Economic Policy Uncertainty and Bitcoin Synchronicity

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ABSTRACT

We investigated the effect of economic policy uncertainty (EPU) on Bitcoin synchronicity (i.e., how much the prices of other cryptocurrencies move together with Bitcoin prices), as measured using the method of Roll (1988). According to our findings, global EPU generally strengthens Bitcoin synchronicity. However, at the country level, global EPU exerts opposite effects depending on how friendly a country is toward cryptocurrency. These findings were robust when tested on the case of Ethereum synchronicity.

Keywords: Bitcoin, cryptocurrency, price synchronicity, economic policy uncertainty (EPU).

JEL Classifications: G15, D81.3

1. Introduction

Bitcoin has become widely adopted since its introduction (Nakamoto, 2008) and is now traded alongside more than 2.4 million other cryptocurrencies that combined have a market capitalization exceeding US$2 trillion, as of the end of August 2024 (Best, 2024; Forbes, 2024). Researchers have found that investors regard cryptocurrencies as assets rather than currencies (Baur et al., 2018; Corbet et al., 2019; Griffin & Shams, 2020; Makarov & Schoar, 2020). Liu and Tsyvinski (2021) and Liu et al. (2022) have thus investigated the factors influencing the prices of cryptocurrencies as assets. Cryptocurrencies, however, differ from traditional financial assets.[1] Recent studies have investigated network or spillover effects in the cryptocurrency market (Guo et al., 2024), seeking to understand the propagation of risks and returns. These network effects are likely to be strong in the case of Bitcoin given its leading status in the cryptocurrency market—Bitcoin accounted for more than 85% of the cryptocurrency market by value from 2010 to 2016. Thus, numerous studies have focused on the interactions between Bitcoin and other assets (Corbet et al., 2018; Dyhrberg, 2016; Georgoula et al., 2015; Pagnottoni, 2023; Pagnottoni & Spelta, 2023; Shahzad et al., 2019; Yen et al., 2023).

We contribute to this literature by investigating Bitcoin synchronicity (i.e., how much Bitcoin returns explain those of other assets), drawing on the literature on stock price synchronicity pioneered by Roll (1988). In essence, stock price synchronicity is a phenomenon whereby individual stock prices move with the overall market rather than with information related to the individual firm itself. Stock price synchronicity is usually measured by the logit-transformed

[1] We can view cryptocurrencies in two ways. First, unlike stocks or bonds, they lack intrinsic value or publicly available indicators such as analyst forecasts or financial disclosures (Bhambhwani et al., 2019; Biais et al., 2023; Cong et al., 2021; Detzel et al., 2021; Liu et al., 2024; Sockin & Xiong, 2023). Second, the cryptocurrency market is far more unregulated relative to traditional financial markets (Hossain, 2021) and is thus prone to manipulation and illegal activity (Foley et al., 2019; Li et al., 2021).

adjusted R-squared, where the adjusted R-squared is obtained from regressions of the returns of individual securities on market, industry, or factor returns.

In capital market research, stock price synchronicity is widely used as a proxy for the informativeness of stock prices. A lower synchronicity suggests that a stock's price movements are more influenced by firm-specific information, indicating higher informativeness. Conversely, higher synchronicity implies that market or industry factors predominantly drive the stock's price variation, reflecting lower incorporation of firm-specific details. This measure has been instrumental in studies examining market efficiency, information dissemination, and corporate governance (Roll, 1988; Morck et al., 2000; Durnev et al., 2003, 2004; Piotroski & Roulstone, 2004; Chen et al., 2007; Hutton et al., 2009; Crawford et al., 2012; Chan & Chan, 2014).

Using the economic interpretation of the stock price synchronicity, we interpret the Bitcoin synchronicity similarly. Specifically, Bitcoin synchronicity captures the extent to which the returns of other cryptocurrencies are explained by Bitcoin returns, rather than by idiosyncratic or cryptocurrency-specific factors. A lower Bitcoin synchronicity indicates that the price movements of other cryptocurrencies are less influenced by Bitcoin and more driven by unique, asset-specific information, such as innovations in their underlying technologies, governance structures, or use cases. Conversely, a higher Bitcoin synchronicity suggests that Bitcoin plays a dominant role in driving the price variation of other cryptocurrencies, reflecting its centrality and influence in the cryptocurrency market. This interpretation enables researchers to examine the informativeness of cryptocurrency prices and the degree to which Bitcoin serves as a benchmark or anchor for the broader crypto market.

