International Journal of Energy Economics and Policy

ISSN: 2146-4553

available at http: www.econjournals.com

International Journal of Energy Economics and Policy, 2025, 15(5), 614-626.

Energy-Related Uncertainty and Crypto-Currency Environmental Attention: Time-Varying Perspective

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Received: 01 May 2025 **Accepted:** 02 August 2025 **DOI:** https://doi.org/10.32479/ijeep.20784

ABSTRACT

The article investigates the time-varying effects of cryptocurrency environmental attention on energy-related uncertainty, distinguishing itself from previous research that focuses on static relationships or disregards the time-varying nature of these interactions in the context of global financial and geopolitical events. A time-varying parameter vector autoregression (TVP-VAR) model is estimated based on global monthly data from February 2014 to October 2022. Geopolitical risk and financial stress are also utilized as control variables. The findings demonstrate that cryptocurrency environmental attention significantly negatively affects energy-related uncertainty in 2019. Additionally, financial stress exhibits a negative response to shocks in cryptocurrency environmental attention during the years 2015 and 2016. Geopolitical risk demonstrates a positive correlation with cryptocurrency environmental attention in 2021, with these relationships showing considerable variation across distinct time periods and global events. This article presents important information for policymakers regarding the regulation of cryptocurrency and energy markets. The results indicate that monitoring environmental factors in cryptocurrency markets may reduce energy-related uncertainties during stable conditions; however, this influence weakens in the face of global crises, including pandemics or geopolitical tensions.

Keywords: Cryptocurrency Environmental Attention, Energy-related Uncertainty, Time-Varying Analysis, Time-Varying Parameter Vector Autoregression, Geopolitical Risk, Financial Stress

JEL Classifications: Q4, G0, C331.

1. INTRODUCTION

The most prominent cryptocurrency so far has been Bitcoin since its establishment in 2009. It is a type of digital/virtual currency that utilizes cryptography for security and operates on decentralized networks constructed on blockchain technology (Nakamoto, 2008). Public agitation has been raised regarding the environmental impact of the rapidly growing cryptocurrency industry, which has seen the inception of thousands of cryptocurrencies like Ethereum, Ripple, and Litecoin, each with their own unique features and applications (Truby, 2018; Krause and Tolaymat, 2018; Veit and Thatcher, 2023). Bitcoin in particular is well-known for its energy-intensive mining process, which has sparked worries about its sustainability (Mora et al., 2018). This is because it consumes more than 65% of the energy needed by all cryptocurrencies (Gallersdörfer et al., 2020). Furthermore, the Proof-of-Work (PoW)-based mining procedures of energy-intensive cryptocurrencies have sparked discussions about sustainability, carbon emissions, and regulatory legislation (Ibañez and Freier, 2023).

In contrast, energy-related uncertainty (EU) describes the unpredictability and fluctuation in supply, demand, and market prices, among other characteristics of energy systems (Riaz et al., 2025). However, the rate at which technology is developing and energy supply efficiency is increasing might lead to uncertainties regarding performance and cost (Guta and Börner, 2017). Weather, economic activity, and consumer behavior are just a few of the many variables that affect energy consumption and are challenging to precisely estimate (EPA, 2016). Energy prices can be extremely variable and are impacted by the actions of market participants (Majidi et al., 2019). Energy planners and operators face additional uncertainty due to factors including fuel pricing, regulatory changes, and geopolitical events that can affect energy prices (Ioannou et al., 2019). To measure the economic impact of these energy price shocks, Dang et al. (2023) develop the EU index, adding 15 words upon the work of Afkhami et al. (2017), consisting of 87 words, by following the methodological protocol that was employed in the creation of the World Uncertainty Index (WUI) by Ahir et al. (2022).

Although there is an ongoing, extended interest among scholars as to whether cryptocurrencies possess economic secure-haven properties like gold during crises (Goodell and Goutte, 2021), the European Central Bank claims that different cryptocurrencies have a large carbon footprint and use almost the same amount of energy annually as individual nations like Austria, the Netherlands, or Spain (Gschossmann et al., 2022). However, the Financial Stability Board (FSB) emphasizes that since these assets are susceptible to the climate policies of various jurisdictions, growing financial exposures to these crypto-assets are anticipated to enhance the financial system's transition risk (FSB, 2022). Despite, merely 0.5% of global cashless transactions conducted in cryptocurrencies, their corresponding electricity consumption reached an outstanding 236 terawatt hours (TWh) in 2021, surpassing that of the conventional transaction system. Additionally, mining activities related to cryptocurrencies are estimated to contribute to massive 139 megatons (Mt) of carbon dioxide equivalent of global GHG emissions, or roughly 0.4% of the global energy-caused carbon emissions in 2021 (IEA, 2022). According to Siddik et al. (2023), although cryptocurrencies only make up a small portion of financial transactions, they have a far greater environmental impact than the traditional financial transaction system.

The present study aims to improve the current body of literature in three distinct ways. First, to the best of our knowledge, this is the first study to analyze the time-varying effects of cryptocurrency environmental attention on energy-related uncertainty. Second, the time-varying nature of the relationship between cryptocurrency environmental attention and energy-related uncertainty was disregarded in previous studies, hence this paper employs a time-varying parameter vector autoregression (TVP-VAR) model to capture the variation in the linkages between cryptocurrency environmental concerns and energy market uncertainties to address this critical gap in literature. Third, this paper also investigates the influence of geopolitical risk and financial stress using text-based indices to propose a more detailed comprehension of the ways in which cryptocurrency environmental attention affects these variables. Our results are crucial for policymakers, as they contribute to the ongoing discussion regarding the environmental impact of digital currencies and inform strategies for environmentally friendly energy management.

The rest of the manuscript is shaped as follows: The second section represents the literature review; the third section provides the definition for data and methodology; the fourth section contains the empirical findings; and the fifth section concludes.

2. LITERATURE REVIEW

The awareness of examining environmental attention in crypto-mining on uncertainties of energy is increasing in literature. Even though there is no study to examine the impact of cryptocurrency environmental attention index (ICEA) on energy uncertainty in the current literature, the theoretical linkage is based on the composites of both variables. ICEA is constructed by Wang et al. (2022) through a text-based approach applying key words such as "cryptocurrency" or "bitcoin" or "Ethereum") and atl1 ("energy" or "energy consumption" or "energy footprint" or "carbon footprint" or "environment" or "environmental" or "environmental impact" or "climate change." On the other hand, EU index is a composite index consisting of various energy variables with text-based approach (Dang et al., 2023). The composites of EU index include energy-related key words, including "clean energy," "crude oil," "renewable energy" and "photovoltaics." Therefore, studies assessing the impact of keywords of ICEA on keywords of the EU index serve as a reference to the theoretical background. More precisely, Wang et al. (2022) examine the impact of ICEA on Brent crude oil (BCO) and find the ICEA shocks can increase the BCO index, meaning an increase in EU. Hassan et al. (2024) explore the dynamic association between ICEA and the clean energy index, which is one of the composites of the EU index. They find that ICEA positively influences the clean energy index, postulating a decline in energy-related uncertainty. Dogan et al. (2022) also argue that the growing use of solar energy in Bitcoin mining can bring sellers and buyers together, reducing transmission and energy distribution. Following them, Mustafa et al. (2024) claim that modernization of Bitcoin mining by adopting renewable energy sources can marginally contribute towards achieving affordable and clean energy goals by cutting the conventional considerable energy consumption and carbon emissions of mining procedures. Będowska-Sójka and Kliber (2024) examine ICEA's influence on dirty and clean cryptocurrency prices. They find that a rise in ICEA elevates the risk of funds flowing towards dirty cryptocurrencies, suggesting that investors of such currencies have to expose themselves to consequential risks related to the energy-overconsumption.

Another strand of the literature examines the effect of climate variables on energy variables. Especially, Njangang et al. (2024) explore the impact of the Global Climate Finance Fund (GCFF) on energy vulnerability among 74 developing countries. Their results confirm that GCFF lowers energy vulnerability. Admittedly, energy vulnerability is another form of energy uncertainty and any climate actions taken in crypto-mining can serve to reduce uncertainties in energy. Similarly, Lee and Fang (2025) analyse GCFF's impact on energy security, and find that former significantly as well as positively affects the latter. Energy security is a contrary to energy uncertainty, thus positive relation from climate action to energy security, might be linked as an existence of negative linkage from ICEA to EU. Borojo et al. (2024) explore the heterogeneous impacts of GCFF on energy efficiency, and find that GCFF's positively contributes to energy efficiency across all quantiles. Since energy efficiency mitigates energy-related uncertainties, climate action in crypto-mining impacts and reduces energy-related uncertainties.

