Does the transition to the proof-of-stake consensus protocol tame the response of cryptocurrency volatility to energy shocks?

Does the transition to the Proof-of-Stake consensus protocol tame the response of cryptocurrency volatility to energy shocks?

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Abstract

This study investigates the impact of transitioning from the Proof-of-Work (PoW) to the Proof-of-Stake (PoS) consensus protocol on the relationship between cryptocurrency volatility and energy shocks. We exploit the staggered and random nature of these transitions as a quasi-natural experiment and analyze four high market capitalization digital currencies using GARCH-type models. Our results provide the first causal evidence that adopting PoS significantly reduces the sensitivity of cryptocurrency volatility to fluctuations in oil prices. Robustness checks using alternative specifications confirm the validity of our findings. These results highlight the environmental and financial benefits of moving away from the energy-intensive PoW mechanism. Importantly, our study contributes to both sustainable finance and financial econometrics by showing how consensus mechanisms influence volatility dynamics. The findings carry practical implications for regulators, investors, and developers as the adoption of PoS protocols not only improves environmental sustainability but also enhances market stability.

Keywords: Cryptocurrency, Energy shocks, Volatility, Proof of Stake, Proof of Work.

JEL codes: C59, G10, G14, G15, G19.

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1. Introduction

Since the inception of Bitcoin, the cryptocurrency market has experienced remarkable growth over the past decade. As of June 2024, the digital currency market has reached a total market capitalization of roughly 2.5 trillion dollars and now encompasses more than 10,000 coins (Source: coinmarketcap.com, accessed on June 20, 2024). The proliferation of cryptocurrencies has captivated both the academic community and the financial industry due to their dual role as digital currencies and highly rewarding, yet volatile, investment assets (Corbet et al., 2019).

On the other hand, cryptocurrencies have also received significant attention from policymakers and the broader community concerning their environmental impact. Assessing the precise carbon footprint of cryptocurrencies is challenging (Sutherland, 2019). Nevertheless, numerous studies highlight concerns about the substantial energy consumption associated with the cryptocurrency market (de Vries, 2019, 2020; Kohli et al., 2023; Zhang et al., 2023). It is estimated that activities related to mining digital currencies account for 1 to 2 percent of total U.S. electricity consumption (U.S. Energy Information Administration, 2022). Moreover, research by Kohli et al. (2023) reveals that the energy consumption of Bitcoin mining alone surpasses that of Sweden, with its CO2 emissions approaching those of Greece and Oman. Although renewable energy sources could potentially be used to meet part of the energy demands of the cryptocurrency market, their seasonal instability makes them less attractive to miners. Thus, the mining nodes are forced to rely on fossil fuels (de Vries, 2019).

The high energy consumption of cryptocurrencies is primarily a function of the consensus protocol underlying blockchain operations. This innovative technology relies on a decentralized public ledger that records all transactions and data of network participants. Each transaction forms part of a block, which must be validated by nodes (network members) using hardware with immense computing power to solve a complex cryptographic puzzle. Upon solving these mathematical equations, the validated block is added to the chain, and the validator receives a reward in the form of a predetermined amount of cryptocurrency. A key characteristic of this process is that once a block is validated, it becomes immutable, and the transaction cannot be reversed, ensuring the security and transparency of the technology. The energy required for this validation process is contingent on the consensus protocol employed by the digital coin.

The standard consensus algorithm adopted by most cryptocurrencies is the Proof-of-Work (PoW) protocol. This mechanism involves the validation of blocks by network participants known as "miners," who engage in a competitive process to solve complex mathematical problems. The probability of a miner successfully validating a block is directly proportional to their computational power and energy expenditure. As cryptocurrency mining intensifies, the complexity of these problems escalates, requiring more computing power and, consequently, higher energy consumption. A graphical illustration of this issue is presented in Figure 1 for Bitcoin.

In response to the high energy demands and environmental concerns associated with PoW, the blockchain community has developed an alternative consensus protocol known as Proof-of-Stake (PoS). Under the PoS mechanism, block validation is carried out by validators who are randomly selected from the network participants based on the quantity of coins they have staked. The probability of being chosen as a validator increases with the amount of staked coins.

Unlike PoW, PoS eliminates the competitive aspect of block validation. There is no need for extensive computational resources or specialized hardware, as the cryptographic puzzles involved are simpler and independent of network size. This lack of competition and reduced need for high-powered machinery significantly decreases the energy consumption associated with PoS. Consequently, the PoS protocol is less CO2-intensive, making it a more environmentally sustainable option compared to PoW (Truby et al., 2022; Bouraga, 2021). Data on electricity consumption and CO_2 emissions reported by the Crypto Carbon Ratings Institute (CCRI) consistently confirm this fact. Indeed, while PoW cryptocurrencies such as Bitcoin and Dogecoin consume 149.7 TWh (Terawatt-hour) and 3.9 TWh of electricity respectively, emitting 73.9 Mt (Metric ton) and 1.9 Mt of CO_2 annually, Ethereum and Cardano, which rely on PoS, consume significantly less—only approximately 6 GWh (Gigawatt hour) and 0.7 GWh of electricity—and emit 1.9 Mt and 0.2 Mt of CO_2, respectively. The statistics also indicate that Ethereum's transition to PoS has led to a 99% reduction in its energy consumption and carbon emissions (carbon-ratings.com, 2023). However, despite these encouraging figures, energy demand is correlated with the size of the network, and therefore the PoS protocol is still more impacting than traditional centralized systems (Sedlmeir et al., 2020). Interested readers are referred to the study of Wendl et al. (2023) for a complete literature review on the energy consumption of PoW and PoS consensus protocols.

To date, the majority of cryptocurrencies—including Bitcoin as the most prominent example—still relies on the PoW consensus protocol. Despite facing resistance from miners, who find their mining activity profitable, some developers have decided to move towards adopting PoS. Ethereum, among others, represented a significant turning point by completing its transition to this consensus mechanism on September 15, 2022. Despite some initial surprise within the community of users, the founders always believed that PoS was the most suitable option for this digital currency. They argued that this protocol's features could reduce the high energy requirements of the blockchain, ensure its efficiency, and enhance network scalability (coindesk.com, 2022; beincrypto.com, 2024).

Since the PoS protocol still requires energy—yet, to a substantially lesser extent than PoW—a question that arises is: Does a move from PoW to the more sustainable PoS consensus protocol affect the sensitivity of cryptocurrency volatility to energy shocks? An answer to this question is not trivial, since lower volatility would benefit digital coin holders. Indeed, it is well-known that cryptocurrencies are extremely volatile and subject to recurring bubbles, as speculative behaviors drive this market (Fry & Cheah, 2016). On the other hand, energy shocks play an important role in heightening asset volatility. As documented by Park and Ratti (2008), oil price shocks account for roughly 6% of the volatility in real returns on stocks in both the US and Europe. Moreover, commodity uncertainty is a priced state variable in economies that affects asset payoffs and investor portfolio choices (Christoffersen & Pan, 2018). Similar volatility dynamics are documented in the cryptocurrency market (Naeem et al., 2023).

While recent studies have explored the relationship between energy markets and cryptocurrency volatility (e.g., Naeem et al., 2023), they have not addressed the environmental dimension of consensus mechanisms. For instance, Naeem et al. (2023) examine oil–cryptocurrency dynamics but do not consider how sustainability aspects may alter volatility outcomes. This omission underscores the rationale of our study, which directly links the transition to PoS with both financial and environmental sustainability. Furthermore, existing research has largely focused on correlations or portfolio approaches. By contrast, our study applies a quasi-natural experiment design, which is uniquely suited to identify causal effects of PoW-to-PoS transitions because it exploits non-overlapping transition dates. This approach allows us to overcome potential spurious correlations and strengthens the validity of our findings.

From a theoretical perspective, PoS may reduce volatility through several channels. Unlike PoW, PoS does not require costly mining competition, leading to more stable validator incentives, improved scalability, and lower operational risks. These features can contribute to lower uncertainty in returns, particularly in response to exogenous shocks such as energy price fluctuations. By explicitly testing this mechanism, our study bridges literature on financial stability, environmental sustainability, and cryptocurrency economics.

To address our research question, we analyze the sensitivity to energy shocks in the conditional volatility processes of four major cryptocurrencies that switched from a PoW to a PoS consensus algorithm. In doing so, we utilize GARCH models within a quasi-natural experimental setting. The link between energy dependence and volatility can be explained through production costs and market incentives. Under a PoW consensus mechanism, mining requires substantial electricity consumption, and fluctuations in global energy markets directly alter miners' costs, profitability, and selling pressure. This channel amplifies the transmission of energy shocks to cryptocurrency volatility. By contrast, PoS eliminates the dependence on energy-intensive mining, stabilizes validator rewards, and reduces uncertainty in supply dynamics. The hypothetical result is a lower sensitivity of volatility to external energy shocks, which forms the theoretical foundation of our empirical analysis.

