.439)	(0.533)	(0.496)	(0.640)	(0.657)	(0.503)	(0.600)
θ	−2.730***	−3.439***	−0.961	−1.896**	−0.564	0.776**	−0.832	−0.699	−1.782	−1.871***	−1.283*	−1.930*	0.367***	−6.125***
	(0.947)	(1.224)	(1.236)	(0.884)	(0.738)	(0.369)	(0.952)	(1.957)	(2.059)	(0.680)	(0.676)	(1.136)	(0.093)	(1.565)
ω	1.858***	1.022***	2.629***	1.001***	2.214***	1.001**	1.933***	2.053	1.982***	1.770***	1.001***	1.001*	12.068***	1.497***
	(0.277)	(0.190)	(0.769)	(0.304)	(0.496)	(0.410)	(0.559)	(8.815)	(0.455)	(0.679)	(0.343)	(0.582)	(2.146)	(0.190)
ν	3.074***	3.077***	3.167***	3.170***	3.174***	3.179***	3.174***	3.182***	3.147***	3.141***	3.172***	3.187***	3.163***	3.106***
	(0.110)	(0.121)	(0.113)	(0.116)	(0.116)	(0.114)	(0.117)	(0.137)	(0.120)	(0.115)	(0.116)	(0.118)	(0.114)	(0.112)
AIC	14285.38	14284.03	14307.66	14307.22	14307.79	14307.80	14307.85	14308.32	14306.49	14305.95	14307.60	14304.92	14303.97	14283.41
BIC	14322.28	14320.93	14344.56	14344.12	14344.69	14344.71	14344.76	14345.23	14343.40	14342.85	14344.50	14341.82	14340.88	14320.32
LL	−7136.69	−7136.01	−7147.83	−7147.61	−7147.89	−7147.90	−7147.93	−7148.16	−7147.25	−7146.97	−7147.80	−7146.46	−7145.99	−7135.71
	Italy	**Japan**	**Mexico**	**Netherlands**	**New Zealand**	**Pakistan**	**Russia**	**Singapore**	**South Korea**	**Spain**	**Sweden**	**UK**	**US**	**Vietnam**
α	0.176***	0.177***	0.180***	0.181***	0.181***	0.186***	0.180***	0.177***	0.190***	0.175***	0.176***	0.176***	0.186***	0.177***
	(0.020)	(0.022)	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.022)	(0.026)	(0.020)	(0.023)	(0.018)	(0.023)	(0.020)
β	0.823***	0.822***	0.819***	0.818***	0.818***	0.813***	0.820***	0.822***	0.809***	0.824***	0.823***	0.823***	0.813***	0.822***
	(0.021)	(0.022)	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.022)	(0.026)	(0.020)	(0.022)	(0.018)	(0.023)	(0.020)
m	5.483***	5.814***	5.617***	6.311***	5.963***	6.390***	6.020***	6.026***	6.036***	5.929***	6.069***	6.332***	6.366***	5.979***
	(0.455)	(0.456)	(1.186)	(0.486)	(0.553)	(0.478)	(0.508)	(0.461)	(0.580)	(0.485)	(1.099)	(0.547)	(0.528)	(0.297)
θ	0.803*	0.488***	3.021	−2.488***	0.091	−1.311*	0.437	−0.716	−3.144*	−0.413*	−1.137	−6.587***	−2.083***	−0.408
	(0.435)	(0.173)	(2.419)	(0.842)	(0.261)	(0.791)	(0.312)	(0.799)	(1.685)	(0.235)	(1.994)	(0.670)	(0.763)	(0.371)
ω	1.003**	16.161***	1.346	1.076***	8.496***	1.025***	9.688***	1.001***	1.152***	5.095***	1.790***	1.432***	1.507***	4.277***
	(0.434)	(0.513)	(1.005)	(0.308)	(0.642)	(0.191)	(0.460)	(0.343)	(0.239)	(1.381)	(0.392)	(0.250)	(0.275)	(0.468)
ν	3.193***	3.157***	3.171***	3.144***	3.173***	3.143***	3.165***	3.172***	3.106***	3.183***	3.171***	3.103***	3.117***	3.186***
	(0.115)	(0.115)	(0.115)	(0.115)	(0.114)	(0.113)	(0.114)	(0.115)	(0.126)	(0.115)	(0.118)	(0.109)	(0.116)	(0.114)
AIC	14308.42	14298.49	14304.01	14299.08	14308.60	14304.21	14306.13	14307.09	14297.65	14306.36	14305.50	14276.52	14300.20	14306.75
BIC	14345.33	14335.39	14340.92	14335.99	14345.50	14341.11	14343.04	14344.00	14334.56	14343.27	14342.40	14313.43	14337.10	14343.65
LL	−7148.21	−7143.24	−7146.01	−7143.54	−7148.30	−7146.10	−7147.07	−7147.55	−7142.83	−7147.18	−7146.75	−7132.26	−7144.10	−7147.37

Notes: See notes in Table 3.

6. Conclusions

This paper applies the GM model to analyze the predictive power of EUI on Bitcoin volatility. Firstly, incorporating EUI into the GM model markedly improves its ability to explain Bitcoin volatility, demonstrating varying levels of effectiveness across different countries. Notably, EUI's influence on Bitcoin volatility is particularly significant when considering approximately 12 lags, indicating a delayed but pronounced impact. Secondly, while there is no evident leverage effect in Bitcoin returns, EUI exhibits an asymmetric impact on volatility. This means that the effects of positive and negative shocks are not equally distributed, highlighting the nuanced and complex role that EUI plays in volatility modeling. This asymmetry underscores the importance of including EUI in such models to capture the intricate dynamics of Bitcoin volatility more accurately. These findings suggest that EUI is a crucial variable for explaining the modeled volatility of Bitcoin.

However, our paper acknowledges certain limitations. First, constraints related to the availability of the EUI data prevented us from capturing the most recent situation to accurately reflect the current state of affairs. Additionally, variations in the sample periods could lead to different outcomes. Second, this study solely utilized GARCH-based models, which may not fully capture the non-linear relationships present in real-world data (Xu et al., 2024; Yu et al., 2024a). Future research should employ a broader range of methodologies to validate and expand upon our findings.

Looking ahead, there is substantial opportunity for both academic and practical advancements in studying low-frequency uncertainty indices. Specifically, the EUI deserves detailed investigation for its potential impact on a wide array of cryptocurrencies and digital assets. As index providers continue to expand their offerings, exploring these new indices is both timely and potentially groundbreaking. Additionally, while GARCH-based models are traditionally favored for volatility analysis, they have well-recognized limitations. Integrating cutting-edge technologies like deep learning and artificial intelligence into these models could significantly improve their robustness, precision, and accuracy (Kwok et al., 2024; Mehta et al., 2023). Such advancements promise to enhance financial analysis tools, aiding decision-making in an increasingly complex market environment.

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