Recent literature has enhanced the understanding of the correlation between ICEA and various financial and environmental metrics; however, substantial gaps remain in our comprehension of their dynamic effects on the EU. Investigations have explored the correlations between global geopolitical risks (GPR) and energy uncertainty (Yilmazkuday, 2024), in addition to the connections between cryptocurrency environmental awareness and green assets (Patel et al., 2024; Kamal and Hassan, 2022). The impact of cryptocurrency environmental awareness on the EU, especially concerning its temporal fluctuations, remains unexamined. This study addresses a critical deficiency by employing the TVP-VAR model, which offers numerous advantages over its linear counterparts. Our methodology builds on the recent significant development of text-based indices, including ICEA (Wang et al., 2022) and the EU index (Dang et al., 2023). It also broadens their use to accurately capture dynamic relationships. Adding GPR and financial stress index (FSI) as control variables helps us better understand how cryptocurrency environmental issues affect energy market uncertainty in different times and market conditions. This approach is very important because cryptocurrency mining is becoming an increasing portion of global energy use and has negative effects on the environment (Gschossmann et al., 2022; IEA, 2022). At the same time, governments are becoming more stringent in response to these problems (Smith, 2024; Cheng, 2024).

3. THEORETICAL BACKGROUND

Behavioral finance theory is adopted as a lens to consider the interrelationship between the researched variables. As it is a multidisciplinary domain of science that explores—mixing components of economics with psychology—how subjects come to financial decisions (Statman, 2008; Gao, 2023). Tversky and Kahneman (1974; 1979) are the scientists who lay the foundation for this theoretical framework via analyzing people's reliance on heuristics (mental shortcuts) under uncertainty decision-making, resulting in biased financial choices, and introduce prospect theory—that describes the ways by which people assess potential losses and gains asymmetrically under risk. These frameworks help to explain market anomalies, such as speculative bubbles and overreactions to news, by showing that investors are not always rational. In contrast, the standard finance or modern portfolio theory posits that investors are rational financial decision makers for whom the substance of wealth dominates over its form (Miller and Modigliani, 1961). Statman (2008; 2014) takes a broader approach by examining how investors behave in real-world financial markets, emphasizing the role of emotions, cognitive biases, and social factors in shaping investment choices, referring to people as normal—neither fully rational nor irrational—that have utilitarian, expressive, and emotional motivations. Therefore, he replaces the following traditional finance assumptions with behavioral alternatives:

- Normal investors instead of rational ones;
- Behavioural portfolio theory instead of mean-variance portfolio theory;
- Behavioural asset pricing models instead of models solely based on risk;
- Markets are hard to beat rather than strictly efficient.

One important consideration is identifying which cognitive biases or heuristics are most relevant to investor reactions when confronted with cryptocurrency developments and environmental news. Via structural equation modeling, recent empirical literature confirms that biases of price anchoring, availability, loss aversion, overconfidence, and representativeness impact risk perception, thereby impacting financial decision-making processes, respectively (Ahmad et al., 2025). While availability bias describes an investor's inclination to depend on easily accessible information—neglecting to consider alternative options or conduct further investigation (Tversky and Kahneman, 1973; Folkes, 1988). In terms, anchoring refers to a cognitive bias in which individuals place disproportionate weight on particular pieces of information—such as daily market returns, trading volumes, or recent news—when making financial decisions (Campbell and Sharpe, 2009). This tendency can significantly influence judgment, as initial data points often serve as mental reference anchors, shaping subsequent evaluations and choices in investment contexts. Loss aversion bias, stemming from the prospect theory, postulates gains do not evoke the same level of emotional response as losses, which are typically experienced more intensely by individuals (Kahneman and Tversky, 1979). Representative bias causes an overreaction to purchase assets that are reputable and to keep away from those that have prior weak yield results (De Bondt and Thaler, 1995). Finally, overconfidence bias leads investors to overestimate their skills and knowledge in financial decision-making, often resulting in excessive risk-taking and misjudgments (Kartini and Nahda, 2021).

The lens of behavioral finance offers a comprehensive framework for understanding cryptocurrency markets and energy dynamics due to irrational behaviors of investors such as overreaction and herd behavior. Cryptocurrency investors often behave irrationally, mimicking the actions of others without relying on their own convictions. Moreover, during upward market trends, the dispersion in market behavior tends to react more swiftly than it does during downward movements (Ballis and Drakos, 2020; Choi et al., 2022). During the time of the uncertainty raised by the COVID-19 crisis as well as the Russian-Ukrainian conflict, herding behavior among crypto-asset investors was present, suggesting that investors were irrational (Rubbaniy et al., 2021; Evrim Mandaci and Cagli, 2022; Theiri, 2025). Additionally, traders often displayed addictive and overly reactive tendencies, engaging in compulsive trading despite potential financial losses. Social media played a significant role in shaping these behaviors by promoting herd mentality and driving impulsive decisions in response to trending market narratives (Badlani et al., 2023; Jain et al., 2025).

Environmental concerns generated by extensive energy usage of cryptocurrencies become salient as a result of behavioral triggers like media framing or public discourse. For instance, the media coverage of nuclear energy in China and biogas in Finland portrays how positive framing can promote renewable energy transition (Lyytimäki et al., 2018; Du and Han, 2020). Therefore, the introduction of the ICEA by Wang et al. (2022) allows capturing media attention surrounding the carbon footprint and/or energy consumption of Bitcoin, Ethereum, and others (Mora et al., 2018; Stoll et al., 2019; Gallersdörfer et al., 2020). The recent empirical findings provide that this attention, coupled with actual energy consumption data, has its effect on cryptocurrency market volatility as well as economic activities, indicating that media attention can influence market behavior and public concern (Yousaf et al., 2024; Ghazouani et al., 2024).

Evidently, investigating through the behavioral lens—the ICEA negatively correlates with the EU—by channels of encouraging green energy investments, enhancing regulatory clarity, and information dissemination. Elevated ICEA drives the crypto-mining toward cleaner energy sources while fostering both green energy investments and production volumes (Qing et al., 2025). More transparent regulations, such as mandates for renewable energy use in mining or limits on carbon emissions, can also stem from high ICEA, which in turn is capable of reducing energy uncertainty, a significant driver of energy market volatility (Ivanovski and Marinucci, 2021; Pata, 2024). Moreover, it may also lead to a herding attitude towards the adoption of sustainable practices by crypto companies or investing in crypto miners consuming renewable energy. This collective transition can align crypto energy demand with stable as well as carbon-neutral energy sources, which reduces volatility and uncertainty in energy markets (Zhao et al., 2022; Chen and Nguyen, 2024). Lastly, it can bring a more transparent crypto atmosphere through information dissemination—making investors better informed to make financial choices—which possibly can lower the EU (Mankala et al., 2023; Gemayel and Preda, 2024). Andrei et al. (2023) additionally reveal that during times of elevated economic uncertainty, investors pay more attention to news and information releases, a circumstance that favorably impacts asset prices. Respectively, the below hypothesis is intended to be investigated within the current work:

H_1: The ICEA negatively impacts the EU.

Regarding control variables, GPR and FSI are affected negatively by the shocks that occur in ICEA, following the same behavioral theoretical principles. Geopolitical circumstances are always openly and globally highlighted in the media, which may impact the risk premium required by investors on top of demand and supply controversies of energy resources. For instance, GPR acts saliently as a reason for both oil price volatility and stock market volatility, while a moderate degree of interconnectedness among geopolitical events, risks, and energy markets has been uncovered (Smales, 2021; Elsayed et al., 2025). Similarly, FSI has a positive and significant effect on EU, proving the theoretical linkage between FSI and energy market volatility, while in the USA, uncertainty shocks have recessionary effects at all times (Alessandri and Mumtaz, 2019; Khodjaniyazov et al., 2025). However, the spillover dynamics between FSI and cryptocurrencies show considerable variation depending on market volatility levels. Under extreme volatility, empirical evidence indicates that cryptocurrencies and commodities primarily act as net recipients of shocks, whereas FSI functions as a net transmitter. Additionally, studies highlight that the strength of correlation between these assets fluctuates over time, with both strong and weak linkages observed in the short and long run, particularly during brief time intervals (Khan et al., 2025). Thereby, the following hypotheses are posited:

H_2: GPR negatively responds to shocks in ICEA;

H_3: FSI negatively reacts to spikes in ICEA.