Our study contributes to the existing literature in several ways. First, we contribute to the field of sustainable finance by examining the environmental impact of transitioning from PoW to PoS consensus protocols. Given the strong interest from institutions and the broader community, the financial industry, and other sectors, must consider the sustainable impact of its externalities. In the context of cryptocurrencies, few studies have examined their sustainability profiles (Corbet et al., 2019). Ren and Lucey (2022) analyze the herding behavior of green and dirty cryptocurrencies, concluding that there is no evidence of herding patterns among investors of clean coins. Pham et al. (2022) investigate the tail dependence among carbon prices, green cryptocurrencies, and non-green ones. They argue that green cryptocurrencies highlight diversification potential against both carbon markets and non-green cryptocurrencies, offsetting their risk during extreme downward market movements. Moreover, green coins can better diversify different global and regional equity portfolios than their non-green counterparts (Ali et al., 2024). More recently, several studies have examined the Ethereum Merge to highlight the benefits of PoS adoption. Choi (2025) shows that PoS improves consensus efficiency and fosters more informed trading. John et al. (2025) provide a comparative model demonstrating that PoS generally achieves higher equilibrium security than PoW, particularly at scale. Liu et al. (2025) find that Ethereum's transition improved liquidity and reduced intraday volatility relative to Bitcoin, while Yang (2025) shows that PoS incentivizes broader validator participation and decentralization. These studies underscore PoS's potential advantages but remain largely confined to Ethereum. Our study complements this literature by broadening the scope to four cryptocurrencies and, importantly, by testing whether PoS adoption reduces the sensitivity of volatility to exogenous energy shocks, thereby linking blockchain governance to both financial econometrics and environmental sustainability.

Second, the opportunity to conduct an event study allows for a causal investigation of this phenomenon. This approach is more robust than others, such as constructing portfolios of PoW and PoS coins, which might lead to misleading inferences due to potential spurious correlations. We utilize a unique opportunity to study this issue as a quasi-natural experiment, because different coins transitioned at different dates, enabling us to treat the cross-section of switches as a quasi-natural experiment. This methodological approach is particularly valuable because it allows us to analyze the same cryptocurrency in a counterfactual way, where the only feature that has changed is the consensus protocol.

Third, we contribute to the literature on energy shocks and cryptocurrency volatility. Previous studies have generally analyzed the response to energy shocks on different cryptocurrencies without distinguishing the effects of energy consumption levels. Okorie and Lin (2020) show unidirectional and bidirectional volatility spillover between the crude oil market and both the top 5 and bottom 5 cryptocurrencies based on market capitalization. Naeem et al. (2023) find a positive correlation between oil prices and cryptocurrencies regardless of market conditions, showing that rising fluctuations in oil demand shocks lead to significant movements in cryptocurrencies. However, Yin et al. (2021), using GARCH-MIDAS models to investigate the connection between the volatility of Bitcoin, Ethereum, and XRP and oil shocks, report contrasting results. They find a negative relationship between oil shocks and the long-term volatility of cryptocurrencies, which vanished when controlling for macroeconomic proxies, indicating that cryptocurrency volatility is mainly affected through the macroeconomic channel. We differentiate from the aforementioned studies by focusing on the impact of energy shocks—proxied by crude oil—on the volatility of cryptocurrencies that have switched to a green protocol.

Finally, we also contribute to the extensive literature on cryptocurrency volatility modeling by examining our research question using extended GARCH-type specifications. A consistent body of literature has investigated the volatility of cryptocurrencies—especially Bitcoin—adopting various

GARCH-type models, including Threshold GARCH, Asymmetric-Power GARCH, Components with Multiple Threshold GARCH, Exponential GARCH, and Markov-Switching GARCH models, among others (Dyhrberg, 2016; Katsiampa, 2017, 2019). For a complete literature review on the volatility of cryptocurrency, refer to the paper by Kyriazis (2021). Following the earlier literature, we adopt GARCH and TGARCH models in our analysis, as these are considered benchmark models for modeling the volatility of financial assets. From a methodological point of view, our study adds to the literature by proposing two novel approaches to this stream of research. First, we employ a modified version of the GARCH and TGARCH models, which account for a dummy variable that considers the volatility response to energy shocks after the consensus algorithm transition. Second, we propose a novel chi-squared joint test that allows us to jointly test the overall volatility response to energy shocks—as traditional event study approaches are not suitable for our analysis.

Our results show that after adopting the PoS consensus protocol, the cryptocurrencies in our sample experienced a significantly reduced sensitivity to energy shocks. More specifically, our estimates suggest that while not all cryptocurrencies exhibit a significant negative effect individually, the joint test of their coefficients using our novel test provides evidence for an overall significant reduction in response to oil fluctuations. Running a TGARCH model as a robustness check, our results hold, and we notice that the leverage effect of negative news on cryptocurrency volatility is only marginally supported by our analysis. These mixed findings align with the previous literature. For example, Grobys (2021) did not observe asymmetric patterns in the volatility processes of Ethereum and Bitcoin, whereas Baur and Dimpfl (2018) found a positive asymmetric response for a set of 20 cryptocurrencies. Conversely, Yu (2019) documented a negative leverage effect. Finally, by re-estimating the GARCH and TGARCH models to include oil innovations in the conditional volatility function as a new measure of oil shocks, the findings derived from our robustness checks strongly corroborate our main results.

The paper is organized as follows: Section 2 describes the data. Section 3 presents the methodology and results of our statistical analyses. Section 4 discusses the empirical results, while Section 5 concludes.

2. Data

We downloaded data on the following cryptocurrencies from coinmarketcap.com: Ethereum, Cardano, Toncoin, and Decred. After thorough research across coin websites, media sources, and social media, we identified only these four coins that made the transition from Proof-of-Work (PoW) to Proof-of-Stake (PoS). The small size of our sample reflects the rarity of such transitions. While some small-cap coins may also have undergone similar switches, reliable information on them is limited. However, this does not pose a concern, as our analysis is centered on large coins that are most relevant for the market and less exposed to liquidity frictions, which could otherwise make the volatility response to energy shocks noisier.

According to media reports and official websites, these cryptocurrencies adopted the PoS consensus protocol on the following dates: Ethereum on 15 September 2022[1], Cardano on 29 July 2020[2], Toncoin on 28 June 2022[3], and Decred on 29 August 2023[4]. Since the event days are non-overlapping and associated with random market environments, we consider the transition from PoW to PoS as an opportunity to study the consensus protocol change as a quasi-natural experiment. In Table 1, we report the specific dates when the respective cryptocurrencies switched from a PoW to a PoS consensus mechanism. The ex-ante sample refers to the 180 days preceding the event date, whereas the ex-post sample refers to the 180 days following the event date. Our final dataset comprises 360 observations per cryptocurrency (180 days before and after each transition), which provides sufficient

[1] https://ethereum.org.
[2] https://www.coindesk.com/tech/2020/07/30/cardano-introduces-proof-of-stake-with-shelley-hard-fork/.
[3] https://www.coindesk.com/business/2022/06/28/final-toncoin-mined-ahead-of-transition-to-proof-of-stake/.
[4] https://www.cypherpunktimes.com/decred-journal-september-2023/.
Decred switched to the BLAKE3 hashing algorithm, which implemented a new block reward split as 89% PoS, 1% PoW, 10% Treasury. This has virtually nullified the dependence on the PoW system.

statistical power while avoiding overlaps across event windows. Focusing on high-capitalization coins minimizes noise from liquidity frictions and ensures that our results are relevant to the broader market. Importantly, the non-overlapping nature of event dates allows us to treat each transition as exogenous, thereby strengthening the quasi-natural experimental design.

In Table 2, we present the corresponding descriptive statistics for the cryptocurrencies for the ex-ante and ex-post event samples. We also provide the descriptive statistics for crude oil (WTI) obtained from the US Energy Information Administration. In our study, we use the return on crude oil as it is an often-used energy proxy for crypto mining (Naeem et al., 2022, 2023). Moreover, Table 2 reports the Augmented Dickey–Fuller test for each time series. As can be seen, the null hypothesis of a unit root is rejected for all variables, confirming that the GARCH model assumption of stationarity is satisfied.