Furthermore, many studies have highlighted the influence of macroeconomic uncertainty risk on the cryptocurrency market. For instance, Bouri et al. (2017) explored the link between uncertainty and Bitcoin returns and found that Bitcoin serves as a hedge against uncertainty. Similarly, Demir et al. (2018) reported a negative correlation between Bitcoin returns and the economic policy uncertainty (EPU) index. Furthermore, Cheng and Yen (2020) found that only China's EPU index positively forecasts Bitcoin returns. Yen et al. (2023) discovered that cryptocurrencies move more tightly with Bitcoin—as indicated by the Pearson correlation—in cases of higher global EPU.

Drawing on findings in the literature, we hypothesized that higher EPU leads to greater Bitcoin synchronicity at global and national levels. The empirical results of this study supported this positive association for global, US, German, and Australian EPU indices. However, this association was negative for Chinese and Russian indices. This difference was explained by the crypto-friendliness of each country. These results held (i.e., were robust) when tested on the case of Ethereum synchronicity.

Our research contributes to three bodies of literature. The first is the literature on EPU. Since Baker et al. (2016) introduced the EPU index, several studies have investigated the relationship between EPU and asset prices, and some recent studies have examined the relationship between EPU and cryptocurrency prices (Cheng & Yen, 2020; Demir et al., 2018; Yen et al., 2023). We contribute to this literature by showing that EPU is also associated with synchronicity and not only prices. The second is the nascent literature on the cryptocurrency market. Studies on this topic have uncovered the unique characteristics of the cryptocurrency market (Bhambhwani et al., 2019; Biais et al., 2023; Cong et al., 2021; Detzel et al., 2021; Foley et al., 2019; Hossain, 2021; Li et al., 2021; Liu et al., 2024; Sockin & Xiong, 2023), identified the factors affecting cryptocurrency returns (Liu et al., 2022; Liu & Tsyvinski, 2021), and elucidated network and spillover effects in this market (Guo et al., 2024). We extend this literature by showing that EPU can indicate the level of Bitcoin synchronicity. The third is the literature on stock price synchronicity. Specifically, we are the first to extend its insights to the relatively unexplored domain of cryptocurrency.

The rest of this paper is organized as follows. Section 2 describes how we measured synchronicity and collected the data for analysis. Section 3 presents our empirical results. Finally, Section 4 concludes this study.

2. Data and empirical methods

2.1 Empirical approach

We drew on the literature on stock price synchronicity to formulate a measure of cryptocurrency price synchronicity. Specifically, we considered Bitcoin returns to be equivalent to returns on the entire cryptocurrency market because of Bitcoin's outsized market capitalization. We fitted the following regression model to data for each cryptocurrency i and each month t.

$$R_{i,t,d} = \alpha + \beta BTCR_{t,d} + \varepsilon_{i,t,d}, \tag{1}$$

where $R_{i,t,d}$ is the daily return of cryptocurrency i at month t and day d and $BTCR_{t,d}$ is the daily return of Bitcoin. This equation is analogous to that for the capital asset pricing model (CAPM) for stocks. The adjusted R-squared for cryptocurrency i at month t, written $R_{i,t}^{2,BTC}$, can then be obtained from the regression results. We defined the Bitcoin synchronicity $BTCSYNC_{i,t}$ for cryptocurrency i at month t to be the logit transformation of this R-squared as follows.

$$BTCSYNC_{\mathrm{i,t}} = \ln\left(\frac{R_{i,t}^{2,BTC}}{1-R_{i,t}^{2,BTC}}\right). \tag{2}$$

Following established methods in the literature, we Winsorized the adjusted R-squared values to be within 0.0001 and 0.9999 (Dong et al., 2016). In our robustness tests, we calculated the

Ethereum synchronicity $ETHSYNC$ in an analogous manner on the basis of the $R^{2,ETH}$ for Ethereum.

$$ETHSYNC = \ln\left(\frac{R^{2,ETH}}{1-R^{2,ETH}}\right). \tag{3}$$

The relationship between EPU and Bitcoin synchronicity was then tested using the following linear regression model:

$$BTCSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta ln(EPU)_{t-k} + \theta X + \varepsilon_{i,t}, \tag{4}$$

where $\Delta ln(EPU)$ is the 1 or 2–month lagged change in the natural logarithm of the global EPU index as the independent variable; X is a vector specifying the cryptocurrency, year, and quarter fixed effects as the control variable; and ε is the error term. Cryptocurrency-clustered standard errors were used.