4. DATA AND METHODOLOGY

4.1. Data

This study employs monthly data from January 2000 to October 2022. The estimation sample is dictated by the availability of energy-related uncertainty variables. In the estimation of the VAR models, the following vector of endogenous variables Y_t is utilized:[1]

$$Y_t^{'} = [ICEA_t \; GPR_t \; FSI_t \; EU_t] \quad (1)$$

The core variable of the model is an index of ICEA, denoted by $ICEA_t$. This index is calculated by Wang et al. (2022)[2]. The index of GPR, developed by Caldara and Iacoviello (2022)[3], is another important variable in the model. Wang et al. (2022) also use global ecouncertainty,y uncertainty which can be proxied as GPR, aa negativefind negative response of global economic policy uncertainty to the shocks of ICEA. Bampinas and Panagiotidis (2024) find that during the GPR; cryptocurrency markets possess limited diversification. Yousaf et al. (2025) also use GPR as a mediating variable when investigating the impact of ICEA on cryptocurrency energy consumption. Furthermore, the FSI,

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1 The order of endogenous variables in the VAR model is designed according to the main objective of the study and previous literature. ICEA is ordered as the first variable as it is the primary variable of interest. Prior studies (Wang et al., 2022) highlight the impact of cryptocurrency market on GPR, FSI, and EU. GPR is ordered before the FSI, as the evidence indicate that geopolitical shocks may lead to financial instabilities, especially in emerging economies (Wang et al., 2024; NguyenHuu and Örsal, 2024). The studies also show that GPR_t has a significant impact on EU_t by surging volatility in the energy market (Qin and Zhang, 2024; Khan et al., 2023). FSI is placed before EU as an increase financial stress might affect energy markets through investment channels. Conversely, some studies evidence that the decline in financial stress leads to an increase in clean energy stocks returns (Dong and Huang, 2023) and mitigates systemic risks in renewable energy (Reboredo, 2014).

2 The ICEA data obtained from: https://www.emerald.com/insight/content/doi/10.1108/CFRI-09-2021-0191/full/html

3 The GPR in a monthly frequency is obtained from: https://www.matteoiacoviello.com/gpr_files/data_gpr_export.xls

developed by Office of Financial Research, denoted as FSI, is utilized[4]. Even though response of FSI to ICEA shock is not explored, the study by Wang et al. (2022) supports the linkage. More precisely, index, employ VIX index representing financial price uncertainty, similarly with FSI, being affected by ICEA shock. Arslan-Ayaydin and Thewissen (2016) also use VIX in their study, and their findings reveal that markets do not depict a favourable attitude towards the environmental concerns of companies within the energy sector. Finally, the EU index, developed by Dang et al. (2023)[5] is employed whose response to ICEA shock is imperative regarding the research objective of the study, and the theoretical linkage with ICEA is supported by literature review more comprehensively. Natural log transformation is applied to all variables except FSI, as this variable contains negative values over the estimation period. Descriptive statistics and graphs of the variables are presented in Table 1 and Figure 1.

Prior to the VAR analysis, unit root tests, including the Augmented Dickey-Fuller (ADF) and KPSS tests, are implemented to determine integration levels of the variables. Furthermore, given the visual inspection of the variables illustrated in Figure 1, the ADF breakpoint test is also conducted because of the clear structural breaks and regime shifts in the time series. It is worth mentioning that the ICEA variable has a significant shift in level after 2021, due to outstanding crypto market cap rise of 187.5%. While Bitcoin was able to earn just 59.8%, many of the other top coins resulted in four- and even five-digit percentage returns, consequently, giving a rise in environmental concerns related to the sector (WEF, 2022).

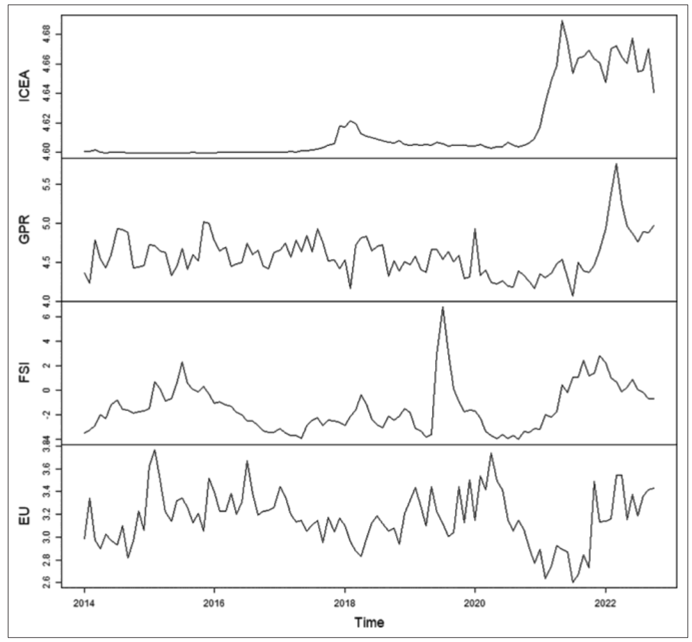
Regarding ICEA, the linear ADF result rejects the null hypothesis of unit root, but the variable becomes stationary after taking the first difference (Table 2). Furthermore, Kwiatkowski-Phillips-Schmidt-Shin statistics remain below the 1% critical value, providing evidence in favor of stationarity. However, the ADF breakpoint test rejects the null hypothesis of unit root, implying that the variable can be treated as I(0) if the shift in the level of the variable leading to structural break is explicitly considered. The breakpoint dated in the beginning of 2021 seems to be associated with the elevated state of public concern in response to enormous energy consumption of crypto assets market that reached USD 3tn in late 2021 (OECD, 2022).

As for the remaining variables, the results corroborate the stationarity of all variables in their levels. Both ADF and KPSS statistics find GPR to be stationary. The ADF breakpoint test also suggests stationarity with a significant structural break in the data by the end of 2021, associated with the escalation of the Russia-Ukraine conflict. FSI similarly exhibits stationarity through significant ADF, KPSS, and ADF breakpoint tests. Finally, unit root tests also evidenced the stationarity of EU. The significance of the structural break dated to April 2020 can be attributed to the disruptions in global energy markets resulting from COVID-19. These lockdown measures implemented in this period led to a significant decline in global economic activity, resulting in a substantial decline in world energy demand.

Table 1: Descriptive statistics

	ICEA	GPR	FSI	EU
Mean	4.615	4.584	−1.463	3.171
Median	4.604	4.537	−1.804	3.150
Maximum	4.690	5.765	6.806	3.767
Minimum	4.600	4.068	−4.010	2.603
Standard deviation	0.024	0.267	1.942	0.238
Skewness	1.590	1.115	1.165	0.074
Kurtosis	3.970	5.852	4.983	2.851

Figure 1: Data



In general, the evidence collected from the unit root test indicates that the variables should be employed in the VAR estimation in their level form. Furthermore, the presence of significant structural breaks indicates that constant parameter specifications might not be convenient for the analysis of the link between the cryptocurrency market and energy uncertainty.

4.2. Methodology

To examine the relationship between ICEA and EU, this article utilizes the time-varying impulse responses based on the estimation of the TVP-VAR model.

For this purpose, we first start with the linear VAR representation of the model that can be specified as follows:

$$Y_t = B_0 + B_1 Y_{t-1} + \cdots + B_p Y_{t-p} + \varepsilon_t,\ t = 1,2,\ldots,T \quad (2)$$

Where Y_t is the previously defined vector of endogenous variables at time t. B_0 signifies the constants, B_i represent time-invariant parameter matrices, and ε is a vector containing residuals of each equation. ε_t is presumed to be satisfying the white noise assumptions of white noise with time-invariant variance-covariance matrix Σ.

4 The FSI is downloaded, in a daily frequency and converted into monthly, from: https://www.financialresearch.gov/financial-stress-index/

5 The EU index is accessed through: https://www.policyuncertainty.com/media/Energy-Related%20Uncertainty%20Indexes.xlsx

The constant parameter specification of the linear VAR might not be a convenient modelling approach given the presence of structural breaks and regime shifts leading to the time-varying nature of the relationship among the variables. Some nonlinear VAR methodologies, e.g., threshold VAR, smooth transition VAR, or MS-VAR, might deal with particular types of nonlinearities. However, they require a priori assumption regarding the identification of regimes. In this context, the TVP-VAR proposes a data-driven, time-varying alternative to track gradual or abrupt changes in the relationships among variables.

This paper uses the TVP-VAR model based on the nonparametric estimation of parameters. This model allows smooth variation of parameters as a function of time. The model can be specified as follows (Casas and Fernandez-Casal 2019):

$$Y_t = A_{0,t} + A_{1,t}\, Y_{t-1} + \cdots + A_{p,t}\, Y_{t-p} + \varepsilon_t,\ t = 1,\ldots,T \quad (3)$$

Apart from the linear VAR, it is observed that $A_{i,t}$ coefficient matrix is assumed to evolve over time. Similar to linear VAR, ε_t signifies the vector of residuals but its variance covariance matrix Σ_t is also function of time.

Following Casas and Fernandez-Casal (2019), the time-varying parameters are estimated nonparametric kernel smoothing technique. The use of this technique has important advantages over the alternatives. First, unlike the Bayesian methodologies employed by Primiceri (2005) and Cogley and Sargent (2005), the prior distribution of the coefficients is not required. Furthermore, in contrast with the Bayesian approach, allowing for the variation in the parameters based on the random walk process, this technique does not impose priori assumptions about the variation of coefficients', permitting it to adapt flexibly to complex or unknown data-generating processes (Fan, 2018, Robinson, 1989).

