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"Event-Driven Changes in Return Connectedness among Cryptocurrencies"

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Event-Driven Changes in Return Connectedness among Cryptocurrencies

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Abstract

Our study presents an in-depth analysis of the connectedness in returns among five major cryptocurrencies over a span from 2018 to 2023. Our work introduces novel insights via employing a recently developed bootstrap-after-bootstrap method of Greenwood-Nimmo et al. (2024) to establish a link between increases in connectedness and various systematic events. We find that major events—including both market and policy-driven shocks—trigger substantial increases in connectedness, with transmission effects persisting for up to one month. For the period under research, we identify Bitcoin and Ethereum as net return transmitters, mainly to Binance coin and Ripple. Moreover, we find that these transmissions increased by up to 20% for up to one month after the shocks occurred. Furthermore, we incorporate event-driven adjustments in portfolio optimization, quantifying optimal asset weight rebalancing in response to cryptocurrency market shocks. Our findings reveal that during the research period, Cardano and Ripple were the most effective choices in portfolio optimization. The implications of this study are significant for devising strategies in portfolio management and risk hedging, offering valuable guidance for policy formulation in the financial sector.

JEL classification: H56, G11, G15, Q4

Keywords: Return connectedness, cryptocurrencies, bootstrap-after-bootstrap procedure, portfolio composition and hedging

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1. Introduction

Since the return transmissions on traditional financial markets have been explored (Greenwood-Nimmo et al., 2024; Albrecht and Kočenda, 2025), a pivotal question that has emerged in recent studies is: "How do returns propagate across the cryptocurrency landscape?" Scholars have acknowledged the complex web of return propagation among specific cryptocurrencies, with heightened connectedness becoming evident during periods of amplified market stress (e.g., Elsayed et al., 2022; Özdemir, 2022; Patel et al., 2023; Sila et al., 2024). Despite the considerable attention dedicated to these assets in various studies, lingering questions persist. Principally, which events serve as conduits for transmission effects among cryptocurrencies? Moreover, how can we identify such events to be truly impactful at a statistically significant level? And is there a detectable time lag between a specific event and an ensuing spike in connectedness for cryptocurrencies? Previous studies have primarily relied on visual inspection to link increases in connectedness with specific events or periods of market stress (Kumar et al., 2022; Bouteska et al., 2023; Iyer and Popescu, 2023). In contrast, our study is the first to statistically validate the causal impact of specific shocks on cryptocurrency connectedness, addressing a crucial gap in the literature. Moreover, prior research has not statistically evaluated the persistence of these shocks over time. Our study fills this gap by not only identifying impactful events but also quantifying their duration and lagged effects, offering a more comprehensive perspective on cryptocurrency market dynamics.

Why are the above questions important? Understanding how stressful events shape cryptocurrency connectedness is essential in four key areas and enables novel insights relevant to market efficiency, investment strategies, and regulatory frameworks. First, for effective risk management, it helps investors anticipate and manage potential risks during volatile periods, enhancing overall risk management strategies (Naeem et al., 2022). Second, studying the link between stressful events and connectedness provides investors with insights into how different cryptocurrencies react during market stress. The impact of uncertainty on connectedness has been demonstrated, but the question of what specific shocks affected such connectedness remains (Sila et al., 2024). Such knowledge provides information for investment decisions, such as portfolio adjustments, hedging, and diversification (Albrecht and Kočenda, 2024). Third, understanding the relationship between stressful events and connectedness contributes to insights on market efficiency and price discovery in cryptocurrencies. Changes in connectedness may signal shifts in market sentiment or the impact of external shocks, aiding researchers and market participants in assessing information incorporation into prices. Fourth, insights into the connection between stressful events and connectedness are crucial for policymakers (Wang et al., 2023) as understanding the issue helps in the development of regulatory frameworks that aim to foster a resilient cryptocurrency market, ensuring stability and investor protection in a rapidly evolving financial landscape.

We aim to close the research gap outlined above and employ the innovative bootstrap-after-bootstrap method (Greenwood-Nimmo et al., 2024), which allows us to endogenously detect impactful events with statistical precision—an approach that, to our knowledge, has not been previously applied to cryptocurrency markets. The new method is the first existing procedure that enables us to identify specific events producing statistically significant surges in connectedness and to quantify the time for which an event's impact lasts. Hence, the method not only helps to establish a statistical nexus between cryptocurrency connectedness and stressful events but also elucidates a temporal lag between such events and surges in transmission effects. This unique phenomenon, yet unexplored in the realm of cryptocurrencies, holds potential advantages for investors as articulated above. Previous studies evaluated the impact of events based on visual inspection of the connectedness plots. However, the new method represents the first approach to endogenously identify underlying shocks causing spikes in the propagation of returns.

Connectedness exhibits a significant impact on hedging strategies (Jayasinghe & Tsui, 2008; Kočenda & Moravcová, 2019), option pricing (James et al., 2012; Feunou and Okou, 2019), and diversification (Garcia & Tsafack, 2011; Kočenda and Moravcová, 2024). Recent studies addressed the association between spikes in connectedness and distress based on visual inspection, however, none of them addressed statistical evidence about the impact of concrete events on connectedness. Despite their valuable contributions, recommendations for diversification and hedging are applicable only if a time window exists for portfolio managers to hedge their portfolios since the time the shocks appeared. In our study, we are the first to identify such events and lags. Considering the 2021 debut of a crypto-ETF (Todorov, 2021) and the growing importance of cryptocurrencies as diversification instruments (Bhuiyan et al., 2023), it is crucial to recognize and comprehend underlying patterns.

Against this backdrop, our study meticulously analyzes the group of five cryptocurrencies with the largest market capitalization over the span from February 2018 to November 2023. For this research period we bring three significant contributions to the current literature. First, we discern return transmissions among the five cryptocurrencies over an extended period, encompassing several impactful shocks. Second, in our analysis, we endogenously identified ten events affecting the connectedness pattern with a statistical probability of 90% or higher up to 30 days in advance. Such an approach is the first used for cryptocurrency markets with crucial implications. It sheds light on the events steering cryptocurrency returns over the last five years and aids in comprehending the dynamics of cryptocurrencies' sensitivity to various events. It represents a significant contribution because previous studies addressed the impact of shocks based on visual inspection without providing statistical evidence (e.g., Bouteska et al., 2023; Patel et al., 2023). Third, we pinpoint the lag between specific events and spikes in return connectedness within a window ranging from one day to one business month. Remarkably, we identify a lag for ten out of ten endogenously chosen events, offering substantial implications for investors by enabling them to actively hedge or diversify their portfolios for a corresponding period. Such a lag identification is critical as it offers a hedging window for informed investors. Moreover, our approach extends beyond the initial step by defining sub-periods based on three significant events. Utilizing the methodology proposed by Kočenda and Moravcová (2019), we determine optimal portfolio weights within specific sub-periods, a novel approach not previously explored for the realm of cryptocurrencies. These concrete portfolio rebalancing strategies offer nuanced insights into the impacts of endogenously detected events with respect to portfolio alterations.