3. Empirical Analysis

To explore whether a change from PoW to PoS consensus protocol has an effect on the sensitivity of cryptocurrency volatility to energy shocks, we employ the following extended GARCH(1,1) model specification:

$$RET_{i,t} = c_i + \varepsilon_{i,t}, \tag{1}$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i,t-1}^2 + \delta_i \left(RET_{Oil,t}^D\right)^2 + \theta_i d_{i,t} \left(RET_{Oil,t}^D\right)^2\right)}\, \epsilon_{i,t}, \tag{2}$$

where $RET_{i,t}$ in the mean equation denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process. Considering the conditional volatility equation, $\varepsilon_{i,t-1}^2$ and $\sigma_{i,t-1}^2$ are defined as the squared residual of the mean equation and the conditional variance at time $t-1$, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time *t*, $d_{i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency i, and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation. Note that in our model specification, squared de-meaned returns on crude oil, $\left(RET_{Oil,t}^{D}\right)^2$, serve as a proxy for measuring the contemporaneous effect of energy shocks on the conditional cryptocurrency volatility. Specifically, θ_i measures how the conditional cryptocurrency volatility *i* responds to energy shocks *after* adopting the PoS consensus protocol. The GARCH models are estimated via maximum-likelihood estimation. We hypothesize in H_1 that the adoption of the PoS consensus protocol should result in a *lowered* sensitivity of conditional cryptocurrency volatilities to energy shocks. That is, we test the following hypothesis pair:

$$H_0\colon\ \theta_i = 0\ \forall\, i = \{ETH, ADA, TON, DCR\} \quad \text{vs.} \quad H_1\colon\ \theta_i < 0\ \forall\, i = \{ETH, ADA, TON, DCR\}.$$

Given the size of our sample, traditional event study methodologies are not suitable for drawing inferences. Therefore, to draw cross-sectional conclusions, we implement the following novel test statistic which is designed to test hypothesis jointly:

$$\lambda_0 = \begin{pmatrix} \hat{\theta}_1 \\ \hat{\theta}_2 \\ \hat{\theta}_3 \\ \hat{\theta}_4 \end{pmatrix}^T \begin{pmatrix} \hat{\sigma}_{\hat{\theta}_1}^2 & 0 & 0 & 0 \\ 0 & \hat{\sigma}_{\hat{\theta}_2}^2 & 0 & 0 \\ 0 & 0 & \hat{\sigma}_{\hat{\theta}_3}^2 & 0 \\ 0 & 0 & 0 & \hat{\sigma}_{\hat{\theta}_4}^2 \end{pmatrix}^{-1} \begin{pmatrix} \hat{\theta}_1 \\ \hat{\theta}_2 \\ \hat{\theta}_3 \\ \hat{\theta}_4 \end{pmatrix}, \tag{3}$$

where $\hat{\theta}_1$, $\hat{\theta}_2$, $\hat{\theta}_3$, $\hat{\theta}_4$ are point estimates obtained from Eq. (2), and $\hat{\sigma}_{\hat{\theta}_1}^2$, $\hat{\sigma}_{\hat{\theta}_2}^2$, $\hat{\sigma}_{\hat{\theta}_3}^2$, $\hat{\sigma}_{\hat{\theta}_4}^2$ are the corresponding estimated parameter variances derived from the GARCH-model specification. Note that our proposed test in Eq. (3) requires $COV(\hat{\theta}_i, \hat{\theta}_j) = 0$ for $i \neq j$. We argue that this holds in our research due to the quasi-experimental setting; that is, the event days do not coincide and, as a consequence, $COV(\hat{\theta}_i, \hat{\theta}_j) = 0$ for $i \neq j$ holds. Using a significance level of 5 percent, we reject the null hypothesis if $\hat{\lambda}_0 > 9.49$ because the test statistic λ_0 is under the null hypothesis distributed as $\chi^2(4)$.

A key methodological choice in this study is the use of a quasi-natural experiment rather than portfolio analysis. Our choice is consistent with Edmans (2024), who argues that quasi-experiments are valid research designs for making inference about causality. Portfolio approaches, while common in the literature, are prone to spurious correlations because they combine heterogeneous assets and are affected by sample composition. By contrast, our quasi-natural experiment design compares the same cryptocurrency before and after its consensus transition, holding all other characteristics constant. This approach isolates the causal effect of the PoS mechanism on volatility sensitivity and avoids endogeneity concerns.

In Table 3 we present the point estimates for the GARCH(1,1) model outlined in Eqs. (1) and (2). The point estimates for θ_i vary between -0.18 (Ethereum and Toncoin) and -0.64 (Decred) with corresponding *t*-statistics varying between -1.60 and -1.96. These estimates imply that after adopting PoS, cryptocurrencies became less sensitive to energy shocks, supporting our central hypothesis. Although the effect is not statistically significant for every coin individually, the joint chi-square test demonstrates an overall significant reduction in volatility sensitivity. This provides strong cross-sectional evidence that PoS adoption dampens the volatility effects of energy shocks.[5] Robustness checks using TGARCH models and alternative definitions of energy shocks confirm these findings, underscoring the reliability of the results. Figure 2 depicts the conditional volatility before and after PoS transitions obtained from fitted GARCH(1,1) models. As shown in Figure 2, the conditional volatility series generally indicate lower volatility sensitivity to energy shocks after the PoW-to-PoS transitions. This visual evidence supports our regression findings and highlights the stabilizing impact of PoS adoption.

In economic terms, the magnitude of the effect is non-trivial. For example, a one standard deviation oil price shock leads to an estimated 30–40% lower increase in volatility in the post-PoS period

[55] Implementing the joint test, we find that $\hat{\lambda}_0 = 13.11 > 9.49$ implying that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative.

compared with the pre-PoS period. This suggests that investors in PoS cryptocurrencies face materially smaller risk exposure to global energy market fluctuations, which translates into more stable returns, lower hedging costs, and enhanced attractiveness for portfolio diversification.

Next, there is a vast amount of literature postulating that negative news affect asset volatility in a more pronounced manner than positive news. To model this issue, we model the error term of Eq. (1) using the Threshold GARCH (TGARCH) model specification as proposed by Glosten et al. (1993):

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\left(RET_{Oil,t}^D\right)^2 + \theta_i d_{2,i,t}\left(RET_{Oil,t}^D\right)^2\right)}\,\epsilon_{i,t}, \qquad (4)$$

whereas the mean equation is defined as in Eq. (1), $\varepsilon_{i,t}$ in Eq. (4) is assumed to be governed by a conditional volatility process. That is, $\varepsilon_{i,t-1}^2$ is defined as the squared residual of the mean equation at time $t-1$, and $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Furthermore, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time *t*, $d_{2,i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation. We then collect the point estimates $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \hat{\theta}_4$ from Eq. (4) as well as the corresponding $\hat{\sigma}_{\hat{\theta}_1}^2, \hat{\sigma}_{\hat{\theta}_2}^2, \hat{\sigma}_{\hat{\theta}_3}^2, \hat{\sigma}_{\hat{\theta}_4}^2$ derived from the modified TGARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_1.

In Table 4 we report the point estimates for the TGARCH(1,1) model outlined in Eqs. (1) and (4). The point estimates for θ_i vary between -0.18 (Toncoin) and -3.32 (Decred) with corresponding t-statistics varying between -1.73 and -5.98. Strikingly, for the vast majority of cryptocurrencies considered, the change from PoW to PoS resulted in a statistically significantly decreased uncertainty with respect to energy shocks. Implementing the joint test, we find that $\hat{\lambda}_1 = 67.55 > 9.49$ which suggests that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative. Interestingly, we observe from Table 4 that the evidence for leverage effect of bad news is mixed: Whereas $\hat{\beta}_1$ for Cardano is estimated at $\hat{\beta}_1 = 0.07$ with a t-statistic of 1.81 indicating only marginal significance on a 10 percent level, for other cryptocurrencies we do not find such evidence. Overall, allowing for asymmetries in the TGARCH specification confirms the robustness of our findings. The results show that the reduction in volatility sensitivity persists even when accounting for potential leverage effects, reinforcing the conclusion that the PoS transition systematically dampens the transmission of energy shocks into return volatility.

Next, one could be concerned about potential autocorrelation of the returns on oil. In Table 5 we present the results from the following regressions:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t}, \tag{5}$$

where $RET_{Oil,t}$ is the return on oil at time t, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Using the overall samples—that is, the ex-ante and ex-post event samples together—the regression results are reported in Table 5. We see from Table 5 that for two-out-of-four samples, the estimated first-order autocorrelation parameter is statistically significant. Therefore, we re-define the energy shocks as the squared innovations from Eq. (5), that is, $\varepsilon^2_{Oil,t}$, and re-estimate the GARCH(1,1) model using Eq. (6) in association with Eq. (1):

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon^2_{i,t-1} + \gamma_i \sigma^2_i + \delta_i \varepsilon^2_{Oil,t} + \theta_i d_{i,t} \varepsilon^2_{Oil,t}\right)} \epsilon_{i,t}, \tag{6}$$

where $\varepsilon^2_{Oil,t}$ denotes the squared residual from Eq. (5) and all other notation is as before. Again, we collect the point estimates $\hat{\theta}_1$, $\hat{\theta}_2$, $\hat{\theta}_3$, $\hat{\theta}_4$ from Eq. (6) as well as the corresponding $\hat{\sigma}^2_{\hat{\theta}_1}, \hat{\sigma}^2_{\hat{\theta}_2}, \hat{\sigma}^2_{\hat{\theta}_3}, \hat{\sigma}^2_{\hat{\theta}_4}$ derived from the modified GARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_2.