Specifically, the coefficients are locally estimated by using weighted least squares (WLS). The weights are determined by a kernel function. The following function is minimized in the WLS estimation (Ruppert and Wand, 1994):

$$\sum_{s=1}^{T}\left\{ Y_s - B_0(z) - B_1(z)Y_{s-1} - \cdot - B_p(z)Y_{s-p}\right\}^2 K_b(z_s - z) \quad (4)$$

In the above equation z denotes rescaled time calculated as z = t/T. $K_b(\cdot)$) is a kernel function with bandwidth b, and $B_0(z),\ldots,B_p(z)$ are the local approximations to the time-varying coefficients at point z. The kernel weights ensure that observations closer in time to t exert more influence on the local estimates, allowing the coefficients to adapt flexibly to local dynamics.

After the estimation of the TVP-VAR time-varying impulse response functions should be computed. For this purpose, the model is converted into time-varying moving average form via Wold decomposition as:

$$Y_t = \sum_{j=0}^{\infty} \Theta_{j,t} U_{t-j} \quad (5)$$

Where $\Phi_{0,t} = I$ is the identity matrix and the $\Phi_{j,t}$ matrices are derived recursively from the time-varying coefficient matrices as follows:

$$\Theta_{j,t} = \sum_{k=1}^{j} \Theta_{j-k,t} B_{k,t}, \circ j = 1, 2, \ldots \quad (6)$$

The time-varying impulse response functions are computed by tracing the effect of a one-unit shock in one variable on the current and future values of all variables, conditional on the system's state at time t. To obtain orthogonalized responses, the time-varying variance-covariance matrix (Σ_t) is decomposed through Cholesky decomposition at each time point, yielding a lower triangular matrix P_t such that . The orthogonalized impulse responses are formulated by:

$$\Psi_{h,t} = \Phi_{h,t} P_t \quad (7)$$

Where ($\Psi_{h,t}$) measures the response at horizon h to a one-unit orthogonalized shock at time t.

5. EMPIRICAL RESULTS

This section presents the results of the TVP-VAR analysis to analyze the impact of ICEA. Before proceeding to TVP-VAR, the constant parameter VAR model is estimated to examine the reaction of the variables to ICEA shocks in a linear context.

Figure 2 illustrates the linear accumulated responses of GPR, FSI and the EU indexes to the one standard deviation shocks in ICEA. The positive shocks to the ICEA have a significant and positive impact on GPR. Although, directly aligning or contradicting findings have not been yet uncovered by specialists in the field, several studies have been conducted with respect to the similar variables in question. For example, Yousaf et al. (2025) reveal that at in the context of higher crypto prices and GPR price fluctuations

Figure 2: Linear responses to impact of cryptocurrency environmental attention index shocks

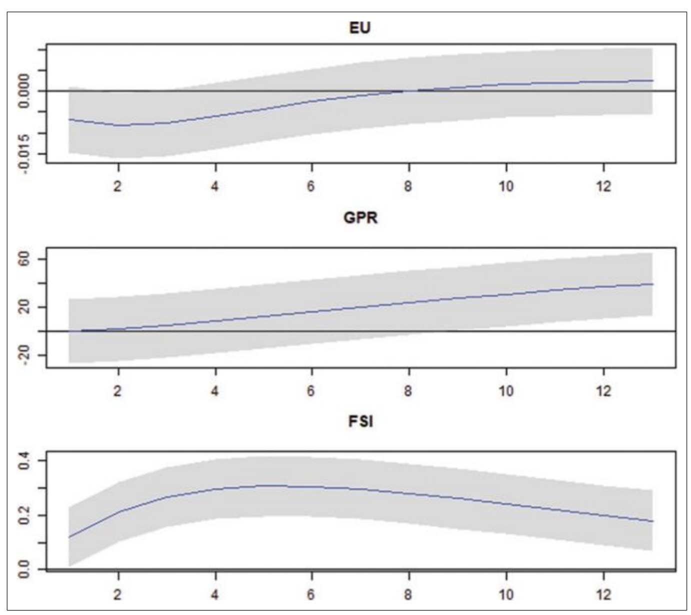


Figure 3: Stability test

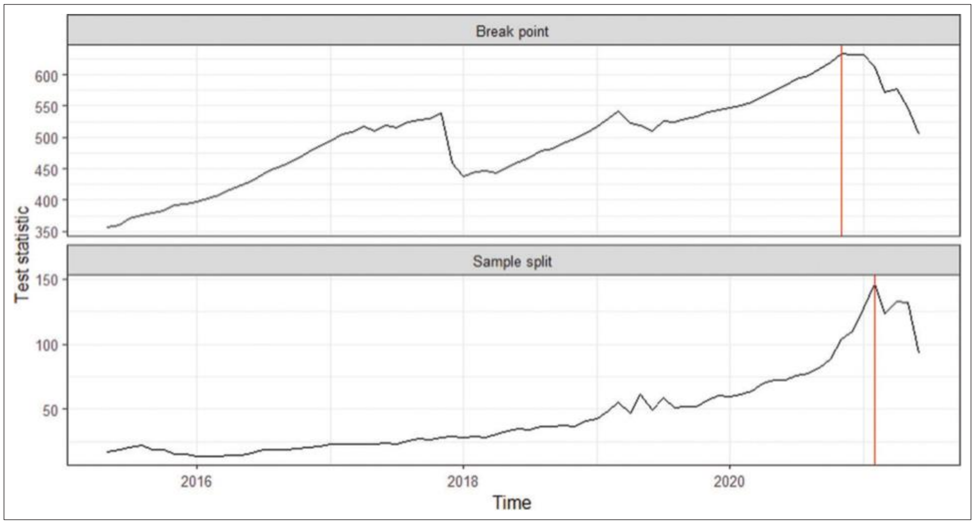
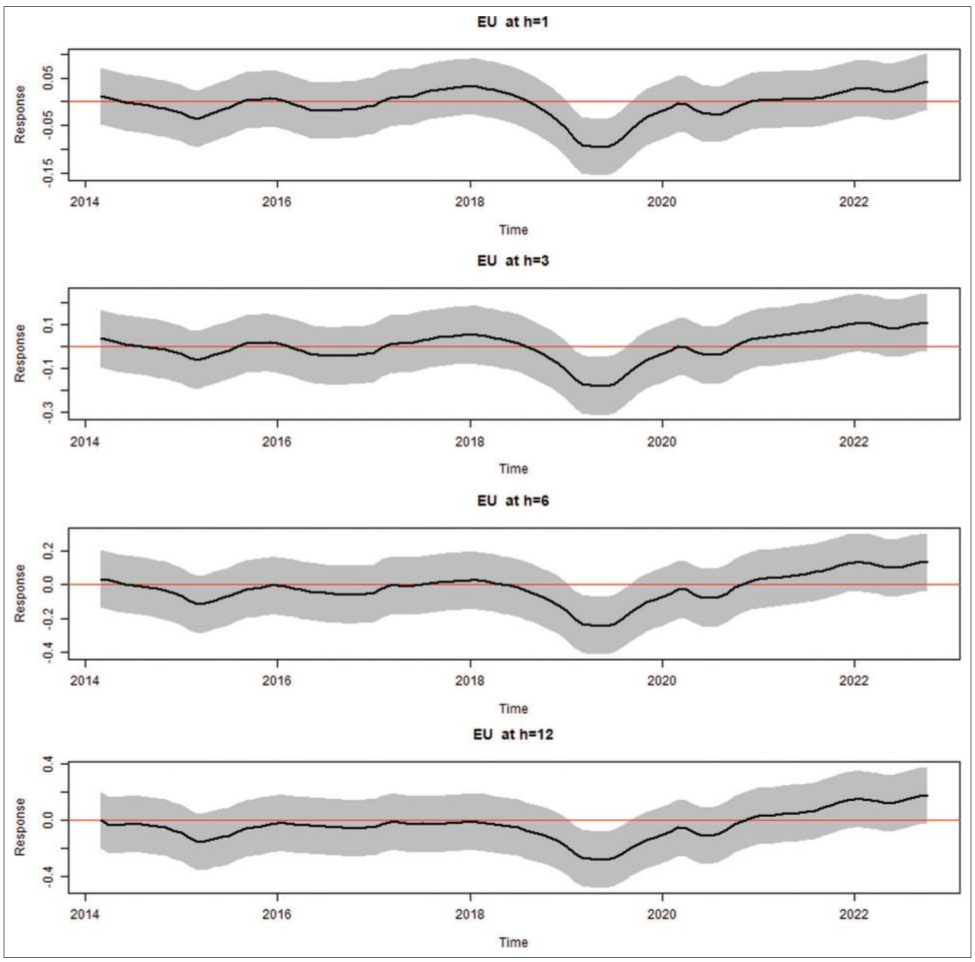