The remainder of the paper is structured as follows: Section 2 offers an overview of existing literature, focusing specifically on connectedness in the cryptocurrency market. Following this, Section 3 outlines the specifics of the data and the methodologies used in our study. Then, in Section 4, we delve into the results we have achieved and analyze these findings. The paper concludes with Section 5, where we summarize our conclusions drawn from the results obtained.

2. Literature Review

The propagation of returns and volatility on traditional financial markets have garnered substantial attention among researchers (Diebold and Yilmaz, 2012; Baruník et al., 2017; Albrecht et al., 2025) where the authors found links between times of financial distress and connectedness of assets. The context of such market movements is that heightened financial uncertainty increases fear about the possible negative revaluation of portfolios and as a result, subjects tend to rebalance their portfolios in order to mitigate risks (Kočenda and Moravcová, 2024). Such transmissions have been identified on stocks (Greenwood-Nimmo et al., 2024), commodities (Kočenda and Moravcová, 2024; Albrecht and Kočenda, 2025), as well as currency markets (Kočenda and Moravcová, 2019; Albrecht and Kočenda, 2024), but raising a question, whether such rebalancing and context work for cryptocurrency markets also.

The dynamic and rapidly evolving nature of the cryptocurrency market, characterized by swift price movements and evolving market structures, has spurred research into the connectedness of cryptocurrency returns (e.g., Polasik et al., 2015; Uzonwanne, 2021; Ahmed, 2022; Apergis, 2023; Patel et al., 2023). Understanding the factors influencing returns and their connectedness is paramount, especially in the context of economic and political shocks. As the literature on connectedness is burgeoning, in our literature review we concentrate only on a subset of studies that are most relevant to our analysis.

Recent studies consistently highlight the association between cryptocurrencies and uncertainty (Gozgor et al., 2019; Erzurumlu et al., 2020; Koumba et al., 2020; Bouri et al., 2021; Qin et al., 2021). In a comprehensive way, Ahmed (2022) examined bitcoin returns from 2015 to 2021 and established a strong relationship between bitcoin and various uncertainties, particularly its vulnerability to economic and political shocks.

Uncertainty arising from robust shocks has been a focal point in recent studies examining return and volatility transmissions (Apergis, 2023; Bouteska et al., 2023; Patel et al., 2023). For instance, Bouteska et al. (2023) presented evidence linking news related to the COVID-19 pandemic and the Russian-Ukraine conflict to subsequent spillover changes. It aligns with earlier findings by Özdemir (2022), who investigated eight major cryptocurrencies during COVID-19 and showed that connectedness elevated during this period, particularly among Bitcoin, Ethereum, and Litecoin. They identified increased connectedness, particularly in association with lockdowns. Further, Mensi et al. (2023) examined associations of spillovers with extreme market conditions and showed that investors might benefit from diversifying in cryptocurrencies, but their gains differ across normal and extreme market conditions. Moreover, Sila et al. (2024) identified eight major cryptocurrencies in which these assets' risk propagation reflects various events, but their demonstration was based on visual inspection without providing statistical evidence. The authors further confirmed asymmetries and several drivers of connectedness, including uncertainty. As a result, they argue that such propagation identification is crucial for traders and portfolio managers.

The link between spillover shocks and connectedness unfolds through an investment channel (Albrecht and Kočenda, 2024). When shocks occur, investors strategically adjust their portfolios, reducing crypto-asset weight to mitigate risks associated with speculative assets (Krištoufek, 2015; Ahmed, 2022), especially during periods of increased risk aversion

(Tran, 2019). Cryptocurrencies, being high-beta assets with respect to market movements, experience frequent reallocations within portfolios (Sovbetov, 2018), impacting cryptocurrency prices and coinciding with periods of market turmoil (Gozgor et al., 2019; Hu et al., 2019; Koumba et al., 2020; Koutmos, 2020). However, to date, no study has demonstrated which specific events (shocks) are statistically significant with respect to increases in connectedness among cryptocurrencies. Moreover, a critical research gap exists in investigating whether there is a lag between the occurrence of events and changes in connectedness, and if so, to what extent.

To bridge this gap, we adopt the methodology developed by Greenwood-Nimmo et al. (2024), employed on various assets, including stocks, based on the data from seminal work of Diebold and Yilmaz (2009), currencies (Albrecht and Kočenda, 2024), and commodities (Kočenda and Bartušek, 2024; Albrecht et al., 2025). The method is the first to examine the association between specific shocks and spikes in connectedness values. Our study makes several contributions to the existing literature, being the first to empirically identify specific events impacting connectedness between cryptocurrencies based on a statistical test. Additionally, we elucidate the nature of lead/lag in the propagation of shocks impacting connectedness over time and identify fundamental events driving return transmissions in the cryptocurrency market—a critical insight as cryptocurrencies gain traction as diversification tools (Bhuiyan et al., 2023).

Then, Kočenda and Moravcová (2019) build on the implications of research on connectedness by proposing that during turbulent periods, the weights of individual assets in a portfolio change, as well as the individual ratios for hedging positions. Based on this, they came up with methods where, for Central European currencies, they showed that in the context of three major economic events, the weights of individual currencies in portfolios changed. The procedure was also repeated by Kočenda and Moravcová (2024) for energy-based-commodities with the same conclusion. Anyway, these assumptions have not yet been tested for cryptocurrencies.

3. Data and methods

3.1. Data

In our study, we analyze the return connectedness among five major cryptocurrencies: Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Ripple (XRP), and Cardano (ADA), all quoted in US dollars. The empirical investigation is based on data extracted from the Bloomberg database, covering the period from November 7, 2017, to November 30, 2023.

For our analysis, we computed daily logarithmic differences in closing prices. It is important to note that the dataset begins with the launch of Cardano (ADA) in November 2017 (Houben and Snyers, 2018).

The cryptocurrencies under research share several common features. They are not stablecoins and together accounted for the largest share of global market capitalization of more than 77 % by the end of the research period (CoinMarketCap, 2025a). Although Bitcoin is the oldest and most popular cryptocurrency, the common feature of all five cryptocurrencies is that they are market leaders and are widely recognized and adopted. Finally, these currencies share a common feature of having strong developer communities (CoinMarketCap, 2025b).