In Table 6 we report the point estimates for the modified GARCH(1,1) model outlined in Eqs. (1) and (6). The point estimates for θ_i vary between -0.18 (Ethereum and Toncoin) and -2.61 (Decred) with corresponding t-statistics varying between -1.60 and -6.99. Implementing the joint test, we find that $\hat{\lambda}_2 = 58.32 > 9.49$ which corroborates with our main findings suggesting that the overall effect across the cryptocurrencies that adopted PoS is indeed statistically significantly negative.

As a final robustness check, we incorporate $\varepsilon_{Oil,t}$, as outlined in Eq. (5), using a TGARCH(1,1) model specification where the mean equations are given as in Eq. (1) and the conditional volatility is modelled as follows:

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\varepsilon_{Oil,t}^2 + \theta_i d_{2,i,t}\varepsilon_{Oil,t}^2\right)}\epsilon_{i,t}, \tag{7}$$

where $\varepsilon_{Oil,t}^2$ denotes the squared residual from Eq. (5) and all other notation is as detailed earlier. We collect the point estimates $\hat{\theta}_1, \hat{\theta}_2, \hat{\theta}_3, \hat{\theta}_4$ from Eq. (7) as well as the corresponding $\hat{\sigma}_{\hat{\theta}_1}^2, \hat{\sigma}_{\hat{\theta}_2}^2, \hat{\sigma}_{\hat{\theta}_3}^2, \hat{\sigma}_{\hat{\theta}_4}^2$ derived from the modified TGARCH-model specification and re-estimate the test statistic given in Eq. (3) which is then denoted as λ_3.

In Table 7, we present the point estimates for the modified TGARCH(1,1) model outlined in Eqs. (1) and (7). The point estimates for θ_i vary between -0.18 (Toncoin) and -3.20 (Decred) with corresponding *t*-statistics varying between -1.60 and -6.52. Implementing the joint test, we find that $\hat{\lambda}_3 = 51.23 > 9.49$ which again supports our main results. Overall, our findings suggest that adopting PoS consensus protocol has the overarching effect that cryptocurrency volatility is less sensitive to energy shocks. This result holds regardless of the model specification.

4. Discussion

4.1. Alignment with Previous Research

Baur and Dimpfl (2018), who employ Glosten et al.'s (1993) Threshold GARCH (TGARCH) model to explore asymmetric volatility responses for a set of 20 cryptocurrencies, find that for virtually all coefficients measuring asymmetries in volatility responses, the coefficient is negative. Their result implies that negative shocks increase volatility less than positive shocks, which contrasts with the positive coefficient generally reported in stock markets. Conversely, in our analysis, we obtain mixed evidence supporting the leverage effect. Indeed, only the coefficient β_1 for Cardano suggests a greater weight on negative news, whereas for Decred, the effect is negative, indicating that its volatility is more sensitive to positive news, as documented by Baur and Dimpfl (2018). No asymmetric response was found for Ethereum and Toncoin. The different outcomes may be an artifact of different time periods and short samples. The sample specificity of results can also be noted in the literature. For instance, while Baur and Dimpfl (2018) find a positive asymmetry volatility response for 20 cryptocurrencies, studies by Klein et al. (2018), Yu (2019), and Catania et al. (2018) show a higher sensitivity of volatility to past negative news for Bitcoin and other major cryptocurrencies in different periods between 2011 and 2018. Interestingly, Bouri et al. (2017), who use a TGARCH model, find that the asymmetry effect of Bitcoin volatility changed over time.

Moreover, our results contrast with those of Kliber and Będowska-Sójka (2024). While the authors find no significant difference in the correlation patterns between PoW and PoS cryptocurrencies with the oil energy index, we find that such a difference indeed does exist. Specifically, our analysis shows that the volatility is indeed lower for cryptocurrencies transitioning to the PoS protocol. This discrepancy may be attributed to the different methodological approaches employed. Kliber and Będowska-Sójka (2024) rely on simple correlation measures that do not account for endogeneity, whereas our quasi-natural experiment isolates the causal impact of consensus shifts. These methodological differences explain the stronger and more consistent results in our study.

Compared to Baur and Dimpfl (2018), who documented positive asymmetric responses for a broad set of cryptocurrencies, our results differ because we focus specifically on consensus transitions. Differences in time periods and sample composition are also likely to contribute to this divergence. In particular, as noted by Babiak and Bianchi (2024), the cryptocurrency market has become more correlated with traditional financial markets after the Covid-19 period. Accordingly, since our sample covers exclusively the post-pandemic period, the mixed evidence we obtain may reflect changes in return dynamics.

4.2. Implications

The findings of this study hold several important implications for policy, practice, and future research. For regulators, the demonstrated stability of PoS coins provides a strong case for promoting consensus transitions through targeted policies. Examples include taxation measures that reduce the profitability of PoW mining, or mandatory disclosure of energy footprints by exchanges to incentivize investor awareness. For investors, reduced volatility sensitivity translates into improved hedging opportunities and portfolio diversification, as well as more stable gas fees for smart contract execution. Developers and issuers of Initial Coin Offerings (ICOs) may also benefit, since lower volatility enhances project success rates and post-ICO performance (Lyandres et al., 2022). Finally, our results point to avenues for future research. As more cryptocurrencies transition to PoS, larger datasets will enable more refined event studies and the application of advanced volatility models beyond GARCH-type approaches.

Beyond statistical significance, our results are also economically meaningful. The reduction in volatility sensitivity implies that PoS coins offer a more predictable risk-return profile, improving their role as diversifiers in institutional and retail portfolios. For exchanges and traders, reduced volatility can lower transaction costs and improve order book stability. From a regulatory perspective, this stability strengthens the argument for supporting PoS adoption as a pathway toward both financial resilience and environmental sustainability.

Several studies suggest the external intervention of regulators to influence and incentivize the transition to PoS (Di Febo et al., 2021; Shanaev et al., 2020; Wendl et al., 2023). Regulations could involve measures to reduce the profitability of mining activities. For instance, economic measures might include higher taxation on the profits of non-environmentally compliant cryptocurrencies or increased taxes on mining hardware. Additionally, promoting greater awareness of the environmental impact of PoW coins through information provided by centralized exchanges could further incentivize the transition.

Complementing these measures, our results demonstrate a strong internal incentive to adopt a more sustainable consensus mechanism. The PoS consensus protocol enhances decentralization and scalability by allowing a larger network of validators, thanks to its lower hardware and energy requirements, while also supporting faster transactions for users (Khan et al., 2021). Moreover, as demonstrated in the present research, PoS-based networks offer greater stability due to their reduced sensitivity to energy shocks. This stability may attract a broader range of users and create a sustainable environment for participants, developers, and validators. Regarding the security of this protocol, PoS blockchains should avoid falling into a "rich-get-richer" dynamic. This occurs because the PoS model is believed to induce wealth concentration, creating a centralizing effect where wealthier participants are more likely to be chosen to validate blocks and receive rewards. Roşu and Saleh (2021) were the first to provide a theoretical model against this issue, in which the share of an investor with a buy-and-hold strategy evolves according to a martingale. This means that while wealthier investors are more likely to earn rewards, they also face proportionally larger losses in shares if not selected, leading to long-term stability of shares around their initial value. This theoretical model was later supported by empirical findings from Irresberger and Yang (2023). The authors found that increases in concentration are not due to unfair advantages large stakes may have in PoS protocols, but rather due to other validators entering or leaving the consensus process.

We believe that the transition to the PoS protocol holds several benefits and economic incentives for crypto stakeholders. First, blockchain users are likely to favor PoS systems as their operations would be less impacted by price fluctuations driven by energy market volatility. Cryptocurrencies were initially envisioned as payment alternatives, yet their extreme volatility prevents them from serving this purpose without a high risk of value loss (Sangari & Mashatan, 2024). Thus, reduced exposure to price volatility caused by energy shocks in a PoS network can make a cryptocurrency more appealing compared to others. Additionally, lower volatility stabilizes the price of gas fees, i.e., the transaction fees paid to validators to process a transaction (Koutmos, 2023). Stable gas fees would make PoS blockchains more attractive for various operations, such as the execution of smart contracts.

Developers also have strong economic incentives to adopt PoS due to the enhanced scalability it offers (Khan et al., 2021). PoS makes block validation easier compared to PoW. As a result, gas fees—determined by the supply and demand of transactions—are expected to be lower and more stable (Kreppmeier et al., 2023). Consequently, the combination of stability, scalability, and energy efficiency makes PoS systems more appealing and sustainable for ongoing development and adoption.