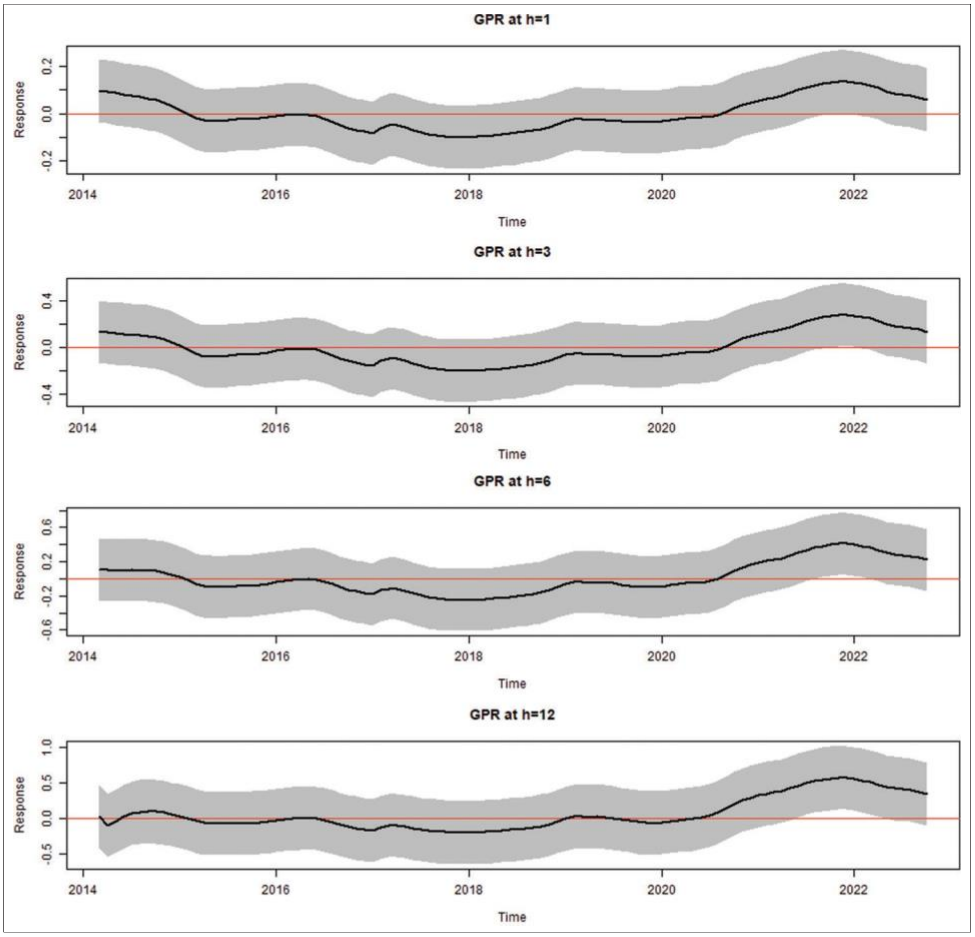
Figure 4: Time-varying responses of energy-related uncertainty to impact of cryptocurrency environmental attention index



considerably impact both the mining and its corresponding environmental impact. While, Kamal and Wahlstrøm (2023) show that the Russia-Ukraine war escalation hurt cryptocurrency liquidity and returns.

The impact of ICEA shocks is found to be also positive on the FSI and the EU indexes. These findings align with that of Wang et al. (2022) who indicate that ICEA has a significantly positive connection with the cryptocurrency uncertainty indices, volatility index, Brent crude oil and Bitcoin prices that are associated with FSI. Additionally, it collaborates with Dong et al. (2024) who suggest that Bitcoin carbon footprint have a strong negative relationship with the uncertainties in economy and climate, energy and finance. Similarly, with Haq (2022) that numerous financial

Figure 5: Time-varying responses of geopolitical risks to impact of cryptocurrency environmental attention index



indices' returns have persistent positive co-movement with all the explored crypto uncertainty or attention indices in the medium-term, indicating time-varying response.

Figure 3 illustrates the results of multivariate Chow breakpoint and sample split tests used to examine VAR parameter stability. The recursively estimated F-statistics presented in the figure provide strong evidence for the existence of structural breaks over time, particularly around 2020-2021. The maximum value of the test statistics marked with the red line at that time seems to be associated with the COVID-19 pandemic, which led to significant structural changes in the linear VAR. This evidence corroborates the use of nonlinear specifications such as TVP-VAR to capture the evolving dynamics between ICEA and EU.

Upon verification of nonlinearity, the TVP-VAR model is estimated to assess the effects of ICEA on GPR, FSI, and EU.[6] Recent studies highlight that constant parameter specifications might not reflect the underlying relationship between uncertainties and stock and commodity markets, especially during periods of high uncertainties (Helmi et al., 2023; Bouteska et al., 2023).

After estimating the model using the nonparametric kernel function described above, the time-varying impulse responses are computed using Equation (7). The responses of EU, GPR and FSI are reported from Figures 4-6. Figures include time series plot of the accumulated time-varying impulse-responses at the horizons $h = 1, 3, 6, 12$ months. The responses are plotted with their 95% confidence intervals represented by the shaded areas to evaluate their significance throughout the analysis period.

The results indicate that the response of the variables to ICEA shocks is not time-invariant and is significantly influenced by global events. The time-varying responses of EU to ICEA are presented in Figure 4. The time-varying responses demonstrate significant fluctuations. Accepting the H_1—in accordance with behavioral finance—significant and negative response is observed during 2019, when several significant global events occurred in the cryptocurrency market. For instance, China turns its attention to blockchain technology, which caused the BTC-USD exchange rate to rise from $7,500 to over $10,000 in a single day due to Xi Jinping's statements. Meanwhile, Trump's words raised concerns that the US president might issue an executive order banning Bitcoin (Interdax, 2021). This means that Bitcoin energy consumption also responds correspondingly as Bitcoin prices Granger-cause electricity consumption (Sapra et al., 2024). This is in line with the heightened ICEA, which started increasing after the mid of 2017 (Figure 1). However, even during the period 2020-2022 the EU is not affected by the ICEA. This might be because of various reasons including disruptions in global energy markets caused by COVID-19, which entailed reduced industrial

6 R tvReg package developed by Casas and Fernandez-Casal (2019) is utilized in the estimation of TVP-VAR.

activity and volatile energy demand overshadowing ICEA's impact on EU (Ha, 2022; Sharif et al., 2024). In addition, during this period governments were focused on responding to pandemic and recovering their economy, postponing significant policy actions on cryptocurrency environmental issues.

The time-varying responses of GPR to the ICEA are shown in Figure 5. The signs of the responses vary over time, but they are insignificant in the majority of the analysis period, implying environmental concerns related to cryptocurrencies had not yet diffuse with the geopolitical sphere. But it is observed that the responses become positive and statistically significant after 2021, particularly at the h = 12 forecasting horizon. Consequently, the H_2 is rejected as the opposite is proven to be partly true in case of GPR. The turning point viably coincides with key global events, such as several countries' including the major China's crackdown on crypto mining due to environmental concerns and the broader international emphasis on sustainability and energy transitions (Cheng, 2024; Smith, 2024).

Table 2: Unit root analysis

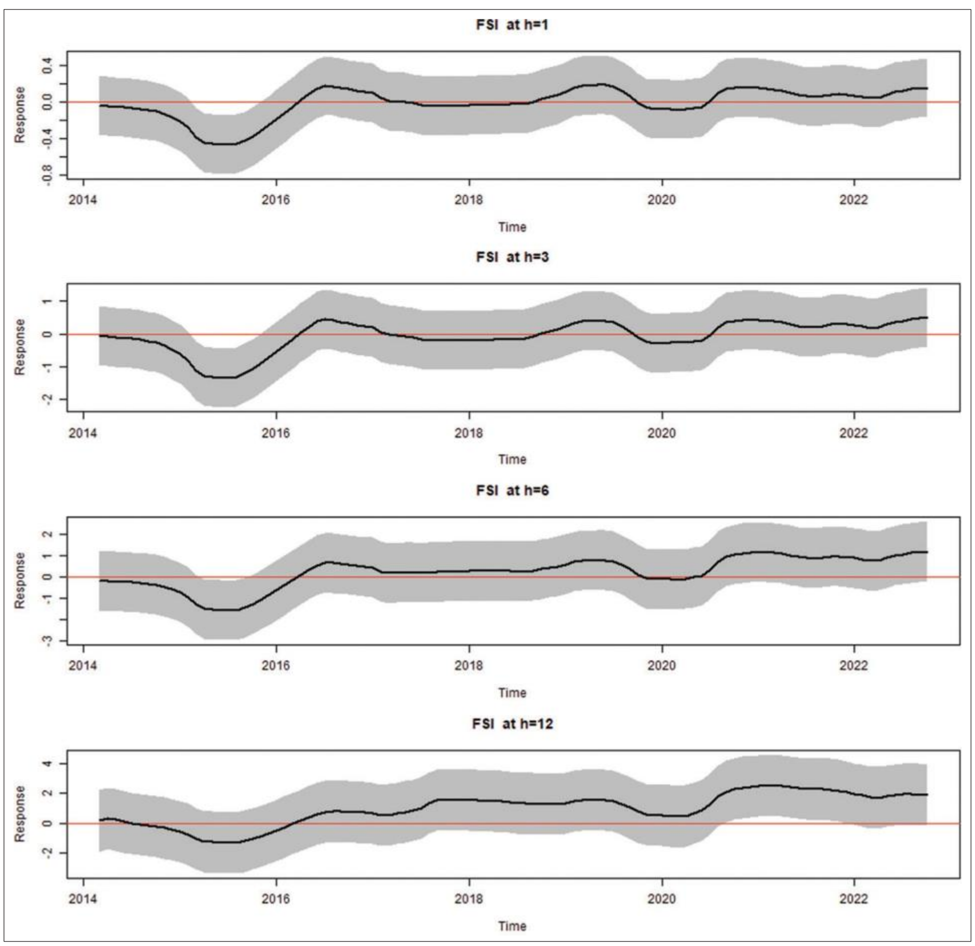
	ADF			
	ICEA	GPR	FSI	EU
Level	−1.432	−4.460***	−3.045**	−5.424***
First difference	−10.603***	-	-	-
	KPSS			
	ICEA	GPR	FSI	EU
Level	0.202	0.124	0.114	0.057
First difference	-	-	-	-
	ADF breakpoint			
	ICEA	GPR	FSI	EU
Level	−7.338***	−7.047***	−4.984***	−6.014***
Breakpoint	2021: 01	2021: 12	2021: 03	2020: 04
First difference	-	-	-	-