We then formulated a measure of the country-specific EPU index; this index was defined as the residual of the regression of a country's EPU on the global EPU. This residual represented the part of the country's EPU that the global EPU could not explain. We considered three crypto-friendly countries—the United States, Germany, and Australia—and two crypto-unfriendly countries—China and Russia. The regression model was as follows.

$$\ln(Country)_t = \gamma_0 + \gamma_1 \ln(EPU)_t + e_t. \tag{5}$$

We denote the change in the natural logarithm of the estimated residual from that in the previous time point as $\Delta ln(\widetilde{Country})$ and used it as the country-specific EPU index.

In country-level analyses, we then determined the association between the country-specific EPU index and Bitcoin synchronicity by using the following regression model.

$$BTCSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta ln(\widetilde{Country})_{t-k} + \theta X + \varepsilon_{i,t}, \quad (6)$$

where these variables have the same definitions as those in the global-level analysis.

2.2 Data

We obtained data for the July 2013 to April 2022 period on cryptocurrency prices and the EPU index from CoinMarketCap and the Economic Policy Uncertainty website (Baker et al., 2016), respectively. Although CoinMarketCap provided data dating back to April 2013, we only used data from July 2013 onward to avoid missing data. Our dataset had 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. Table 1 presents the summary statistics of the variables considered.

[Table 1 inserted here]

The mean of the Bitcoin synchronicity indicated that the average adjusted R-squared of regression model (1) was more than 1%. The distribution of Bitcoin synchronicity was slightly more right-skewed than was that of Ethereum synchronicity. The EPU indexes for the United States and Russia had slight and considerable fluctuations, respectively.

3. Empirical results

The panel linear regression results based on Equation (4) indicated that higher global EPU was associated with stronger Bitcoin synchronicity (Table 2).

[Table 2 inserted here]

Specifically, the coefficients of $\Delta ln(EPU)_{t-1}$ and $\Delta ln(EPU)_{t-2}$ were positive and significant at the 1% level.

This positive association may have stemmed from two reasons. First, investors are more risk averse in cases of higher global EPU (Pastor & Veronesi, 2012, 2013), thereby flocking to alternative assets, such as gold, the US dollar, or Bitcoin, as a means to diversify their holdings away from traditional financial markets (Dyhrberg, 2016). Second, investors may be more concerned about macroeconomic uncertainty in cases of higher global EPU. Thus, they focus less on individual cryptocurrencies and engage in category-based investing instead (Hirshleifer et al., 2009; Hirshleifer & Teoh, 2003; Peng & Xiong, 2006), where they consider the cryptocurrency market as a whole and use Bitcoin as a proxy for the entire cryptocurrency market. The results also suggest that the cryptocurrency price informativeness may fall as investors are uncertain about economic policies, holding Bitcoin rather than other cryptocurrencies or practicing category-based investing.

The results for the country-specific regression based on Equation (6) indicated that the positive association between EPU and Bitcoin synchronicity held for the crypto-friendly countries of the United States, Germany, and Australia but did not hold for the crypto-unfriendly countries of China and Russia (Table 3).

[Table 3 inserted here]

Specifically, the coefficients of $\Delta ln(\widetilde{Country})$ were all positive and significant at the 1% level for the crypto-friendly countries; this positive association was strongest for the United States, followed by Germany and then Australia. The coefficients of $\Delta ln(\widetilde{Country})$ were all negative and significant at the 1% level for the crypto-unfriendly countries. The effect of the 1-month lagged EPU on Bitcoin synchronicity was larger in Russia than in China, but the effect of the 2-month lagged EPU on Bitcoin synchronicity was larger in China than in Russia.