These cryptocurrencies are also distinct in a few aspects. They exhibit differences in consensus mechanism as they use Proof of Work (Bitcoin, Ethereum), Proof of Stake (Binance Coin, Cardano), and Ripple Protocol Consensus Algorithm (XRP) that affect their energy consumption and transaction validation processes (Nguyen et al., 2019). Further, each cryptocurrency serves distinct primary functions, ranging from Bitcoin's role as a store of value to Ethereum's platform for decentralized applications and Cardano's focus on scalability and interoperability. Additionally, the level of their decentralization differs, with Bitcoin and Ethereum being highly decentralized, while Binance Coin operates on a more centralized Binance Smart Chain, impacting governance and control (Gad et al., 2022).

The research period (2018-2023) covers several shocks associated with cryptocurrency markets, which were endogenously chosen by the procedure described in Section 3.3. Hence, our study is the first one covering the cryptocurrency markets that employs a testing procedure enabling the selection of events endogenously based on their statistically significant impact. This way, we entirely discard visual inspection for event identification that leads to often arbitrary and less than accurate event selection adopted in earlier studies. The period starts with a contentious Bitcoin Cash hard fork (2018) and continues with the tech-grade improvement of Bitcoin by the rating agency (2019) and limitations of payments by cryptocurrencies in China by the Chinese central bank (2019). Further, there was a period associated with the COVID-19 virus pandemic (2020-2021) and bans by Chinese government to payments in cryptocurrencies (2021). In 2021, the cryptocurrency markets experienced also the introduction of Cardano Smart Contracts system and historically highest market cap of the crypto market. Then, 2022 was marked by several stressful events including the LUNA crash, the crackdown on the Tornado Cash by the US government, and the FTX exchange downfall. Based on the source, we attributed these events to two main categories – market shocks and policy shocks.

In Table A1, we present the descriptive statistics of the cryptocurrencies. The associated dates of endogenously detected events are provided in Table A2. The connectedness measures are processed in MATLAB, and the events' statistical significance calculations are done in Gauss.

3.2. Connectedness

In computing the connectedness index, Diebold and Yilmaz (2009, 2012) utilized a method based on vector autoregressions (VAR) and grounded in variance decomposition. The method introduced permits the determination of various proportions of variance in the *H*-step forecast errors x_i, against shocks x_i, and among variables labeled as connectedness. The technique involves connecting the variance decomposition matrix to the vector autoregression model with *N*-variables. Connectedness refers to the proportion of the *H*-stepped forecast errors contained in the forecast x_i against shocks in the x_j variable ($i,j=1,2,\ldots, N$). The definition of the contribution of the *j* component to the forecast error in the *i* component is as follows:

$$\theta_{ij}^{g}(H) = \frac{\sigma_{jj}^{-1} \sum_{h=0}^{H-1} \left(e_i' A_h \Sigma e_j\right)^2}{\sum_{h=0}^{H-1} \left(e_i' A_h \Sigma A_h' e_i\right)}. \quad (1)$$

At moment t, A_h denotes the coefficient for the moving average forecast. It is essential to note that the cumulative variances in each row might not sum to 1, given that $\sum_{j=1}^{N} \theta_{ij}^{g}(H) \neq 1$. The error component's standard deviation is symbolized by σ_{jj}, and both e_j and e_i function as selection vectors. The total connectedness index, as outlined by the authors (Diebold and Yilmaz, 2012), captures the influence of shocks on the collective forecast error variance within the variable set:

$$S^H = \frac{\sum_{\substack{j=1 \\ j\neq i}}^{N} S_{i\leftarrow j}^{H}}{\sum_{i,j=1}^{N} S_{i\leftarrow j}^{H}} = \frac{\sum_{\substack{i,j=1 \\ i\neq j}}^{N} S_{i\leftarrow j}^{H}}{N}. \quad (2)$$

We capture the dynamics of the connectedness by using a rolling window spanning 200 days from *t-199* to *t*. For normalization of volatility spillover and the contribution from variable shocks, total forecast error variance decompositions are employed. The sum of *H*-step spillovers for each matrix row remains constant at 1 ($\sum_{j=1}^{N} S_{i\leftarrow j}^{H} = 1$), whereas the total spillovers for all variables sum up to N ($\sum_{i,j=1}^{N} S_{i\leftarrow j}^{H} = N$). Consistent with previous studies

(Baruník et al., 2017; Patel et al., 2023), a VAR lag length of 2 and a forecast horizon of $H=10$ have been selected[1].

3.3. Links between connectedness and impactful events

To assess the statistical significance of individual spikes in connection with specific events, we employ a bootstrap-based method introduced by Greenwood-Nimmo et al. (2024). The procedure enables to endogenously detect events that impact connectedness in a statistically significant manner. As such, the assessment does not suffer from the event selection imperfections rooted in a simple visual inspection of the plotted connectedness. The method comprises two stages of bootstrapping. In the first stage, bias-corrected bootstrap estimates are generated. The steps of the method applied to an orthogonalized connectedness index (which relies on variable ordering) are summarized as follows: (i) estimate and store the residuals $\hat{u}_t$, the (orthogonalized) connectedness index values S^{Ho}, and the parameter estimates $\hat{A}_j$; (ii) obtain B bootstrap samples from x_t:

$$x_t^{(b)} = \sum_{j=1}^{p} \hat{A}_j x_{t-j}^{(b)} + u_t^{(b)}. \tag{3}$$

To compute $u_t^{(b)}$, utilizing the VAR residuals, with p specified as the initial value, is the first step. Subsequently, in the third step, B bootstrap samples are generated and applied to re-estimate the VAR model, leading to fresh assessments for the residuals, connectedness index, and parameters. The fourth step involves employing a formula to determine the bias between the bootstrap measurements, represented as $\hat{Y}_O = B^{-1} \sum_{b=1}^{B} S_{Ho}^{(b)} - S_{Ho}$. Following this, the entire sequence of steps from (ii) to (iv) is reiterated to acquire new B estimates through bootstrapping, with the subtraction of the bias $\hat{Y}_O$ at each iteration. Lastly, all the steps (i)-(v) are replicated for each observation within the rolling sample, furnishing statistical insights for all observations.

To determine the likelihood of a statistically significant connection between a given event (day) and a specific value (spike) of the connectedness measure, we apply the previously described procedure. For insights into the reaction preceding and following the shock within the designated timeframe, computation of the generalized connectedness index is undertaken. The index delivers an average value throughout the chosen period; results are presented in Section 4.1. Then, as a sensitivity check, we follow Greenwood-Nimmo et al.

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[1] In the context of vector autoregressive (VAR) models, we adhere to established conventions in the academic literature. This approach ensures that our empirical outcomes remain directly comparable to previously reported results in the field (e.g., Diebold and Yilmaz, 2014; Uluceviz and Yilmaz, 2020).