(**) significant at the 5%; (***) significant at the 1%. Asymptotic critical values for the KPPS unit root test are 0.216, 0.146 and 0.119 for 1%, 5% 10% respectively

Additionally, they become significant in 2021 when the Russian escalation of Ukraine started, leading to heightened concerns over the role of cryptocurrencies in bypassing sanctions, supporting war efforts, thus contributing to geopolitical tensions exacerbated by herding behavior of crypto investors (Rubbaniy et al., 2021; Evrim Mandaci and Cagli, 2022; Theiri, 2025). During this period the cryptocurrency community responds to criticism of high energy consumption with initiatives like Ethereum's sustainability upgrades (Ethereum, 2024), the Crypto Climate Accord (CCA, 2021), and the Bitcoin Mining Council (BMC, 2021), which encourage transparency and renewable energy use, as institutional and public attention to the environmental impact of cryptocurrencies increases (Arora et al., 2025).

The time-varying responses of FSI to ICEA are illustrated in Figure 6. The response of FSI to ICEA shocks varies across time

Figure 6: Time-varying responses of financial stress index to impact of cryptocurrency environmental attention index



and forecasting horizons h. The response of FSI is negative and significant between 2015 and 2016 at the earlier forecast horizons h = 1, 3, and 6, which aligns with H_3 of behavioural finance notions. This adverse effect might be linked with a 2015 cyberattack, when users who kept bitcoins at a well-known exchange have been informed that they will lose 36% of their assets (Baraniuk, 2016) and China's yuan devaluation causing stock markets of the U.S., Europe, and Latin America to fell in 2015 (Inman and Farrer, 2017). But it is not found to be statistically significant for the remaining analysis period. However, at h = 12 after 2021 the impact of ICEA on FSI turns into positive and significant. This might be attributed to the introduction of more environmental cryptocurrencies, Facebook's new cryptocurrency Libra, which has a lower environmental impact than some of its well-known blockchain siblings, such as Bitcoin (Griggs, 2019).

6. CONCLUSION AND POLICY IMPLICATIONS

This study explores the impact of cryptocurrency environmental attention on energy-related uncertainty and considers geopolitical risk and financial stress as control variables in the variable system of the TVP-VAR model. The results shed light on existing literature. The time-varying responses indicate notable fluctuations in the variables' reactions over time. Our findings reveal that the response of energy-related uncertainty to the shocks of cryptocurrency environmental attention is negative and significant in 2019. Moreover, the response of geopolitical risk to crypto-currency environmental attention shock is significantly positive in 2021. Furthermore, the negative response of financial stress to the cryptocurrency environmental attention shock is significant in 2015 and 2016, whereas positive and significant response is observed in 2021. Significant impacts of cryptocurrency environmental attention on the energy-related uncertainty, geopolitical risk and financial stress are observed mostly in the later periods of the data. This is because the fluctuations of cryptocurrency environmental attention start after 2017 (Figure 1). However, not all variables significantly response to the shocks occurred in cryptocurrency environmental attention during the COVID-19 pandemic and Russo-Ukrainian War.

The negative impact of cryptocurrency environmental attention on the energy-related uncertainty obtained by the estimations is in line with the behavioral finance theory. More precisely, climate actions including crypto-mining lead to coping with energy issues thus reduce uncertainties. In the context of fighting against climate change crypto-mining, energy-saving and energy-efficient technologies and regulations are implemented. Moreover, energy-wasting actions and using fossil fuels are discouraged by the government regulations. Consequently, crypto-mining shifts to renewable sources and energy-saving technologies in order to reduce their costs associated with crypto-mining. As a result, uncertainties related to energy will be mitigated since the fossil fuel dependence is reduced. The reason for the significant and negative effect is more pronounced in 2019 before the COVID and Russo-Ukrainian War that during such kind of global crisis coping with energy demand and coping with climate change becomes tough. Therefore, investing in renewable energy, especially in crypto-mining is more common during the periods without shocks in energy markets. During tough times, climate actions are slowed down. Therefore, the significant and negative effect is highlighted before those events.

Our findings serve as a valuable guide for policymakers in the field of cryptocurrency and energy. Since the results show that cryptocurrency environmental attention impact on energy-related uncertainty negatively, and especially during the periods when no global pandemic and war do not exist, they might expect future fluctuations associated with cryptocurrency and energy. The results allow policymakers to what extent energy markets are sensitive and vulnerable to the shocks of crypto markets, especially during the pandemic and war times. During those periods, environmental attention in crypto-mining does not allow to mitigate energy-related uncertainties. Furthermore, policymakers should take geopolitical risk and financial stress factors when analysing the relation from cryptocurrency environmental attention impact to energy-related uncertainty. Even though the study has promising contributions to literature, some limitations still exist. More specifically, it would be interesting to explore the cryptocurrency environmental attention with disaggregated data. However, this could be done in the future work once the disaggregated data is available. This drawback does not diminish the scientific value of the work.

REFERENCES

Afkhami, M., Cormack, L., Ghoddusi, H. (2017), Google search keywords that best predict energy price volatility. Energy Economics, 67, 17-27.

Ahir, H., Bloom, N., Furceri, D. (2022), The World Uncertainty Index. National Bureau of Economic Research Working Paper Series.

Ahmad, U., Van Keulen, M., Briassouli, A., Saad, M. (2025), Cognitive biases, robo advisor and investment decision psychology: An investor's perspective from New York stock exchange. Acta Psychologica (Amst), 256, 105048.

Alessandri, P., Mumtaz, H. (2019), Financial regimes and uncertainty shocks. Journal of Monetary Economics, 101, 31-46.

Andrei, D., Friedman, H., Ozel, N.B. (2023), Economic uncertainty and investor attention. Journal of Financial Economics, 149(2), 179-217.

Arora, R., Kapoor, M., Singh, N., Yaqub, M.Z. (2025), Green cryptocurrency and business strategies: Framework and insights from a stewardship literature review. Business Strategy and the Environment, 34(1), 804-829.

Arslan-Ayaydin, O., Thewissen, J. (2016), The financial reward for environmental performance in the energy sector. Energy and Environment, 27(3-4), 389-413.

Badlani, B., Yadav, R.A., Kumar, A. (2023), Psychological impact of cryptocurrency volatility on investor emotions and decision making. Journal for Reattach Therapy and Developmental Diversities, 6(7), 204-214.

Ballis, A., Drakos, K. (2020), Testing for herding in the cryptocurrency market. Finance Research Letters, 33, 101210.

Bampinas, G., Panagiotidis, T. (2024), How would the war and the pandemic affect the stock and cryptocurrency cross-market linkages? Research in International Business and Finance, 70, 102272.

Baraniuk, C. (2016), Bitfinex Users to Share 36% of Bitcoin Losses after Hack. BBC News. Available from: https://www.bbc.com/news/technology-37009319

Będowska-Sójka, B., Kliber, A. (2024), Do investors in dirty and clean cryptocurrencies care about energy efficiency in the same way? Finance Research Letters, 67, 105852.

Borojo, D.G., Yushi, J., Gong, X., Zhang, H., Miao, M. (2024), The heterogeneous impacts of climate finance on energy efficiency and renewable energy production in developing countries. Renewable Energy, 236, 121427.