[Table 4 inserted here]

Several implications follow from these results. First, crypto-friendly economies tend to be more mature, and EPU in such countries is unlikely to entail large shifts in cryptocurrency regulations. Thus, investors treat cryptocurrencies as a unified asset class, leading to higher Bitcoin synchronicity. Second, the cryptocurrency market in crypto-friendly economies tend to be highly integrated with traditional financial markets, causing broader economic uncertainty to reverberate uniformly throughout the cryptocurrency market. By contrast, EPU in crypto-unfriendly countries may lead investors to speculate on which particular cryptocurrencies would be more affected by large regulatory shifts, as evident in China's banning of cryptocurrency trading and mining in 2021 and 2022 and Russia's banning of the use of digital assets for payments (Yen et al., 2023).

In the robustness test, the findings also held for the case of Ethereum synchronicity. Notably, among cryptocurrencies, Ethereum has the second-largest market capitalization after Bitcoin (Table 5).

[Table 5 inserted here]

4. Conclusion

EPU positively influences Bitcoin synchronicity across the globe and in crypto-friendly countries, such as the United States, Germany, and Australia, but not in crypto-unfriendly countries, such as China and Russia. These results remained robust when applied to the case of Ethereum synchronicity. The findings highlight the sensitivity of cryptocurrency market dynamics to the regulatory landscape. Our research also explores cryptocurrency price informativeness through the lens of the Bitcoin synchronicity.

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Appendix A

Variable	Definition
$BTCSYNC$	$ln\left(\frac{R^2}{1-R^2}\right)$, where R^2 is the adjusted R-squared of the regression results of the daily returns of each cryptocurrency at any given month on daily Bitcoin returns
$ETHSYNC$	$ln\left(\frac{R^2}{1-R^2}\right)$, where R^2 is the adjusted R-squared of the regression results of the daily returns of each cryptocurrency at any given month on daily Ethereum returns
$\Delta ln(EPU)$	Monthly change in the natural logarithm of the global economic policy uncertainty index
$\Delta \widetilde{ln(US)}$	Monthly change in the residual of the natural logarithm of the US economic policy uncertainty index; this residual is that of the regression of the natural logarithm of the US economic policy uncertainty index on the natural logarithm of the global economic policy uncertainty index
$\Delta ln(\widetilde{Germany})$	Monthly change in the residual of the natural logarithm of the German economic policy uncertainty index; this residual is that of the regression of the natural logarithm of the German economic policy uncertainty index on the natural logarithm of the global economic policy uncertainty index
$\Delta ln(\widetilde{Australia})$	Monthly change in the residual of the natural logarithm of the Australian economic policy uncertainty index; this residual is that of the regression of the natural logarithm of the Australian economic policy uncertainty index on the natural logarithm of the global economic policy uncertainty index
$\Delta ln(\widetilde{China})$	Monthly change in the residual of the natural logarithm of the Chinese economic policy uncertainty index; this residual is that of the regression of the natural logarithm of the Chinese economic policy uncertainty index on the natural logarithm of the global economic policy uncertainty index
$\Delta ln(\widetilde{Russia})$	Monthly change in the residual of the natural logarithm of the Russian economic policy uncertainty index; this residual is that of the regression of the natural logarithm of the Russian economic policy uncertainty index on the natural logarithm of the global economic policy uncertainty index

Table 1: Summary Statistics

This table presents the number of observations (N), mean (Mean), standard deviation (S.D.), minimum (Min.), 25th percentile (P25), median (P50), 75th percentile (P75), and maximum (Max.) of each variable. Panel A shows the summary statistics of the panel (cryptocurrency and month) variables. Panel B shows the summary statistics of the time-series (monthly) variables. The dataset comprised 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. The data covered the period from July 2013 to April 2022. The variables are defined in Appendix A.

Panel A: Panel Variables

VARIABLES	N	Mean	S.D.	Min.	P25	P50	P75	Max.
$BTCSYNC$	127,292	-4.199	4.064	-9.210	-9.210	-2.903	-1.150	9.210
$ETHSYNC$	123,134	-4.280	3.992	-9.210	-9.210	-2.959	-1.103	9.210

Panel B: Time-Series Variables

VARIABLES	N	Mean	S.D.	Min.	P25	P50	P75	Max.
$\Delta ln(EPU)$	106	0.010	0.186	-0.455	-0.100	-0.010	0.120	0.610
$\Delta ln(\widetilde{US})$	106	-0.007	0.209	-0.620	-0.166	0.010	0.137	0.449
$\Delta ln(\widetilde{Germany})$	106	0.006	0.285	-0.583	-0.226	-0.021	0.219	0.853
$\Delta ln(\widetilde{Australia})$	106	-0.004	0.365	-1.226	-0.261	0.013	0.215	0.794
$\Delta ln(\widetilde{China})$	106	0.000	0.293	-0.817	-0.196	0.019	0.215	0.649
$\Delta ln(\widetilde{Russia})$	106	0.006	0.593	-1.496	-0.328	-0.020	0.292	1.612