(2024) and Albrecht and Kočenda (2024) and perform robustness analysis by averaging the returns to a 5-day window and recalculating the bootstrap analysis; technical details and results are presented in Section 4.2. The probability analysis adheres to the three parameters used by Greenwood-Nimmo et al. (2024), incorporating a 2-step VAR lag value, a 10-step ahead forecast, and a 200-step window; the robustness analysis with respect to the three parameters is provided with full details in Section 4.3.

We apply the method to endogenously detect statistically significant increases/spikes in connectedness. The adopted approach follows Greenwood-Nimmo et al. (2024; section 2.4) and involves assessing whether there are statistically discernible alterations in spillover intensity across successive rolling samples relative to one or more preceding rolling samples. Specifically, we employ the method to compute the probabilities in the specification (4) continuously as the rolling samples evolve:

$$Prob\left(100 \times \left[\frac{S_{t+i} - \bar{S}_{t-j}}{\bar{S}_{t-j}}\right] > \alpha\right), i \in \{0,1,\ldots\}, j \in \{1,2,\ldots\}, \tag{4}$$

where S_{t+i} represents the spillover index computed using bootstrapping techniques on a rolling sample that ends on day $t+i$. Here, $\bar{S}_{t-j}$ serves as the reference point, representing the average spillover index across multiple bootstrap samples in the specified rolling window.

An illustration of how to identify events with large changes in the spillover index is to set $j = 1$, $i \in \{0,1,5,10,22\}$ and $\alpha = 5\%$. The α value specifies the extent of the connectedness index variation. Anytime the likelihood at time $t+i$ with $i = 0$ is higher than or equal to *90%*, day *t* is identified as a statistically significant event that results in a change in the value of *5%* or greater in the connectedness index. If we specify $i \in \{0,1,5,10,22\}$, we can derive statistical inferences about the impact of the shock on connectedness that occurs 1, 5, 10, and 22 days after the event happened.

Due to its novelty, the procedure does not have an alternative. The method is designed for Diebold and Yilmaz (2009, 2012) connectedness index (DYCI) rooted in a frequentist approach. As such, it cannot be easily adapted to the TVP-VAR approach, which is a Bayesian one. Its strengths are its uniqueness and precise identification of shocks derived from the widely used procedure of Diebold and Yilmaz (2009, 2012), which dominates the field.[2]

[2] Greenwood-Nimmo et al. (2024; section 2.3) performed a simulation exercise. They showed that whether the shift in the connectedness measure (Diebold-Yilmaz Spillover Index) is temporary or permanent, their method is able to detect such changes in the relationship among the data series in the model. Hence, their simulation exercise strongly supports the credibility of the method in identifying statistically significant changes in connectedness.

3.4. Hedge ratios and portfolio weights

Our analysis examines the impact of various periods of market distress. To determine hedge ratios and calculate the weights of realized variances of most traded cryptocurrencies in an optimal portfolio, we estimate the ADCC-GARCH (asymmetric dynamic conditional correlation) model. Markowitz (1991) presents a theory of optimal portfolio where the highest expected return for a given level of market risk is achieved by the optimal portfolio.

Our approach begins by identifying suitable GARCH models for individual cryptocurrencies across distinct time frames. Subsequently, we compute optimal diversification for global currencies using time-varying conditional correlations obtained from the second stage of ADCC model estimation. Notably, the methodologies proposed by Kroner and Sultan (1993) and Kroner and Ng (1998) play a pivotal role in this context. These methods leverage conditional variance and covariance to calculate hedge ratios and formulate optimal portfolio weights. Specifically, the hedge ratio, as defined by these established techniques, is expressed as $\beta_{j,k,t,} = h_{j,k,t}/h_{k,k,t}$, where $h_{j,k,t}$ represents the conditional covariance between cryptocurrencies *j* and *k*, and $h_{k,k,t}$ denotes the conditional variance of cryptocurrency *k* at time *t*. The formula implies that a long position in one cryptocurrency (e.g., *j*) can be offset by taking a short position in another cryptocurrency (e.g., *k*). For a two-cryptocurrency portfolio, the optimal weights for cryptocurrencies *j* and *k* at a specific time *t* are determined using the following formula:

$$w_{j,k,t} = \frac{h_{kk,t} - h_{j,k,t}}{h_{jj,t} - 2h_{jk,t} + h_{kk,t}}. \tag{5}$$

In equation (5), the weight assigned to cryptocurrency *j* is denoted by $w_{jk,t}$, while the weight of currency *k* is represented by (1 – $w_{jk,t}$). These weights determine the composition of the portfolio, adhering to the specified conditions:

$$w_{j,k,t} = \begin{cases} 0, & if\ w_{jk,t} < 0 \\ w_{jk,t} & if\ 0 \leq w_{jk,t} \leq 1 \\ 1, & if\ w_{jk,t} > 1 \end{cases}. \tag{6}$$

The empirical finance research field has recently applied this methodology. Notably, Kočenda and Moravcová (2019) explored Central European currencies using this approach, while their study in 2024 focused on energy commodities. However, to the best of our knowledge, such an approach has not been used for cryptocurrencies yet.

4. Results

In this study, we conduct an empirical investigation into the dynamics of return transmission across different cryptocurrencies, employing a static sample that encapsulates the entirety of the analyzed period. As shown in Table A3, the findings are based on the spillover index framework developed by Diebold and Yilmaz (2009), providing a quantitative assessment of volatility spillover effects among cryptocurrencies. Our findings presented in Section 4 apply to the research period (2018-2023). Our analysis reveals a heterogeneous pattern in the volatility transmission received by different currencies, with Bitcoin, Ethereum, and Cardano being net return transmitters, in contrast to the Binance coin and Ripple, which receive returns from these cryptocurrencies of up to ten percent.

Further, all cryptocurrencies exhibit around thirty percent of returns from their own past values, and the rest is received from other cryptocurrencies. While these preliminary findings offer valuable insights into the overall patterns of volatility transmissions across the examined period, incorporating a dynamic sample in our analysis facilitates a more granular and comprehensive exploration of these return interactions.

----Figure 1 about here----

Figure 1 illustrates that the connectedness among the five cryptocurrencies ranged between 40% and nearly 80%. Throughout most of the sample period, these assets shared over 60% of their variability. Notably, two distinct periods deviated from this trend. First, from the beginning of the sample until November 2018, the connectedness was 50%. Then, a contentious Bitcoin Cash hard fork triggered a spike in return propagation, which reached 70%. Second, the onset of the COVID-19 pandemic corresponded with a decline in return propagation to 45% following its announcement.