On the other hand, miners may initially perceive the transition to PoS as a threat to their activity. Indeed, a transition to PoS would render their hardware investments obsolete. Nonetheless, as demonstrated by Islam et al. (2023), the long-term profitability of mining is unsustainable, as both power consumption and capital investment can erode profit margins. The competitive cycle of continually upgrading hardware to mine more blocks increases costs exponentially, which becomes unsustainable unless the cryptocurrency's price rises accordingly. In the long term, miners stand to gain from PoS's stability, as it ensures a more predictable profit margin without the need for constant hardware investments and high energy costs. While miners may focus on short-term gains, they ultimately have a strong economic incentive to support the shift to PoS for long-term profitability. Furthermore, reduced volatility resulting in more stable returns improves the reward-to-risk ratio. This, in turn, could make cryptocurrencies more attractive to other stakeholders such as potential investors.

Our findings also have implications for the asset management industry, suggesting that institutions can improve their portfolio diversification strategies by investing in cryptocurrencies utilizing PoS blockchains. This approach can mitigate exposure to volatility dynamics resulting from energy shocks. Further implications derived from our results extend to innovative financing methods such as Initial Coin Offerings (ICOs). This new financing channel democratizes financial investments, allowing broader access to acquire funding for businesses compared to traditional approaches (e.g., IPO), while also significantly reducing costs by eliminating the need for third-party intermediaries. As documented by Campino et al. (2022), a project's success in terms of capital raised is negatively impacted by cryptocurrency return volatility, among other factors. Moreover, Lyandres et al. (2022) show that higher volatility negatively affects post-ICO operating performance. Thus, our results suggest that ICO projects should leverage PoS cryptocurrencies, as these can reduce coin volatility and potentially enhance project success rates.

4.3. Limitations

Our study presents some limitations that warrant acknowledgment. Firstly, we analyze the transition effect exclusively for four cryptocurrencies with high market capitalization. To enhance the generalizability of our findings, future research should consider a larger sample that includes digital currencies with lower market capitalizations. As more coins presumably switch to the PoS mechanism, future studies could also re-examine this issue using methodologies that require a larger sample size. While our proposed chi-squared joint test is suitable for small samples, traditional event study approaches may be more appealing for investigating this issue using larger datasets.

To ensure robustness, we not only estimated baseline GARCH(1,1) specifications but also employed TGARCH models to account for asymmetry and used alternative definitions of energy shocks. Across all models, the main finding of reduced volatility sensitivity under PoS remained intact. While these models provide rigorous evidence, future research could extend our framework with more advanced approaches such as GARCH-MIDAS, stochastic volatility, or machine learning-based volatility forecasts, particularly as longer time series become available. Moreover, future studies could extend the analysis by employing GARCH models with error terms based on alternative distributional assumptions, such as the Student's t-distribution or the GED distribution, in place of the normal distribution.

Finally, one might question whether the effect on volatility had been discounted prior to the event day due to the transition announcement. It is possible to argue that events of this nature, known as "forks," do not always culminate successfully, and the associated uncertainty may mitigate any potential discounting effect. Given the decentralized nature of blockchain networks, such events require community consensus and significant collaborative efforts among developers and validators, hence, holding inherent uncertainties. Even though switching a consensus protocol may result from a governance decision, it does not necessarily reflect the unified will of the entire community, which is called upon to approve the change. In this regard, analyzing this phenomenon by setting the event window around the announcement day could provide additional valuable insights. However, since this exceeds the scope of the present study, this is left for future research.

5. Conclusion

Recently, there have been growing concerns about the environmental sustainability of digital currencies. The PoW consensus mechanism is increasingly viewed as unsuitable to meet current carbon footprint reduction targets. However, the alternative PoS algorithm appears as a promising avenue to mitigate blockchain energy consumption. To date, only a handful of cryptocurrencies have transitioned to PoS—with the majority still reliant on PoW.

This study examines the impact of the change of consensus protocol on the volatility sensitivity of four high market capitalization cryptocurrencies—Ethereum, Cardano, Toncoin, and Decred—to energy shocks. Using data from coinmarketcap.com, we utilize the random transition features of these coins as a quasi-natural experimental setting. By employing extended GARCH and TGARCH models to assess cryptocurrency volatility, we find evidence of a significant negative overall effect. This implies that following the transition to PoS, cryptocurrencies demonstrate diminished sensitivity of their volatility to energy shocks, proxied by oil shocks.

From a policy perspective, our results indicate that encouraging the adoption of PoS consensus mechanisms can simultaneously enhance financial stability and environmental sustainability. This makes PoS not only a technological upgrade but also a tool for reducing systemic risk in crypto markets. For future research, extending the analysis to smaller-cap coins and alternative volatility models would provide additional insights as the PoS ecosystem continues to evolve.

Our findings suggest that digital currencies still using the PoW mechanism should consider migrating to PoS, as this shift can benefit stakeholders by reducing the uncertainty of cryptocurrency price changes. Since cryptocurrencies are notorious for extremely high levels of price change uncertainty, this is not a trivial issue. Future research could extend our study by analyzing a larger sample of cryptocurrencies or employing other volatility models to depict volatility dynamics.

References

Ali, F., Khurram, M. U., Sensoy, A., & Vo, X. V. (2024). Green cryptocurrencies and portfolio diversification in the era of greener paths. *Renewable and Sustainable Energy Reviews*, *191*, 114137. https://doi.org/10.1016/j.rser.2023.114137

Babiak, M., & Bianchi, D. (2024). Mispricing and Risk Compensation in Cryptocurrency Returns. *SSRN Electronic Journal*

Bakshi, G. S., & Chen, Z. (1996). Inflation, Asset Prices, and the Term Structure of Interest Rates in Monetary Economies. *The Review of Financial Studies*, *9*(1), 241–275.

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, 173, 148–151. https://doi.org/10.1016/j.econlet.2018.10.008

Beincrypto, (2024). Vitalik Buterin Defends Ethereum's Transition to Proof-of-Stake (PoS). https://beincrypto.com/vitalik-buterin-ethereum-pos/

Bouoiyour, J., & Selmi, R. (2016). Bitcoin: a beginning of a new phase?. *Economics Bulletin*, AccessEcon, 36(3), 1430-1440.

Bouraga, S. (2021). A taxonomy of blockchain consensus protocols: A survey and classification framework. *Expert Systems with Applications*, *168*, 114384. https://doi.org/10.1016/j.eswa.2020.114384

Bouri, E., Azzi, G., & Dyhrberg, A. H. (2017). On the return-volatility relationship in the Bitcoin market around the price crash of 2013. *Economics*, *11*(1). https://doi.org/10.5018/economics-ejournal.ja.2017-2

Campino, J., Brochado, A., & Rosa, Á. (2022). Initial coin offerings (ICOs): Why do they succeed? *Financial Innovation*, *8*(1), 17. https://doi.org/10.1186/s40854-021-00317-2

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using Markov-Switching GARCH models. *Research in International Business and Finance*, *48*, 143–155. https://doi.org/10.1016/j.ribaf.2018.12.009

Carbon-ratings (2023). https://carbon-ratings.com.

Catania, L., Grassi, S., & Ravazzolo, F. (2018). Predicting the Volatility of Cryptocurrency Time-Series. In M. Corazza, M. Durbán, A. Grané, C. Perna, & M. Sibillo (A c. Di), *Mathematical and Statistical Methods for Actuarial Sciences and Finance* (pp. 203–207). Springer International Publishing. https://doi.org/10.1007/978-3-319-89824-7_37

Christoffersen, P., & Pan, X. (Nick). (2018). Oil volatility risk and expected stock returns. *Journal of Banking & Finance*, *95*, 5–26. https://doi.org/10.1016/j.jbankfin.2017.07.004

Coindesk, (2022). What Is the Ethereum Merge? https://www.coindesk.com/learn/what-is-the-merge-and-why-has-it-taken-so-long/#:~:text=Ethereum's%20shift%20to%20proof%2Dof,most%20anticipated%20events%20in%20cryptocurrency.&text=The%20%E2%80%9CMerge%E2%80%9D%20is%20intended%20to,faster%20and%20more%20e.

Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, *62*, 182–199. https://doi.org/10.1016/j.irfa.2018.09.003

de Vries, A. (2019). Renewable Energy Will Not Solve Bitcoin's Sustainability Problem. *Joule*, *3*(4), 893–898. https://doi.org/10.1016/j.joule.2019.02.007

de Vries, A. (2020). Bitcoin's energy consumption is underestimated: A market dynamics approach. *Energy Research & Social Science*, *70*, 101721. https://doi.org/10.1016/j.erss.2020.101721

Di Febo, E., Ortolano, A., Foglia, M., Leone, M., & Angelini, E. (2021). From Bitcoin to carbon allowances: An asymmetric extreme risk spillover. *Journal of Environmental Management*, *298*, 113384. https://doi.org/10.1016/j.jenvman.2021.113384

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar – A GARCH volatility analysis. *Finance Research Letters*, *16*, 85–92. https://doi.org/10.1016/j.frl.2015.10.008

Edmans, A. (2024). *May contain lies: How stories, statistics, and studies exploit our biases—And what we can do about it*. University of California Press.