Table 2: Effect of Global Economic Policy Uncertainty Index on Bitcoin Synchronicity

This table presents the regression results based on Equation (4):

$$BTCSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta ln(EPU)_{t-k} + \theta X + \varepsilon_{i,t},$$

where $BTCSYNC$ is the Bitcoin synchronicity for cryptocurrency i at month t; $\Delta ln(EPU)$ is the change in the natural logarithm of the global EPU index; X is a vector specifying the cryptocurrency, year, and quarter fixed effects; and ε is the error term. The dataset comprised 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. The data covered the period from July 2013 to April 2022. The variables are defined in Appendix A. The parentheses indicate cryptocurrency-clustered standard errors. Coin FE, Year FE, and Quarter FE refer to the cryptocurrency, year, and quarter fixed effects, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) $BTCSYNC$	(2) $BTCSYNC$	(3) $BTCSYNC$
$\Delta \ln(EPU)_{t-1}$	1.212***		1.353***
	(0.059)		(0.062)
$\Delta ln(EPU)_{t-2}$		0.197***	0.560***
		(0.060)	(0.062)
Constant	-4.222***	-4.198***	-4.223***
	(0.001)	(0.000)	(0.001)
Observations	127,292	127,292	127,292
Coin FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Adj. R-Squared	0.251	0.248	0.251

Table 3: Effect of Country-Specific Economic Policy Uncertainty Index on Bitcoin Synchronicity for Crypto-Friendly Countries

This table presents the country-level regression results based on Equation (6) for the crypto-friendly countries of the United States, Germany, and Australia.

$$BTCSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta ln(\widetilde{Country})_{t-k} + \theta X + \varepsilon_{i,t},$$

where $BTCSYNC$ is the Bitcoin synchronicity for cryptocurrency *i* at month *t*; $ln(\widetilde{Country})$ is the estimated residual of the regression model based on Equation (5); $\ln(Country)_t = \gamma_0 + \gamma_1 \ln(EPU)_t + e_t$; X is a vector specifying the cryptocurrency, year, and quarter fixed effects; and ε is the error term. The dataset comprised 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. $\Delta ln(\widetilde{Country})$ refers to the $\Delta ln(\widetilde{US})$, $\Delta ln(\widetilde{Germany})$, or $\Delta ln(\widetilde{Australia})$. The data covered the period from July 2013 to April 2022. The variables are defined in Appendix A. The parentheses indicate cryptocurrency-clustered standard errors. Coin FE, Year FE, and Quarter FE refer to the cryptocurrency, year, and quarter fixed effects, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) US	(2) Germany	(3) Australia
$\Delta ln(\widetilde{Country})_{t-1}$	1.292***	0.355***	0.219***
	(0.056)	(0.035)	(0.027)
$\Delta ln(\widetilde{Country})_{t-2}$	0.820***	0.369***	0.276***
	(0.056)	(0.035)	(0.028)
Constant	-4.189***	-4.214***	-4.205***
	(0.000)	(0.001)	(0.001)
Observations	127,292	127,292	127,292
Coin FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes
Adj. R-Squared	0.252	0.249	0.249

Table 4: Effect of Country-Specific Economic Policy Uncertainty Index on Bitcoin Synchronicity (Crypto-Unfriendly Countries)

This table presents the country-level regression results based on Equation (6) for the crypto-unfriendly countries of China and Russia.