4.1. Association between stressful events and spikes in connectedness values

In our study, we address a notable gap in the empirical finance literature concerning the empirical linkage between discrete events and the resultant fluctuations in the connectedness across cryptocurrency markets. Previous research has identified a broad, positive correlation between economic distress and heightened market connectedness (Apergis, 2023), yet it falls short of establishing a statistically robust relationship between specific exogenous shocks and consequent variances in the crypto-market connectedness. It is an analogy to the situation where estimation yields statistically insignificant coefficients. In such a case, naturally, an inference would not be made based on a statistically insignificant coefficient.

To advance this inquiry, we adopt the innovative bootstrap-after-bootstrap methodology developed by Greenwood-Nimmo et al. (2024). Their novel statistical approach enables us to robustly ascertain the causal relationships between endogenously detected shocks tied to cryptocurrencies and the ensuing spikes in the connectedness metric. Therefore, the shocks described below are not identified by us exogenously, but they represent all statistically significant shocks chosen endogenously by the method during the selected period.

Our empirical investigation identifies ten critical events, selected through an endogenous process, which demonstrably affected market connectedness within a one-business-month horizon, with a 90% or greater statistical confidence level. A nuanced analysis is conducted to evaluate the temporal dynamics of market reactions, encompassing immediate responses on the day of the event, subsequent market adjustments on the following day, and extended market responses observed at intervals of five-, ten-, and twenty-two days post-event, effectively capturing the market's behavior over a typical business month.

We divided the events into two categories based on the background of the shock. The first type is a market shock including technology improvements and other market-related news. The second type of shock is policy-related, as these shocks can be associated with steps taken by the policymakers. There are three major observed distinctions between these two types of shocks. First, the market shocks have a more transitory and stable impact as they affect markets similarly for a few periods. Moreover, political shocks are more heterogeneous as some have almost instant impact, while others affect the connectedness on the last day of the studied period. Additionally, political shocks tend to have more long-lasting effects with trending impacts. As can be seen in Table 1, when some political shock occurred, its impact rose from day one until the end of the business month. On the other hand, the impact of a market shock was rather spiky and then its effect declined.

The first event significantly affecting the connectedness among the selected cryptocurrencies was a contentious Bitcoin Cash hard fork on November 15, 2018. The event caused Bitcoin Cash to decrease by 70%, which further impacted other cryptocurrencies, including Bitcoin. Within the following days, Bitcoin fell by over 35% (Bouraga, 2022). Figure 1 indicates an increase in the value of connectedness, which is statistically confirmed in Table 1. An important finding is that the shock had an effect on the connectedness ten and twenty-two days ahead. Such a window offers valuable insights for both policymakers and investors.

----Table 1 about here----

Another positive shock occurred on March 26, 2019, when the Weiss Crypto Ratings agency improved the tech grade of Bitcoin to “A.” The improvement ranked Bitcoin among the best three cryptocurrencies from the point of technology and adoption among 122 candidates. Also, due to its lower volatility compared to other cryptocurrencies, Bitcoin was labelled with an overall rating of the “B-“ degree. The ratings of the company evaluated processing speed, improvement of technology, and its development during turmoil. Further, the rating agency ranked Ripple (XRP) as the second best, while Ethereum (ETH) and Cardano (ADA) also ended in the top five (Gil-Pulgar, 2019). The publication of this report led to positive returns, followed by increased connectedness (Figure 1). Moreover, the connectedness among cryptocurrencies was lagged to the event by one business month (Table 1). Identification of such a lag goes one step further when compared to the recent works trying to identify the relationship between events and connectedness (Patel et al., 2023).

Then, on November 22, 2019, the People's Bank of China (PBOC) publicly stated that it would "dispose of" virtual currency business activities. The announcement was followed by the shutdown of Bithumb's and Binance's offices by authorities in China. Even if this information was later refuted by Binance's CEO, it affected the crypto market as China represents the second biggest country in the world in the ownership of cryptocurrencies (Steinmetz et al., 2021). The event was associated with decreasing prices of cryptocurrencies. However, none of the studies statistically confirmed its linkage with connectedness. Such a finding is crucial as it has further implications for hedging (Albrecht and Kočenda, 2024). In Table 1, we confirm that there was a 92,6% probability of a surge in connectedness one business month after the shock occurred.

During the beginning of 2020, the COVID-19 pandemic affected financial markets unprecedentedly, including the crypto market. Bouteska et al. (2023) brought the most recent findings about the impact of the pandemic on cryptocurrencies. However, they did not bring statistical evidence about spikes of connectedness and specific events related to the pandemics. Using the bootstrap-after-bootstrap analysis, we identified the impact of the WHO's announcement (March 11, 2020) on connectedness. We follow up on the research identifying such linkage on currency markets (Albrecht and Kočenda, 2024) and find that the spike in connectedness lagged the announcement by one day. Further, there is a 90% or higher probability of a surge from one day up to one business month since the event occurred (Table 1).

One year later, on May 18, 2021, China started a distressful period for the entire cryptocurrency market as they banned financial and payment institutions from providing cryptocurrency services. Within the next few days, the event led to a loss of one trillion in the crypto market cap, which was one of the most significant drops in this market. However, even this kind of shock led to a surge in connectedness from one week to one month ahead (Table 1). Such a finding is of particular importance as it brings at least a five-day hedging window to the investors and reaction time to policymakers. The fact that it led to a connectedness increase of almost 30% (Figure 1) further highlights the importance of the results.

Another event where we endogenously identified the relationship between a shock and a spike in connectedness was the launch of the Cardano Smart Contract (September 12, 2021). These smart contracts are programs validating scripts. The concept of smart contracts improves the cost-effectiveness and speed of transaction processing (Macrinici et al., 2018). Following the previous shock, this launch led to a high return connectedness of 75% (Figure 1). However, this connectedness increased as a result of the event ten days after the event occurred (Table 1).

The same year, on November 10, 2021, the crypto market cap reached three trillion dollars for the first time. As mentioned by Sila et al. (2024), the moment was associated with the peak of crypto optimism and attention to the market, also marked by the record-breaking value of Bitcoin. The events' impact has been indicated by the authors based on visual inspection. However, based on their helpful contributions, we take a step further to provide statistical significance and lag identification. The existence of a lag allows the investors to hedge portfolios following the event (Albrecht and Kočenda, 2024). These impactful changes were a result of a couple of positive news for the market, including the allowance of Bitcoin legal payments in El Salvador and the news about the first launch of the Bitcoin ETF (Todorov, 2021). We highlight the importance of this event as we find a statistical association between the surge in connectedness ten and twenty-two days after this event occurred (Table 1). Specifically, the pattern of the lagged nature of the connectedness to the events brings valuable insights because it offers a hedging window, which was not identified for cryptocurrencies before.