Bouteska, A., Hajek, P., Abedin, M.Z., Dong, Y. (2023), Effect of twitter investor engagement on cryptocurrencies during the COVID-19 pandemic. Research in International Business and Finance, 64, 101850.

Casas, I., Fernandez-Casal, R. (2019), tvReg: Time-varying coefficient linear regression for single and multi-equations in R. R J, 14, 79-100.

Caldara, D. and Iacoviello, M. (2022). Measuring geopolitical risk. American Economic Review, 112 (4), 1194–1225.

Campbell, S.D., Sharpe, S.A. (2009), Anchoring bias in consensus forecasts and its effect on market prices. Journal of Financial and Quantitative Analysis, 44(2), 369-390.

Casas, I., Fernández-Casal, R. (2019), TvReg: Time-varying coefficient linear regression for single and multi-equations in R.

CCA. (2021), Crypto Climate Accord. Available from: https://cryptoclimate.org/accord [Last accessed on 2025 Jan 13].

Chen, A.S., Nguyen, H.T. (2024), A new perspective on how investor sentiment affects herding behavior in the cryptocurrency market. Finance Research Letters, 67, 105737.

Cheng, K.Y. (2024), China's crackdown on crypto mining from a climate perspective: Unified efforts from administrative authorities and the judiciary. International Journal of Digital Law and Governance, 1(1), 91-112.

Choi, K.H., Kang, S.H., Yoon, S.M. (2022), Herding behaviour in Korea's cryptocurrency market. Applied Economics, 54(24), 2795-2809.

Cogley, T., Sargent, T.J., (2005), Drift and volatilities: Monetary policies and outcomes in the post WWII US. Review of Economic Dynamics, 8(2), 262-302.

Dang, T.H.N., Nguyen, C.P., Lee, G.S., Nguyen, B.Q., Le, T.T. (2023), Measuring the energy-related uncertainty index. Energy Economics, 124, 106817.

De Bondt, W.F.M., Thaler, R.H. (1995), Financial decision-making in markets and firms: A behavioral perspective. Handbooks in Operations Research and Management Science. 9, 385-410.

Dogan, E., Majeed, M.T., Luni, T. (2022), Are clean energy and carbon emission allowances caused by bitcoin? A novel time-varying method. Journal of Cleaner Production, 347, 131089.

Dong, X., Huang, L. (2023), Exploring ripple effect of oil price, fintech, and financial stress on clean energy stocks: A global perspective. Resources Policy, 89, 104582.

Dong, X., Jiang, Z., Yoon, S. (2024), Impact of global financial and energy markets, uncertainty, and climate change attention on Bitcoin carbon footprint. Finance Research Letters, 70, 106254.

Du, Q., Han, Z. (2020), The framing of nuclear energy in Chinese media discourse: A comparison between national and local newspapers. Journal of Cleaner Production, 245, 118695.

Elsayed, A.H., Hoque, M.E., Billah, M. (2025), Multilayer connectedness across geopolitical risks, clean, and dirty energy markets: The role of global uncertainty factors and climate surprise. Energy Economics, 144, 108342.

EPA. (2016), Climate Impacts on Energy. Available from: https://19january2017snapshot.epa.gov/climate-impacts/climate-impacts-energy-.html [Last accessed on 2025 Feb 16].

Ethereum. (2024), Ethereum Roadmap: The Merge. Available from: https://ethereum.org/en/roadmap/merge [Last accessed on 2025 Jan 13].

Evrim Mandaci, P., Cagli, E.C. (2022), Herding intensity and volatility in cryptocurrency markets during the COVID-19. Finance Research Letters, 46, 102382.

Fan, J. (2018), Local Polynomial Modelling and Its Applications: Monographs on Statistics and Applied Probability. Vol. 66. UK: Routledge.

Folkes, V.S. (1988), Recent attribution research in consumer behavior: A review and new directions. Journal of Consumer Research, 14, 548-565.

FSB. (2022), Assessment of Risks to Financial Stability from Crypto-Assets. Financial Stability Board. Available from: https://www.fsb.org/uploads/p160222.pdf#page=7.11 [Last accessed on 2025 Jan 10].

Gallersdörfer, U., Klaaßen, L., Stoll, C. (2020), Energy consumption of cryptocurrencies beyond bitcoin. Joule, 4(9), 1843-1846.

Gao, L. (2023), The foundations of behavioral finance-learning and elaborations of the basic theories. Journal of Mathematical Finance, 13(3), 355-368.

Gemayel, R., Preda, A. (2024), Herding in the cryptocurrency market: A transaction-level analysis. Journal of International Financial Markets Institutions and Money, 91, 101907.

Ghazouani, I., Ghazouani, I., Omri, A. (2024), Powering perception, echoing green voices: The interplay of cryptocurrency's energy footprint and environmental discourse in steering the direction of the market. Borsa Istanbul Review, 24, 91-101.

Goodell, J.W., Goutte, S. (2021), Diversifying equity with cryptocurrencies during COVID-19. International Review of Financial Analysis, 76, 101781.

Griggs, M.B. (2019), Facebook's Libra Won't be as Power-Hungry as Bitcoin. The Verge. Available from: https://www.theverge.com/2019/6/20/18693014/facebook-libra-cryptocurrency-bitcoin-environment-energy-data-center

Gschossmann, I., Anton, V.D.K., Benoit, P., Rocher, E. (2022), Mining the Environment is Climate Risk Priced into Crypto-Assets? European Central Bank. Available from: https://www.ecb.europa.eu/press/financialstabilitypublications/macroprudentialbulletin/html/ecb.mpbu202207_3~d9614ea8e6.en.html [Last accessed on2025 Jan 12].

Guta, D., Börner, J. (2017), Energy security, uncertainty and energy resource use options in Ethiopia: A sector modelling approach. International Journal of Energy Sector Management, 11(1), 91-117.

Ha, L.T. (2022), Storm after the Gloomy days: Influences of COVID-19 pandemic on volatility of the energy market. Resources Policy, 79, 102921.

Haq, I. (2022), Time-frequency comovement among green financial assets and cryptocurrency uncertainties. Economic Notes, 52, e12216.

Hassan, M.K., Hasan, M.B., Halim, Z.A., Maroney, N., Rashid, M.M. (2022), Exploring the dynamic spillover of cryptocurrency environmental attention across the commodities, green bonds, and environment-related stocks. The North American Journal of Economics and Finance, 61, 101700.

Helmi, M.H., Çatık, A.N., Akdeniz, C. (2023), The impact of central bank digital currency news on the stock and cryptocurrency markets: Evidence from the TVP-VAR model. Research in International Business and Finance, 65, 101968.

Ibañez, J.I., Freier, A. (2023), Bitcoin's carbon footprint revisited: Proof of work mining for renewable energy expansion. Challenges, 14(3), 35.

IEA. (2022), Global Energy Review: CO_2 Emissions in 2021. International Energy Agency. Available from https://iea.blob.core.windows.net/assets/c3086240-732b-4f6a-89d7-db01be018f5e/globalenergyreviewco2emissionsin2021.pdf [Last accessed on 2025 Jan 21].

Inman, P., Farrer, M. (2017), China Stuns Financial Markets by Devaluing Yuan for Second Day Running. The Guardian. Available from: https://www.theguardian.com/business/2015/aug/12/china-yuan-slips-again-after-devaluation

Interdax. (2021, December 13), Top 10 Cryptocurrency Events and Themes in 2019 Interdax Blog Medium. Available from: https://medium.com/interdax/2019-in-review-top-10-cryptocurrency-events-themes-cae71a4aa38c

Ioannou, A., Fuzuli, G., Brennan, F., Yudha, S.W., Angus, A. (2019), Multi-stage stochastic optimization framework for power generation system planning integrating hybrid uncertainty modelling. Energy Economics, 80, 760-776.

Ivanovski, K., Marinucci, N. (2021), Policy uncertainty and renewable energy: Exploring the implications for global energy transitions, energy security, and environmental risk management. Energy Research and Social Science, 82, 102415.

Jain, L., Velez-Figueroa, L., Karlapati, S., Forand, M., Ahmed, R., Sarfraz, Z. (2025), Cryptocurrency trading and associated mental health factors: A scoping review. Journal of Primary Care and Community Health, 16. Doi: 10.1177/21501319251315308.

Kahneman, D., Tversky, A. (1979), Prospect theory: An analysis of decision under risk. Econometrica, 47(2), 263-291.

Kamal, J.B., Hassan, M.K. (2022), Asymmetric connectedness between cryptocurrency environment attention index and green assets. The Journal of Economic Asymmetries, 25, e00240.

Kamal, M.R., Wahlstrøm, R.R. (2023), Cryptocurrencies and the threat versus the act event of geopolitical risk. Finance Research Letters, 57, 104224.

Kartini, K., Nahda, K. (2021), Behavioral biases on investment decision: A case study in Indonesia. Journal of Asian Finance Economics and Business, 8(3), 1231-1240.