Fakhfekh, M., & Jeribi, A. (2020). Volatility dynamics of crypto-currencies' returns: Evidence from asymmetric and long memory GARCH models. *Research in International Business and Finance*, *51*, 101075. https://doi.org/10.1016/j.ribaf.2019.101075

Fry, J., & Cheah, E.-T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, *47*, 343–352. https://doi.org/10.1016/j.irfa.2016.02.008

Glosten, L. R., Jagannathan, R. & Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominalexcess return on stocks. *Journal of Finance*, 48(5), 1779–1801.

Grobys, K. (2021). When the blockchain does not block: On hackings and uncertainty in the cryptocurrency market. *Quantitative Finance*, *21*(8), 1267–1279. https://doi.org/10.1080/14697688.2020.1849779.

Hyung-Eun Choi (2025). Transition to proof-of-stake and informed trading, *Finance Research Letters*, 72, 106570.

Irresberger, F., & Yang, R. (2023). Coin concentration of Proof-of-Stake blockchains. *Economics Letters*, *229*, 111219. https://doi.org/10.1016/j.econlet.2023.111219

Islam, N., Marinakis, Y., Olson, S., White, R., & Walsh, S. (2023). Is BlockChain Mining Profitable in the Long Run? *IEEE Transactions on Engineering Management*, 70(2), 386–399. https://doi.org/10.1109/TEM.2020.3045774

John, K., Rivera, T. J., & Saleh, F. (2025). Proof-of-work versus proof-of-stake: A comparative economic analysis. *The Review of Financial Studies*, 38(7), 1955-2004.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3–6. https://doi.org/10.1016/j.econlet.2017.06.023

Katsiampa, P. (2019). An empirical investigation of volatility dynamics in the cryptocurrency market. *Research in International Business and Finance*, 50, 322–335. https://doi.org/10.1016/j.ribaf.2019.06.004

Khan, D., Jung, L. T., & Hashmani, M. A. (2021). Systematic Literature Review of Challenges in Blockchain Scalability. *Applied Sciences*, 11(20). https://doi.org/10.3390/app11209372

Klein, T., Pham Thu, H., & Walther, T. (2018). Bitcoin is not the New Gold – A comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis*, *59*, 105–116. https://doi.org/10.1016/j.irfa.2018.07.010

Kliber, A., & Będowska-Sójka, B. (2024). Proof-of-work versus proof-of-stake coins as possible hedges against green and dirty energy. Energy Economics, 138, 107820. https://doi.org/10.1016/j.eneco.2024.107820

Kohli, V., Chakravarty, S., Chamola, V., Sangwan, K. S., & Zeadally, S. (2023). An analysis of energy consumption and carbon footprints of cryptocurrencies and possible solutions. *Digital Communications and Networks*, *9*(1), 79–89. https://doi.org/10.1016/j.dcan.2022.06.017

Koutmos, D. (2023). Network Activity and Ethereum Gas Prices. *Journal of Risk and Financial Management*, 16(10). https://doi.org/10.3390/jrfm16100431

Kreppmeier, J., Laschinger, R., Steininger, B. I., & Dorfleitner, G. (2023). Real estate security token offerings and the secondary market: Driven by crypto hype or fundamentals? *Journal of Banking & Finance*, 154, 106940. https://doi.org/10.1016/j.jbankfin.2023.106940

Kyriazis, N. A. (2021). A Survey on Volatility Fluctuations in the Decentralized Cryptocurrency Financial Assets. *Journal of Risk and Financial Management*, *14*(7), Articolo 7. https://doi.org/10.3390/jrfm14070293

Leslie, M. (2020). Will Cryptocurrencies Break the Energy Bank? *Engineering*, *6*(5), 489–490. https://doi.org/10.1016/j.eng.2020.03.011

Liu, B., Prodromou, T., Suardi, S., & Xu, C. (2025). Ethereum's Merge: Market liquidity, efficiency and volatility in the Proof of Stake Era. *Economics Letters*, 247, 112202.

Lyandres, E., Palazzo, B., & Rabetti, D. (2022). Initial Coin Offering (ICO) Success and Post-ICO Performance. *Management Science*, *68*(12), 8658–8679. https://doi.org/10.1287/mnsc.2022.4312

Naeem, M. A., Karim, S., Abrar, A., Yarovaya, L., & Shah, A. A. (2023). Non-linear relationship between oil and cryptocurrencies: Evidence from returns and shocks. *International Review of Financial Analysis*, *89*, 102769. https://doi.org/10.1016/j.irfa.2023.102769

Naeem, M. A., Karim, S., Uddin, G. S., & Junttila, J. (2022). Small fish in big ponds: Connections of green finance assets to commodity and sectoral stock markets. International Review of Financial Analysis, 83, 102283. https://doi.org/10.1016/j.irfa.2022.102283

Okorie, D. I., & Lin, B. (2020). Crude oil price and cryptocurrencies: Evidence of volatility connectedness and hedging strategy. *Energy Economics*, *87*, 104703. https://doi.org/10.1016/j.eneco.2020.104703

Park, J., & Ratti, R. A. (2008). Oil price shocks and stock markets in the U.S. and 13 European countries. *Energy Economics*, *30*(5), 2587–2608. https://doi.org/10.1016/j.eneco.2008.04.003

Pham, L., Karim, S., Naeem, M. A., & Long, C. (2022). A tale of two tails among carbon prices, green and non-green cryptocurrencies. *International Review of Financial Analysis*, *82*, 102139. https://doi.org/10.1016/j.irfa.2022.102139

Ren, B., & Lucey, B. (2022). Do clean and dirty cryptocurrency markets herd differently? *Finance Research Letters*, *47*, 102795. https://doi.org/10.1016/j.frl.2022.102795

Roşu, I., & Saleh, F. (2021). Evolution of Shares in a Proof-of-Stake Cryptocurrency. *Management Science*, *67*(2), 661–672. https://doi.org/10.1287/mnsc.2020.3791

Sangari, M. S., & Mashatan, A. (2024). What is driving consumer resistance to crypto-payment? A multianalytical investigation. *Psychology & Marketing*, 41(3), 575–591. https://doi.org/10.1002/mar.21935

Sedlmeir, J., Buhl, H. U., Fridgen, G., & Keller, R. (2020). The Energy Consumption of Blockchain Technology: Beyond Myth. *Business & Information Systems Engineering*, *62*(6), 599–608. https://doi.org/10.1007/s12599-020-00656-x

Shanaev, S., Sharma, S., Ghimire, B., & Shuraeva, A. (2020). Taming the blockchain beast? Regulatory implications for the cryptocurrency Market. *Research in International Business and Finance*, *51*, 101080. https://doi.org/10.1016/j.ribaf.2019.101080

Sriman, B., Ganesh Kumar, S., & Shamili, P. (2021). Blockchain Technology: Consensus Protocol Proof of Work and Proof of Stake. In S. S. Dash, S. Das, & B. K. Panigrahi (A c. Di), *Intelligent Computing and Applications* (pp. 395–406). Springer. https://doi.org/10.1007/978-981-15-5566-4_34

Sutherland, B. R. (2019). Blockchain's First Consensus Implementation Is Unsustainable. *Joule*, *3*(4), 917–919. https://doi.org/10.1016/j.joule.2019.04.001

Truby, J., Brown, R. D., Dahdal, A., & Ibrahim, I. (2022). Blockchain, climate damage, and death: Policy interventions to reduce the carbon emissions, mortality, and net-zero implications of non-fungible tokens and Bitcoin. *Energy Research & Social Science*, *88*, 102499. https://doi.org/10.1016/j.erss.2022.102499

U.S. Energy Information Administration (2022). Electric Power Annual 2022.

Vaughan, C., Samaties P., Kemp B.,& Sanaulla F. (2022). How crypto mining will transform the energy industry. Roland Berger.

Wendl, M., Doan, M. H., & Sassen, R. (2023). The environmental impact of cryptocurrencies using proof of work and proof of stake consensus algorithms: A systematic review. *Journal of Environmental Management*, *326*, 116530. https://doi.org/10.1016/j.jenvman.2022.116530

Yang, W. (2025). Incentivizing Blockchain Participation Through Task Assignment Mechanisms: Evidence From a Natural Experiment of Consensus Protocols on Ethereum. *Journal of Operations Management* (forthcoming).