In 2022, Terra-LUNA cryptocurrency crashed. LUNA was a stablecoin pegged to the US dollar with a market cap of 18.7 billion USD. Nevertheless, from May 09, 2022, the cryptocurrency dramatically fell to the value of 0.50 USD within two days. The crash represented distress for the entire crypto market (Lee et al., 2023) and led to an increase in connectedness among five non-stable cryptocurrencies examined in this paper (Figure 1). Similarly to previous events, this turmoil changed connectedness with a 90% or higher probability from ten to twenty-two days.

A few months later (on August 12, 2022), the US Treasury Department cracked down on the Tornado Cash platform, which increased the uncertainty in the market. The platform was suspicious of being used to launder stolen funds, and as a result, the US Treasury Department froze millions of dollars in stablecoins (Sun, 2022). Linked to this event, the connectedness of five significant cryptocurrencies spiked one business month after it occurred.

The last examined shock took place on November 2, 2022, as one of the biggest crypto exchanges, FTX, collapsed. The fallout of the FTX is closely linked to the report by CoinDesk on November 2, 2022, which raised serious doubts about the capital reserves of the FTX and its close partner, Alameda Research Fund. Within weeks, the company, worth 32 billion US dollars, went bankrupt due to financial instability. The detected increase in connectedness on November 1, 2022 (Table 1) is in line with the beginning of the FTX fallout (Sila et al., 2024). A one-day difference signals a strong suspicion of the news leakage before the report was officially circulated. Further, the connectedness of cryptocurrencies spiked as a result of this turmoil one business month after the first signs of instability.

These ten events linked to the cryptocurrency market were endogenously identified by the procedure, and we find valuable indications in the results. All of these results lead to a spike in connectedness with a hedging window of at least one day. Such a window offered reasonable time to hedge positions held in cryptocurrencies against transmissions of returns during the selected period. Further, we build on the recent study of Patel et al. (2023), who suggested a link between shocks and surges in connectedness values. We take a step further by statistically identifying specific events and a lag between when a shock occurs and when the connectedness spikes.

4.2. Robustness with respect to varying volatility computations

The following robustness test focuses on the two pre-event comparison periods. One is the trading day immediately prior to a given event. Then, we account for the possibility that conditions on the day prior to an event may not always be representative of pre-event conditions (e.g. due to outlying observations in the data or to the leakage of information prior to an event). For that, we compute the average spillover over the week prior to a given event instead of the spillover in a day prior to the event (Greenwood-Nimmo et al., 2024). This alternative approach provides us with a 5-day average of the spillovers.

Simply speaking, rather than relying on daily volatilities, we computed the average volatilities over a five-day period to capture a slightly extended timeframe over which spillovers propagate. Consequently, we conducted a validation assessment of our initial probability analysis reported in preceding Section 4.1. In Appendix Table A4, we present the outcomes of this robustness check based on the five-day volatility average. Employing this approach, we follow robustness tests performed in previous research (Greenwood-Nimmo et al., 2024; Albrecht and Kočenda, 2024). Our objective was to determine whether a specific shock impacts future connectedness and the likelihood of its effects.

Notably, the empirical probabilities presented in Table A4 yielded results remarkably consistent with those from our previous analysis (Table 1). Still, we detected three marginal variations in terms of statistical significance that do not represent a material difference, though. They are related to three events where the probability of their association with a spike in connectedness did not exceed 90%. The first event was the improvement of the tech/adoption grade of Bitcoin on March 26, 2019. On the other side, the probability of a surge in connectedness achieved 85.40% (Table A4) one business month after the event, which is still a remarkably high number. Another event with slightly different results was the crackdown on the Tornado Cash platform by the U.S. Treasury Department (August 12, 2022), followed by FTX's downfall (November 1, 2022). However, Table A4 confirms probability exceeds 80% for both events. The first of these two events affected the connectedness one month ahead with a probability of 86.40%. Then, the FTX downfall increased connectedness ten days ahead. Such results agree with Table 1 as all the other seven shocks confirmed the results from the table. Moreover, the other three events are attributed to three types of events, so it could not be specified, if some type of event has a higher impact.

Moreover, we indirectly confirm the linkage between economic distress and cryptocurrency connectedness in Table A5, where we compute correlations between the market capitalization of selected cryptocurrencies and the connectedness index computed in Section 4.1. As we can see, all cryptocurrencies negatively correlate with the index value. It could be interpreted that an increase in connectedness is associated with a decrease in the market capitalization of each cryptocurrency (price decline). Such results confirm the transmission leading from shocks (increasing connectedness among cryptocurrencies) to a decrease in their prices (Table A5).

4.3. <u>Robustness with respect to key VAR-related parameters</u>

The testing procedure of Greenwood-Nimmo et al. (2024) is designed for Diebold and Yilmaz (2009, 2012) connectedness index (DYCI), a method that is based on vector autoregressions (VAR) and grounded in variance decomposition as shown in section 3.2. As such, there are three key parameters related to the VAR specification—namely, the forecast horizon, the VAR order length, and the window size—which can influence the results of the testing procedure. Given the absence of an alternative method to endogenously detect events that affect connectedness, we assess the robustness of the testing procedure by systematically varying the set of above parameters. The subsection provides a detailed account of the robustness checks, with the corresponding results presented in tables in Appendix B (Tables B1–B9).

First, in the procedure for detecting endogenous changes in connectedness, we initially employ a 10-step ahead forecast, with the results displayed in Table 1. To verify the robustness of our findings, we also perform calculations using alternative forecast horizons: an 8-step ahead forecast (Table B1) and a 12-step ahead forecast (Table B2). It can be seen in both tables that variations in the forecast horizon do not alter the probabilities of a connection between events and spikes in connectedness.

Second, to detect endogenous changes in connectedness, we adopt a VAR lag order of 2, with the primary results reported in Table 1. To ensure robustness, we repeat the analysis using alternative lag orders of 1 (Table B3) and 3 (Table B4), as detailed in Appendix B. The findings remain consistent across these specifications, thereby confirming the reliability of our chosen lag parameter.

Third, to detect endogenous changes in connectedness, our primary analysis employs simple returns (Table 1). To ensure robustness, we first calculate five-day average returns, thereby capturing volatility over an extended period (Table A4). Additionally, we replicate our analysis using alternative forecast horizons—specifically, an 8-step ahead forecast (Table B5) and a 12-step ahead forecast (Table B6)—as well as alternative VAR lag orders of 1 (Table B7) and 3 (Table B8). These complementary checks consistently support our initial findings.

Fourth, our primary analysis employs a 200-day window to detect endogenous changes in connectedness, with the corresponding results reported in Table 1. For robustness, we re-estimate the model using a 100-day window—applying this specification to both the bootstrap procedure and the TCI metric—with the results presented in Table B9. We do not extend alternative computations (such as the 8-step and 12-step ahead forecasts, VAR lag orders of 1 and 3, and five-day average returns) to this specification, as the 100-day window is used solely as a supplementary check. In all robustness analyses, we present both orthogonalized and generalized computations to ensure consistency across various parameter alternatives.