Khan, K., Khurshid, A., Cifuentes-Faura, J. (2023), Energy security analysis in a geopolitically volatile world: A causal study. Resources Policy, 83, 103673.

Khan, N., Yaya, O.S., Vo, X.V., Zada, H. (2025), Quantile time-frequency connectedness and spillovers among financial stress, cryptocurrencies and commodities. Resources Policy, 103, 105527.

Khodjaniyazov, N., Mirkhoshimova, M., Kalandarov, F., Matyokubova, D., Khudayberganov, M., Utegenova, S., Makhmudov, S. (2025), Time-varying impacts of financial stress on energy-related uncertainty. International Journal of Energy Economics and Policy, 15(3), 689-698.

Krause, M.J., Tolaymat, T. (2018), Quantification of energy and carbon costs for mining cryptocurrencies. Nature Sustainability, 1(11), 711-718.

Lee, C.C., Fang, Y. (2025), Climate finance for energy security: An empirical analysis from a global perspective. Economic Analysis and Policy, 85, 963-978.

Lyytimäki, J., Pulkka, A., Rantala, S., Nygrén, N.A. (2018), Energy transition looming behind the headlines? Newspaper coverage of biogas production in Finland. Energy Sustainability and Society, 8(1), 15.

Majidi, M., Mohammadi-Ivatloo, B., Soroudi, A. (2019), Application of information gap decision theory in practical energy problems: A comprehensive review. Applied Energy, 249, 157-165.

Mankala, S., Durai, A., Padiyar, A., Gkountouna, O., Mahabir, R. (2023), Understanding public discourse surrounding the impact of bitcoin on the environment in social media. GeoJournal, 88(4), 4243-4267.

Miller, M., Modigliani, F. (1961), Dividend policy, growth, and the valuation of shares. Journal of Business, 34(4), 411-433.

Mora, C., Rollins, R.L., Taladay, K., Kantar, M.B., Chock, M.K., Shimada, M., Franklin, E.C. (2018), Bitcoin emissions alone could push global warming above 2°C. Nature Climate Change, 8(11), 931-933.

Mustafa, F., Mordi, C., Elamer, A.A. (2024), Green gold or carbon beast? Assessing the environmental implications of cryptocurrency trading on clean water management and carbon emission SDGs. Journal of Environmental Management, 367, 122059.

Nakamoto, S. (2008), Bitcoin: A Peer-to-Peer Electronic Cazsh System. Satoshi Nakamoto. Available from: https://bitcoin.org/bitcoin.pdf

NguyenHuu, T., Örsal, D.K. (2024), Geopolitical risks and financial stress in emerging economies. World Economy, 47(1), 217-237.

Njangang, H., Padhan, H., Tiwari, A.K. (2024), From aid to resilience: Assessing the impact of climate finance on energy vulnerability in developing countries. Energy Economics, 134, 107595.

Organization for Economic Co-Operation and Development (OECD). (2022), Environmental Impact of Digital Assets: Crypto-Asset Mining and Distributed Ledger Technology Consensus Mechanisms OECD Business and Finance Policy. Paris: OECD Publishing.

Pata, U.K. (2024), Does energy policy uncertainty matter for renewable energy and energy efficiency technologies? An affordable and clean energy perspective. Geoscience Frontiers, 15, 101932.

Patel, R., Gubareva, M., Chishti, M.Z. (2024), Assessing the connectedness between cryptocurrency environment attention index and green cryptos, energy cryptos, and green financial assets. Research in International Business and Finance, 70, 102339.

Primiceri, G.E. (2005), Time varying structural vector autoregressions and monetary policy. Review of Economic Studies, 72(3), 821-852.

Qin, Y., Zhang, Z. (2024), Transmission mechanisms of the effects of geopolitical risk on energy returns and volatility. International Review of Financial Analysis, 95, 103363.

Qing, L., Alnafrah, I., Dagestani, A.A. (2025), Environmental attention in cryptocurrency markets: A catalyst for clean energy investments. International Review of Economics and Finance, 99, 104063.

Reboredo, J.C. (2014), Is there dependence and systemic risk between oil and renewable energy stock prices? Energy Economics, 48, 32-45.

Riaz, A., Ullah, Z., Hashmi, S.H. (2025), A temporal exploration of resilience of renewable energy consumption to the energy-related uncertainty shocks in the US. Journal of Cleaner Production, 493, 144946.

Robinson, P.M. (1989), Nonparametric estimation of time-varying parameters. In: Hackl, P., editor. Statistical Analysis and Forecasting of Economic Structural Change. Berlin: Springer.

Robinson, P.M. (1989), Nonparametric estimation of time-varying parameters. In: Hackl, P. editors. Statistical Analysis and Forecasting of Economic Structural Change. Berlin, Heidelberg: Springer.

Rubbaniy, G., Polyzos, S., Tessema, A., Rizvi, S.K.A. (2021), COVID-19, lockdowns and herding towards a cryptocurrency market-specific implied volatility index. Economics Letters, 207, 110017.

Ruppert, D., Wand, M.P. (1994), Multivariate locally weighted least squares regression. The Annals of Statistics, 22(3), 1346-1370.

Sapra, N., Shaikh, I., Roubaud, D., Asadi, M., Grebinevych, O. (2024), Uncovering bitcoin's electricity consumption relationships with volatility and price: Environmental repercussions. Journal of Environmental Management, 356, 120528.

Sharif, T., Ghouli, J., Bouteska, A., Abedin, M.Z. (2024), The impact of COVID-19 uncertainties on energy market volatility: Evidence from the US markets. Economic Analysis and Policy, 84, 25-41.

Siddik, M.A.B., Amaya, M., Marston, L.T. (2023), The water and carbon footprint of cryptocurrencies and conventional currencies. Journal of Cleaner Production, 411, 137268.

Smales, L.A. (2021), Geopolitical risk and volatility spillovers in oil and stock markets. Quarterly Review of Economics and Finance, 80, 358-366.

Smith, N. (2024), Countries Say no to Energy Guzzling Bitcoin Mines. Greenpeace. Available from: https://www.greenpeace.org/usa/countries-say-no-to-bitcoin-mines [Last accessed on 2025 Jan 14].

Statman, M. (2008), What is behavioral finance? In: Fabozzi, F.J., editor. Handbook of Finance. Hoboken, NJ: John Wiley and Sons, Inc.

Statman, M. (2014), Behavioral finance: Finance with normal people. Borsa Istanbul Review, 14(2), 65-73.

Stoll, C., Klaaßen, L., Gallersdörfer, U. (2019), The carbon footprint of bitcoin. Joule, 3(7), 1647-1661.

Theiri, S. (2025), Herding behavior of cryptocurrencies during uncertain periods. In: Studies in Big Data. Vol. 170. Berlin: Springer.

Truby, J. (2018), Decarbonizing bitcoin: Law and policy choices for reducing the energy consumption of blockchain technologies and digital currencies. Energy Research and Social Science, 44, 399-410.

Tversky, A., Kahneman, D. (1973), Availability: A heuristic for judging frequency and probability. Cognitive Psychology, 5(2), 207-232.

Veit, D.J., Thatcher, J.B. (2023), Digitalization as a problem or solution? Charting the path for research on sustainable information systems. Journal of Business Economics, 93(6-7), 1231-1253.

Wang, F., Zhang, W., Zhang, D. (2024), The time-varying impact of geopolitical risks on financial stress in China: A TVP-VAR analysis. Finance Research Letters, 69, 106134.

Wang, Y., Lucey, B., Vigne, S.A., Yarovaya, L. (2022), An index of cryptocurrency environmental attention (ICEA). China Finance Review International, 12(3), 378-414.

World Economic Forum (WEF). (Jan 26, 2022). Financial and Monetary Systems. How the Top Cryptocurrencies Performed in 2021. Available from: https://www.weforum.org/stories/2022/01/top-cryptocurrencies-performance-2021/#:~:text=the%20returns%20of%20top%20cryptocurrencies%20in%202021andtext=market%20leader%2C%20bitcoin.-,while%20bitcoin%20only%20managed%20to%20return%2059.8%25%20last%20year%2c%20the,even%20five%2ddigit%20percentage%20returns [Last accessed on 2025 Jun 16].

Yilmazkuday, H. (2024), Geopolitical risks and energy uncertainty: Implications for global and domestic energy prices. Energy Economics, 2024, 107985.

Yousaf, I., Abrar, A., Yousaf, U.B., Goodell, J.W. (2024), Environmental attention and uncertainties of cryptocurrency market: Examining linkages with crypto-mining stocks. Finance Research Letters, 59, 104672.

Yousaf, I., Mohammed, K.S., Yousaf, U., Serret, V. (2025), The effect of crypto price fluctuations on crypto mining, and CO_2 emissions amid geopolitical risk. Finance Research Letters, 72, 106551.

Zhao, Y., Liu, N., Li, W. (2022), Industry herding in crypto assets. International Review of Financial Analysis, 84, 102335.