Yin, L., Nie, J., & Han, L. (2021). Understanding cryptocurrency volatility: The role of oil market shocks. *International Review of Economics & Finance*, *72*, 233–253. https://doi.org/10.1016/j.iref.2020.11.013

Yu, M. (2019). Forecasting Bitcoin volatility: The role of leverage effect and uncertainty. *Physica A: Statistical Mechanics and its Applications*, *533*, 120707. https://doi.org/10.1016/j.physa.2019.03.072

Zhang, D., Chen, X. H., Lau, C. K. M., & Xu, B. (2023). Implications of cryptocurrency energy usage on climate change. *Technological Forecasting and Social Change*, *187*, 122219. https://doi.org/10.1016/j.techfore.2022.122219

Figure 1. Bitcoin network complexity and energy consumption.

This figure reports a comparison of the energy consumed by the Bitcoin blockchain and its relative measure of complexity in mining a new block.
Source: Vaughan et al. (2022)

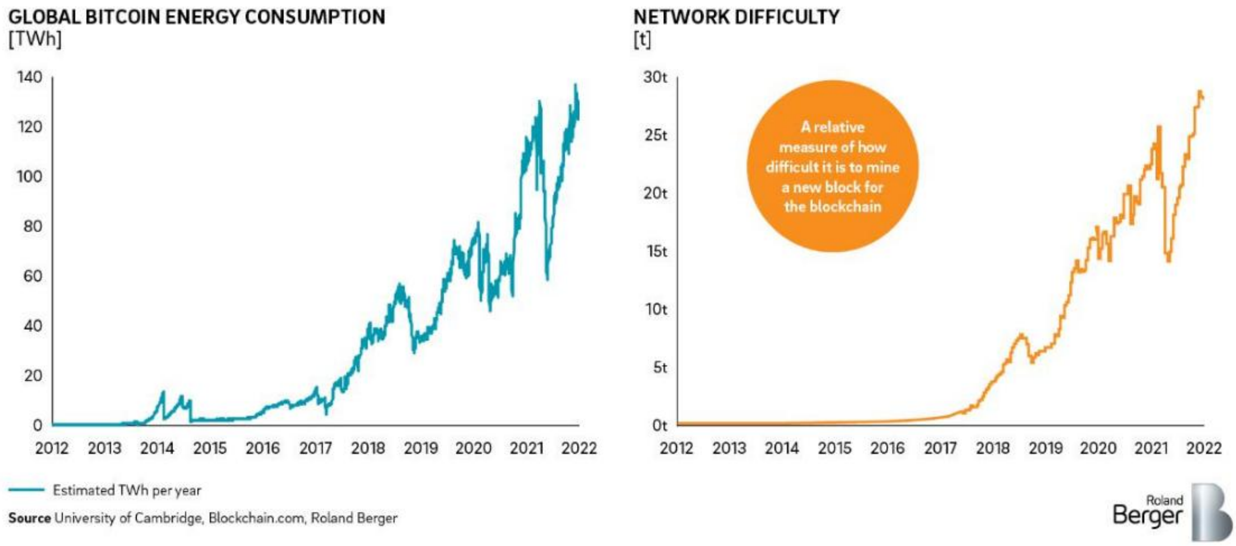

Figure 2. Conditional volatility before and after PoS transitions.

This figure presents the conditional volatility series obtained from fitted GARCH(1,1) models for the four cryptocurrencies in our sample. A dashed vertical line marks the halfway point of the sample, illustrating the period before and after each PoW-to-PoS transition. The plots visually demonstrate that conditional volatility becomes less sensitive to energy shocks after the adoption of PoS, complementing our econometric results.
Source: Authors own work

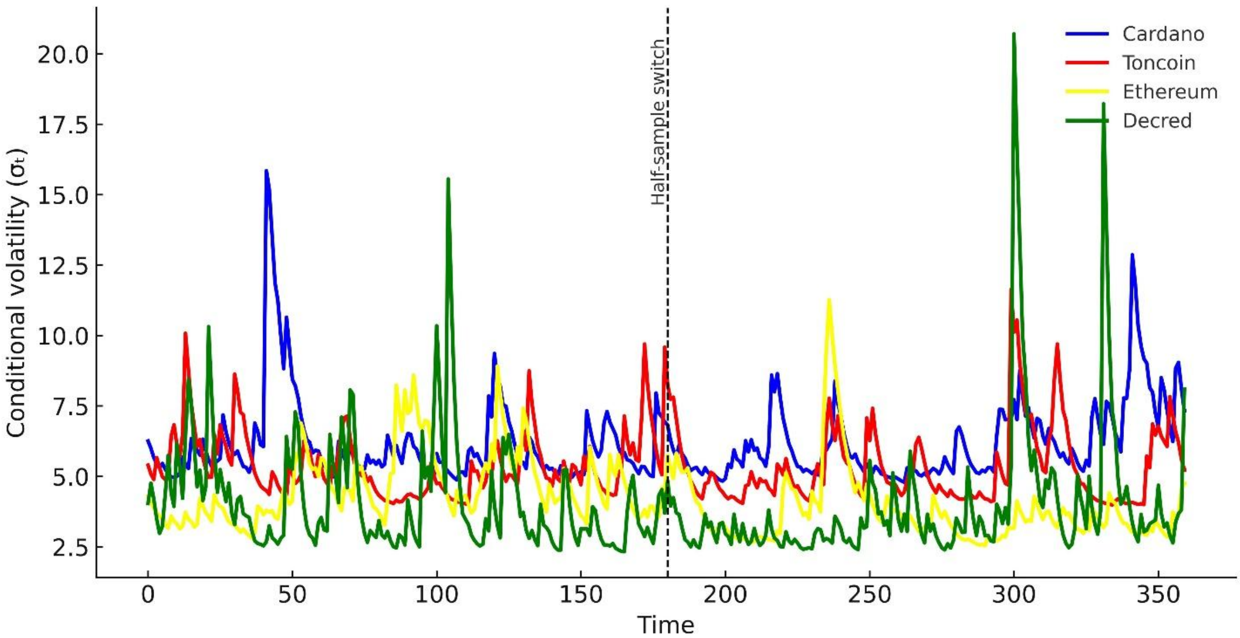

Table 1. Event dates

This table reports the specific date when a cryptocurrency switched from a Proof of Work (PoW) to a Proof of Stake (PoS) consensus mechanism. The ex-ante sample refers to the preceding 180 days from the event date, while the ex-post sample refers to the subsequent 180 days after the event date.

Cryptocurrency	**Event Day**	**Ex-ante sample**	**Ex-post sample**
Cardano	29.07.2020	31.01.2020 – 28.07.2020	30.07.2020 – 25.01.2021
Toncoin	28.06.2022	30.12.2021 – 27.06.2022	29.06.2022 – 25.12.2022
Ethereum	15.09.2022	19.03.2022 – 14.09.2022	16.09.2022 – 14.03.2023
Decred	29.08.2023	02.03.2023 – 28.08.2023	30.08.2023 – 25.02.2024

Table 2. Descriptive statistics.

Descriptive statistics for the price returns of Cardano (ADA), Toncoin (TON), Ethereum (ETH), Decred (DCR), and West Texas Intermediate (WTI) from coinmarketcap.com and the US Energy Information Administration. The ex-ante sample refers to the returns of the past 180 days from the event date, while the ex-post sample refers to the returns of the next 180 days after the event date.

Cryptocurrency	Cardano		WTI_C		Toncoin		WTI_T		Ethereum		WTI_E		Decred		WTI_D	
Sample period	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**	**Ex-ante**	**Ex-post**
Mean	0.0078	0.0069	0.0027	0.0017	-0.0045	0.0052	0.0024	-0.0017	-0.0021	0.0016	-0.0008	-0.0009	-0.0025	0.0032	0.0003	-0.0001
Median	0.0048	0.0046	0.0000	0.0012	-0.0038	-0.0002	0.0023	-0.0004	-0.0014	-0.0014	0.0005	-0.0004	-0.0032	0.0024	0.0007	0.0003
Maximum	0.2019	0.2849	0.5309	0.0491	0.2073	0.2673	0.0856	0.0504	0.1793	0.1811	0.0669	0.0504	0.2126	0.2844	0.0409	0.0579
Minimum	-0.3957	-0.1736	-0.5134	-0.0526	-0.1712	-0.1495	-0.1199	-0.0792	-0.1665	-0.1746	-0.0792	-0.0589	-0.1238	-0.1135	-0.0534	-0.0553
Std. Dev.	0.0628	0.0627	0.0892	0.0165	0.0557	0.0520	0.0251	0.0208	0.0485	0.0365	0.0226	0.0180	0.0398	0.0409	0.0162	0.0159
Skewness	-0.9003	0.5876	0.9893	-0.1577	0.7558	0.7304	-0.3340	-0.4351	0.0206	-0.2191	-0.4544	-0.1519	1.1143	2.8246	-0.5526	-0.2223
Kurtosis	12.5250	5.3438	19.1805	4.2425	5.6251	7.1433	7.2422	4.0771	4.7442	9.7168	4.4134	4.0786	8.1847	21.6134	4.1963	4.6850
Jarque-Bera	700.8405	51.2700	1981.8590	12.2560	68.4387	143.9517	137.5481	14.3001	22.7016	337.9160	21.0596	9.3656	237.5317	2822.0190	19.7844	22.6511
Probability	(0.0000)	(0.0000)	(0.0000)	(0.0022)	(0.0000)	(0.0000)	(0.0000)	(0.0008)	(0.0000)	(0.0000)	(0.0000)	(0.0093)	(0.0000)	(0.0000)	(0.0001)	(0.0000)
ADF Test	-15.8039	-13.3404	-15.1653	-11.4373	-11.8159	-14.2082	-12.7339	-11.9474	-13.6843	-13.6517	-12.8706	-11.1905	-16.2120	-14.7249	-11.2990	-12.3542
Probability	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Observations	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179	179

Table 3. Estimates for a generalized conditional heteroskedasticity model accounting for de-demeaned returns on oil.