The above robustness checks yield the following findings. In steps one through three, the same events were consistently identified across all alternative computations, aligning with those reported in Sections 4.1 and 4.2. For the majority of events, the estimated probability linking an event to a spike in connectedness exceeds 90%, with the remaining events exhibiting probabilities between 70% and 90%. In step four, an alternative computation confirmed the same 10 events presented in our paper. Among these, five events maintained a probability above 90%, whereas four events—detected at the 22-day horizon with a 200-day window—did not reach statistical significance when assessed with a 100-day window.[3] More importantly, events with substantial impacts were identified under both rolling window specifications (100-day and 200-day). Based on the results detailed in Tables B1–B9, we conclude that our findings are robust to alternative testing procedure specifications.

4.4. *Analysis of net spillovers among cryptocurrencies*

We can obtain several insights from the analysis of the dynamic sample (Figure 2). First, the results match the results of the static sample (Table A3); however, they provide more details. Bitcoin and Ethereum are predominantly net return transmitters, mainly to Binance coin and Ripple, throughout the entire period. The transmitted returns gain values of more than 20%. Moreover, even though Cardano was a net return transmitter on a static sample (Table A3), it tends to move more neutrally from the perspective of Figure 2.

----Figure 2 about here----

Such findings might be helpful for investors and policymakers when we consider the (1) fact that connectedness among cryptocurrencies arises with a probability of 90% and

[3] Shorter sample windows naturally assign greater weight to recent observations when estimating VAR coefficients (Alter and Beyer, 2014). Consequently, events identified over a 22-day horizon may not achieve the necessary level of statistical significance. Moreover, we adopt a 200-step window length—rather than a 100-step window—as per the methodology of Greenwood-Nimmo et al. (2024) for two primary reasons. First, a 200-step window is consistent with the specifications employed by Diebold and Yilmaz (2009, 2012). Second, using a significantly shorter window may introduce discontinuities in rolling sample estimates due to instability (Diebold and Yilmaz, 2012).

more when shocks occur and (2) the fact that such event leads to increased connectedness one business month ahead, excluding immediate market reaction. These two insights gain value when we consider (3) the findings about Bitcoin and Ethereum transmitting returns to Binance coin and Ripple.

We follow the results of Bouteska et al. (2023) and Patel et al. (2023) about the linkage between stressful events and connectedness among cryptocurrencies. However, we take one step further with the identification of the delayed reaction of connectedness to the shock and having identified two primary return transmitters. Therefore, investors and policymakers have a window of up to twenty-two days to hedge positions in Binance coin and Ripple when a shock emerges. Further, having identified the magnitude, investors have indications that the returns from Bitcoin and Ethereum might transmit 20% of the values.

4.5. Hedging ratios and portfolio weights

Given the dynamic nature of today's financial markets, it becomes crucial to calculate hedge ratios and portfolio weights precisely. These metrics are subject to significant variation over time. The hedge ratio represents the optimal amount of the specific asset contracts investors should include in their portfolios to safeguard against adverse market movements. Similarly, the need to adjust portfolio weights over time is widely acknowledged. Our research delves into the fluctuations in portfolio weights and hedge ratios for the most traded cryptocurrencies across various time frames. The insights from this assessment have direct implications for international portfolio diversification and effective risk management strategies. We investigate the extent to which optimal diversification approaches have evolved during these periods in response to changes in volatility and observed connectedness patterns.

Our approach builds on Kočenda and Moravcová (2019, 2024) and begins with estimating an asymmetric dynamic conditional correlation (ADCC) model. Initially, we focus on identifying the most suitable univariate GARCH models for each time series, employing a two-phase approach. In the subsequent phase, we apply the ADCC model using standardized residuals obtained from the first phase; the details are provided in Section 3.4. The process is crucial for assessing the evolving volatilities, covariances, and correlations across various cryptocurrencies during distinct time intervals. However, we distinguish our approach from previous studies as we identify changes in the weights of portfolios in the context of the shocks that affected selected cryptocurrencies across various timeframes. Based on our results presented in Sections 4.1, 4.2, and 4.3, we identify three distinctive shocks exhibiting close-to-immediate impact that concurrently last up to one business month (Table A4). The shocks are the COVID-19 pandemic, the Chinese ban on financial payment institutions from providing cryptocurrency services, and the LUNA crash. These three shocks divide the span of connectedness into four periods during which their impacts varied. Hence, the hedging during these four periods might also exhibit distinctive variations.

Hedging strategies play a pivotal role in mitigating potential portfolio losses. However, this risk reduction often comes at the expense of reduced profit potential due to associated costs (referred to as hedging costs) (Jayasinghe and Tsui, 2008). To achieve effective and profitable hedging, investors must recognize that strategies vary based on the magnitude and direction of market spillovers (Kočenda and Moravcová, 2024). We present the averaged hedge ratios and portfolio weights in the Appendix Tables A6 to A9. For the pre-covid period (Table A6), we can notice that the most effective hedging tool is Cardano (ADA). This is because Cardano has the lowest hedging ratios. For example, a value of 0.671 for ETH - ADA implies that to hedge a 1-USD long position in ETH, one needs to open a short of 0.671 USD to optimally hedge the position during the period before the COVID-19 pandemic (Table A6). It has the lowest hedge ratio against BTC (0.471), which can be mainly explained by the fact that BTC, as the most traded cryptocurrency, has the lowest volatility. Such a position is confirmed even during the second period (COVID-19 period), where a 1-USD long position in various cryptocurrencies could be hedged from 0.360 to 0.556 USD short positions in Cardano. Additionally, as shown in Table A7, Ripple is also a suitable hedging instrument, achieving hedging ratios ranging from 0.439 against Bitcoin to 0.568 against Binance Coin. Moreover, we can see similar results for the following two periods, first being the Chinese ban on payment in cryptocurrencies in 2021 (Table A8) and then followed by LUNA crash in 2022 (Table A9).

On the other side, we can see important implications from these measurements. Results from Tables A6 to A9 suggest changes in ratios in the context of shocks in the markets. The lowest weight in the portfolio of Binance coin of 0.056 during the pre-Covid period in a portfolio with Bitcoin (Table A6). Then, the optimal weight increased to 0.206 during COVID-19 (Table A7) having its peak of 0.412 (Table A9) after the LUNA crash in 2022. Such a change represents a significant variation in portfolio weights. Following these indications, investors could benefit from such a perspective as it has direct implications for their strategies.