$$BTCSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta ln(\widetilde{Country})_{t-k} + \theta X + \varepsilon_{i,t},$$

where $BTCSYNC$ is the Bitcoin synchronicity for cryptocurrency i at month t; $ln(\widetilde{Country})$ is the estimated residual of the regression (5) $\ln(Country)_t = \gamma_0 + \gamma_1 \ln(EPU)_t + e_t$; X is the vector specifying the cryptocurrency, year, and quarter fixed effects; and ε is the error term. The dataset comprised 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. $\Delta ln(\widetilde{Country})$ refers to $\Delta ln(\widetilde{China})$ or $\Delta ln(\widetilde{Russia})$. The data covered the period from July 2013 to April 2022. The variables are defined in Appendix A. The parentheses indicate cryptocurrency-clustered standard errors. Coin FE, Year FE, and Quarter FE refer to the cryptocurrency, year, and quarter fixed effects, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) China	(2) Russia
$\Delta ln(\widetilde{Country})_{t-1}$	-0.323***	-0.581***
	(0.040)	(0.020)
$\Delta ln(\widetilde{Country})_{t-2}$	-0.584***	-0.400***
	(0.043)	(0.023)
Constant	-4.212***	-4.184***
	(0.001)	(0.001)
Observations	127,292	127,292
Coin FE	Yes	Yes
Year FE	Yes	Yes
Quarter FE	Yes	Yes
Adj. R-Squared	0.250	0.253

Table 5: Effect of Country-Specific Economic Policy Uncertainty Index on Ethereum Synchronicity

This table presents the results for the tests of robustness on Ethereum synchronicity. This test proceeded analogously to those of Bitcoin synchronicity based on Equations (4) and (6) in which the Bitcoin synchronicity is replaced with the Ethereum synchronicity, defined on the basis of Equation (3). The regression for global EPU was similar to that based on Equation (4) and was

$$ETHSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta \ln(EPU)_{t-k} + \theta X + \varepsilon_{i,t},$$

where $ETHSYNC$ is the Ethereum synchronicity for cryptocurrency i at month t; $\Delta ln(EPU)$ is the change in the natural logarithm of the global EPU index; X is a vector specifying the cryptocurrency, year, and quarter fixed effects; and ε is the error term.

The regression for country-specific EPU was similar to that based on Equation (6) and was

$$ETHSYNC_{i,t} = \beta_0 + \sum_{k=1}^{2} \beta_k \Delta \ln(\widetilde{Country})_{t-k} + \theta X + \varepsilon_{i,t},$$

where $ETHSYNC$ is the Ethereum synchronicity for cryptocurrency i at month t; $ln(\widetilde{Country})$ is the residual of the regression based on equation (5), $\ln(Country)_t = \gamma_0 + \gamma_1 \ln(EPU)_t + e_t$; X is a vector specifying the cryptocurrency, year, and quarter fixed effects; and ε is the error term.

Ethereum synchronicity is defined as

$$ETHSYNC = \ln\left(\frac{R^{2,ETH}}{1-R^{2,ETH}}\right),$$

where the adjusted R-squared $R^{2,ETH}$ was obtained from a regression similar to that based on Equation (1)

$$R_{i,t,d} = \alpha + \beta ETHR_{t,d} + \varepsilon_{i,t,d},$$

Where $R_{i,t,d}$ is the daily return of a cryptocurrency at day d, and $ETHR_{t,d}$ is the daily return of Ethereum. The dataset comprised 127,292 cryptocurrency-month observations for 7,716 cryptocurrencies. $\Delta \ln(Measure)$ refers to $\Delta\, ln(EPU)$, $\Delta ln(\widetilde{US})$, $\Delta ln(\widetilde{Germany})$, $\Delta ln(\widetilde{Australia})$, $\Delta ln(\widetilde{China})$, or $\Delta ln(\widetilde{Russia})$. The data covered the period from July 2013 to April 2022. The variables are defined in Appendix A. The parentheses indicate cryptocurrency-clustered standard errors. Coin FE, Year FE, and Quarter FE refer to cryptocurrency, year, and quarter fixed effects, respectively. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Global	(2) US	(3) Germany	(4) Australia	(5) China	(6) Russia
$\Delta ln(Measure)_{t-1}$	1.317***	1.266***	0.268***	0.147***	-0.125***	-0.430***
	(0.060)	(0.054)	(0.034)	(0.027)	(0.040)	(0.020)
$\Delta \ln(Measure)_{t-2}$	0.646***	1.037***	0.247***	0.332***	-0.615***	-0.330***
	(0.063)	(0.055)	(0.035)	(0.028)	(0.041)	(0.023)
Constant	-4.303***	-4.268***	-4.290***	-4.284***	-4.292***	-4.266***
	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	123,134	123,134	123,134	123,134	123,134	123,134
Coin FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-Squared	0.306	0.307	0.304	0.304	0.305	0.306