This table reports the estimated parameters for the following generalized conditional heteroskedasticity (GARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i-1}^2 + \delta_i \left(RET_{Oil,t}^D\right)^2 + \theta_i d_{i,t} \left(RET_{Oil,t}^D\right)^2\right)}\,\epsilon_{i,t},$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process, where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time *t*, $d_{i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.10	1.32**	0.15***	0.78***	0.12	-0.18
	(0.45)	(2.48)	(4.49)	(15.47)	(0.87)	(-1.60)
Cardano	0.68**	5.15**	0.11***	0.78***	-0.00	-0.29**
	(2.00)	(2.41)	(3.26)	(10.42)	(-0.15)	(-1.96)
Toncoin	0.03	4.83***	0.16***	0.72***	-0.10	-0.18*
	(0.12)	(4.15)	(3.81)	(13.00)	(-1.61)	(-1.94)
Decred	-0.16	2.71***	0.56***	0.45***	0.46	-0.64*
	(-0.88)	(4.98)	(10.75)	(9.19)	(1.26)	(-1.73)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 4. Estimates for a threshold generalized conditional heteroskedasticity model accounting for de-demeaned returns on oil.

This table reports the estimated parameters for the following threshold generalized conditional heteroskedasticity (TGARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\left(RET_{Oil,t}^D\right)^2 + \theta_i d_{2,i,t}\left(RET_{Oil,t}^D\right)^2\right)}\,\epsilon_{i,t}.$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Furthermore, $RET_{Oil,t}^D$ denotes the de-meaned return on oil at time *t*, $d_{2,i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	-0.01	13.23**	-0.02	0.05	0.58***	-0.42***	-0.49***
	(-0.04)	(2.87)	(-0.26)	(0.85)	(3.53)	(-27.03)	(-5.98)
Cardano	0.62*	4.82**	0.10***	0.07*	0.77***	-0.00	-0.26*
	(1.85)	(2.38)	(3.22)	(1.81)	(10.57)	(-0.07)	(-1.73)
Toncoin	0.02	4.67***	0.14***	0.02	0.73***	-0.11	-0.18**
	(0.07)	(4.11)	(2.93)	(0.36)	(13.37)	(-1.60)	(-1.96)
Decred	0.16	5.84***	1.20***	-1.08***	0.09	3.15***	-3.32***
	(0.90)	(6.86)	(9.14)	(-6.98)	(1.53)	(4.70)	(-5.00)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 5. Oil returns autocorrelation.

To explore whether the returns on oil are autocorrelated, we run the following regressions:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time t, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Using the overall samples—that is, the ex-ante and ex-post event samples together—the regression results are reported in this table.

Sample	Cardano 31.01.2020 - 25.01.2021	Toncoin 30.12.2021 - 25.12.2022	Ethereum 19.03.2022 - 14.03.2023	Decred 02.03.2023 - 25.02.2024
WTI_{t-1}	-0.1238**	0.0796	0.0737	0.1232**
	(-2.36)	(1.51)	(1.39)	(2.35)
Constant	0.0024	0.0004	-0.0009	0.0001
	(0.72)	(0.32)	(-0.87)	(0.07)
R-squared	0.0153	0.0063	0.0054	0.0152
Observations	359	359	359	359

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level

Table 6. Estimates for a generalized conditional heteroskedasticity model accounting for oil innovations.

This table reports the estimated parameters for the following generalized conditional heteroskedasticity (GARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{(\alpha_i + \beta_i \varepsilon_{i,t-1}^2 + \gamma_i \sigma_{i,t-1}^2 + \delta_i \varepsilon_{Oil,t}^2 + \theta_i d_{i,t} \varepsilon_{Oil,t}^2)}\epsilon_{i,t},$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process defined where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $\varepsilon_{Oil,t}$ are the regression residuals from the following regression:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time *t*, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Furthermore, $d_{i,t}$ denotes a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_i, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_i$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.14	1.28**	0.15***	0.78***	0.13	-0.18
	(0.67)	(2.49)	(4.49)	(15.67)	(0.91)	(-1.60)
Cardano	0.64*	5.17**	0.11***	0.77***	-0.00	-0.27*
	(1.87)	(2.42)	(3.27)	(10.43)	(-0.16)	(-1.93)
Toncoin	0.05	4.90***	0.16***	0.72***	-0.09	-0.18*
	(0.17)	(4.11)	(3.79)	(12.69)	(-1.38)	(-1.79)
Decred	-0.20	7.83***	0.80***	-0.08**	2.37***	-2.61***
	(-1.33)	(8.60)	(10.56)	(-2.46)	(6.53)	(-6.99)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.

Table 7. Estimates for a threshold generalized conditional heteroskedasticity model accounting for oil innovations.

This table reports the estimated parameters for the following threshold generalized conditional heteroskedasticity (TGARCH) model:

$$RET_{i,t} = c_i + \varepsilon_{i,t},$$

$$\varepsilon_{i,t} = \sqrt{\left(\alpha_i + \beta_{0i}\varepsilon_{i,t-1}^2 + \beta_{1i}d_{1,i,t}\varepsilon_{i,t-1}^2 + \gamma_i\sigma_{i,t-1}^2 + \delta_i\varepsilon_{Oil,t}^2 + \theta_i d_{2,i,t}\varepsilon_{Oil,t}^2\right)}\epsilon_{i,t}.$$

Considering the mean equation, $RET_{i,t}$ denotes the returns on cryptocurrency *i* at time *t*, and c_i denotes the corresponding regression intercept, whereas $\varepsilon_{i,t}$ is assumed to be governed by a conditional volatility process where $\varepsilon_{i,t-1}^2$ ($\sigma_{i,t-1}^2$) are defined as the squared residual (conditional variance) of the mean equation at time $t-1$, and $\varepsilon_{Oil,t}$ are the regression residuals from the following regression:

$$RET_{Oil,t} = c_{Oil} + \rho RET_{Oil,t-1} + \varepsilon_{Oil,t},$$

where $RET_{Oil,t}$ is the return on oil at time *t*, c_{Oil}, and ρ are parameters to be estimated, and $\varepsilon_{Oil,t}$ denotes an error term that is assumed to be a white noise process. Furthermore, $d_{1,i,t}$ is a dummy variable that has a value of 0 if $\varepsilon_{i,t} > 0$, and a value of 1 if $\varepsilon_{i,t} < 0$. Moreover, $d_{2,i,t}$ is a dummy variable that has a value of 0 before the event for cryptocurrency *i* and a value of 1 after the event, whereas $\epsilon_{i,t}$ is assumed to be a white noise error term, such as $\epsilon_{i,t} \sim N(0,1)$. In the variance equation, the parameters for α_i, β_{0i}, β_{1i}, γ_i, δ_i, and θ_i are estimated via quasi-maximum likelihood estimation.

Coin	$\hat{c}_i$	$\hat{\alpha}_i$	$\hat{\beta}_{0,i}$	$\hat{\beta}_{1,i}$	$\hat{\gamma}_i$	$\hat{\delta}_i$	$\hat{\theta}_i$
Ethereum	0.05	2.32**	0.05	0.20***	0.70***	0.24	-0.27
	(0.22)	(2.77)	(1.35)	(3.08)	(9.09)	(1.21)	(-1.60)
Cardano	0.59*	4.84**	0.10***	0.07*	0.76***	-0.00	-0.25*
	(1.73)	(2.40)	(3.22)	(1.82)	(10.58)	(-0.08)	(-1.72)
Toncoin	0.04	4.78***	0.15***	0.02	0.72***	-0.10	-0.18*
	(0.13)	(4.05)	(2.94)	(0.26)	(12.95)	(-1.34)	(-1.80)
Decred	0.15	6.55***	1.32***	-1.18***	0.02	3.03***	-3.20***
	(0.86)	(8.22)	(8.75)	(-6.59)	(0.46)	(6.23)	(-6.52)

*, **, *** denotes statistical significance on a 10%, 5%, or 1% level.