5. Conclusion

In our study, we extensively analyzed the connectedness among the top five non-stable cryptocurrencies (Bitcoin, Ethereum, Ripple, Binance Coin, and Cardano) over the five-year span (2018-2023) and presented our detailed results applicable to that research period. Unlike previous studies (e.g., Bouteska et al., 2023; Sila et al., 2024), which relied on visual inspection to associate stressful events with spikes in connectedness, our study pioneers the use of the bootstrap-after-bootstrap methodology (Greenwood-Nimmo et al., 2024) to establish statistically significant causal links between endogenously selected events and return connectedness dynamics.

Another contribution of our study is that we identify a systematic lag between the occurrence of shocks and the ensuing spikes in connectedness, offering new insights into the temporal dynamics of return spillovers in cryptocurrency markets. Furthermore, we are the first to quantify the impact of systematic events on optimal portfolio rebalancing, providing actionable insights for portfolio managers seeking to hedge risks and enhance asset allocation strategies amid cryptocurrency market turbulence. Our research revealed seven market-related and three policy-related events that significantly influenced the connectedness of these digital assets. We find that connectedness showed a more stable reaction to market shocks, while the political shocks had rather heterogeneous effects. Additionally, the impact of political shocks was rising over time. On the other hand, the market shocks' effect spiked and then declined.

Notably, we observed a lag from one to twenty-two days in the response of these cryptocurrencies to various global economic and political shocks. Such lag presents strategic opportunities for both policymakers and investors in the digital currency space. Our analysis also demonstrates an apparent return 'transmitter' effect, where Bitcoin (BTC) and Ethereum (ETH) consistently acted as return transmitters, particularly influencing the market movements of Ripple and Binance Coin. The finding is crucial for understanding the dynamics of market influence and risk within the cryptocurrency ecosystem since the transmitted returns gained values of up to 20%. Then, we expand on the impact of the three most influential shocks and segment the dataset into four sub-periods. Our aim is to analyze the best portfolio weights and hedging ratios for investors. Drawing inspiration from Kočenda and Moravcová (2019), we calculate precise hedging ratios and portfolio allocations. Our findings reveal that, during our research period, Cardano and Ripple consistently exhibit the most favorable hedging properties for portfolio optimization, offering a new perspective on risk mitigation strategies in cryptocurrency markets. Our study represents the first examination of these ratios for the most traded cryptocurrencies.

From a policy perspective, our study suggests that regulators and policymakers should consider these delayed periods and transmitter effects when formulating guidelines for digital currency markets. For investors, the identified lag presents a critical window of up to one business month for strategic decisions, such as portfolio adjustments or risk hedging, following significant global events. Our research significantly contributes to understanding return connectedness in cryptocurrency markets. It provides executable insights for policymakers and investors in this rapidly evolving field about how and with what delay transmissions change in the context of economic distress.

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Figure 1: Total connectedness index

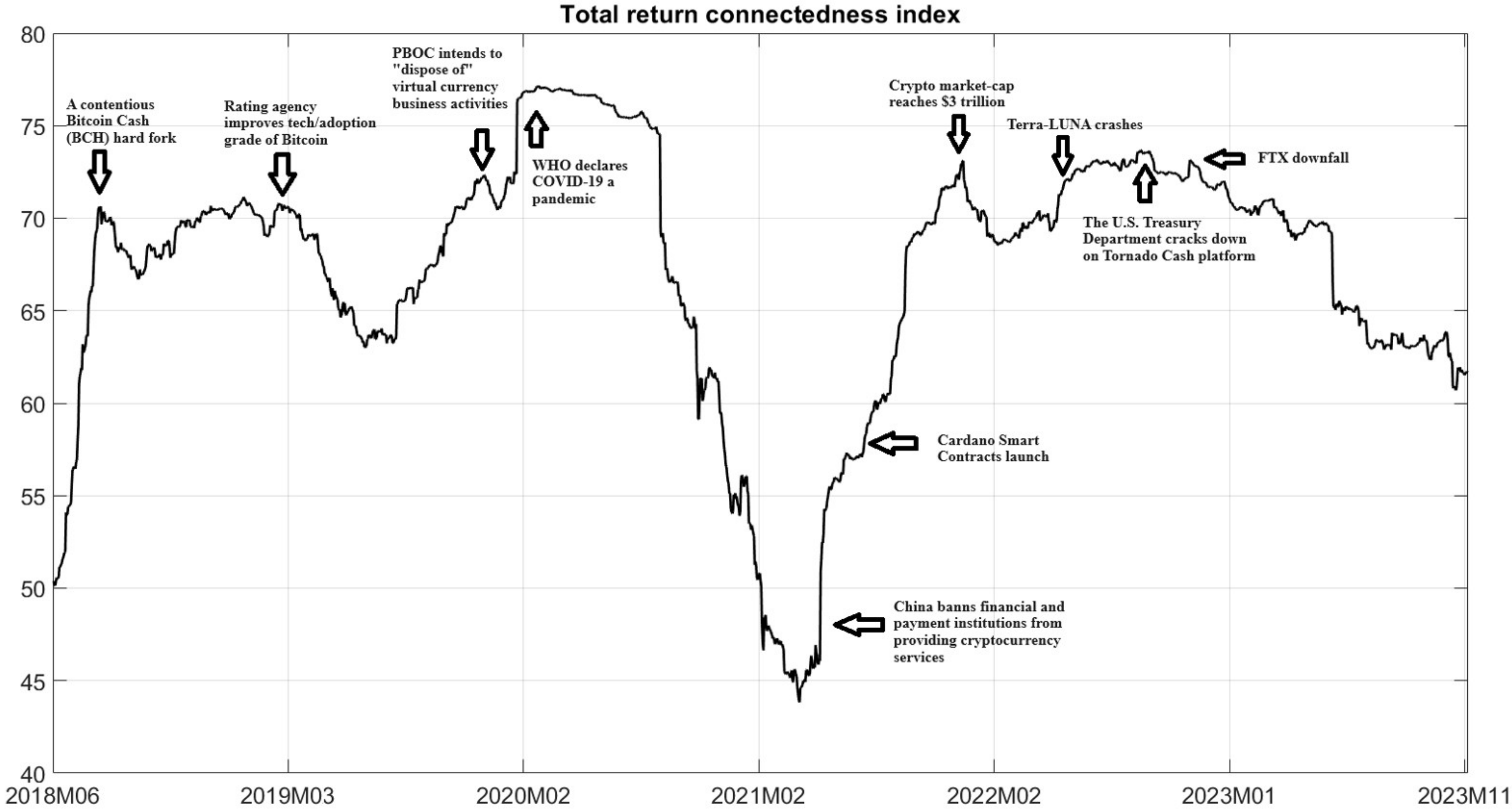

Figure 2: Net spillovers

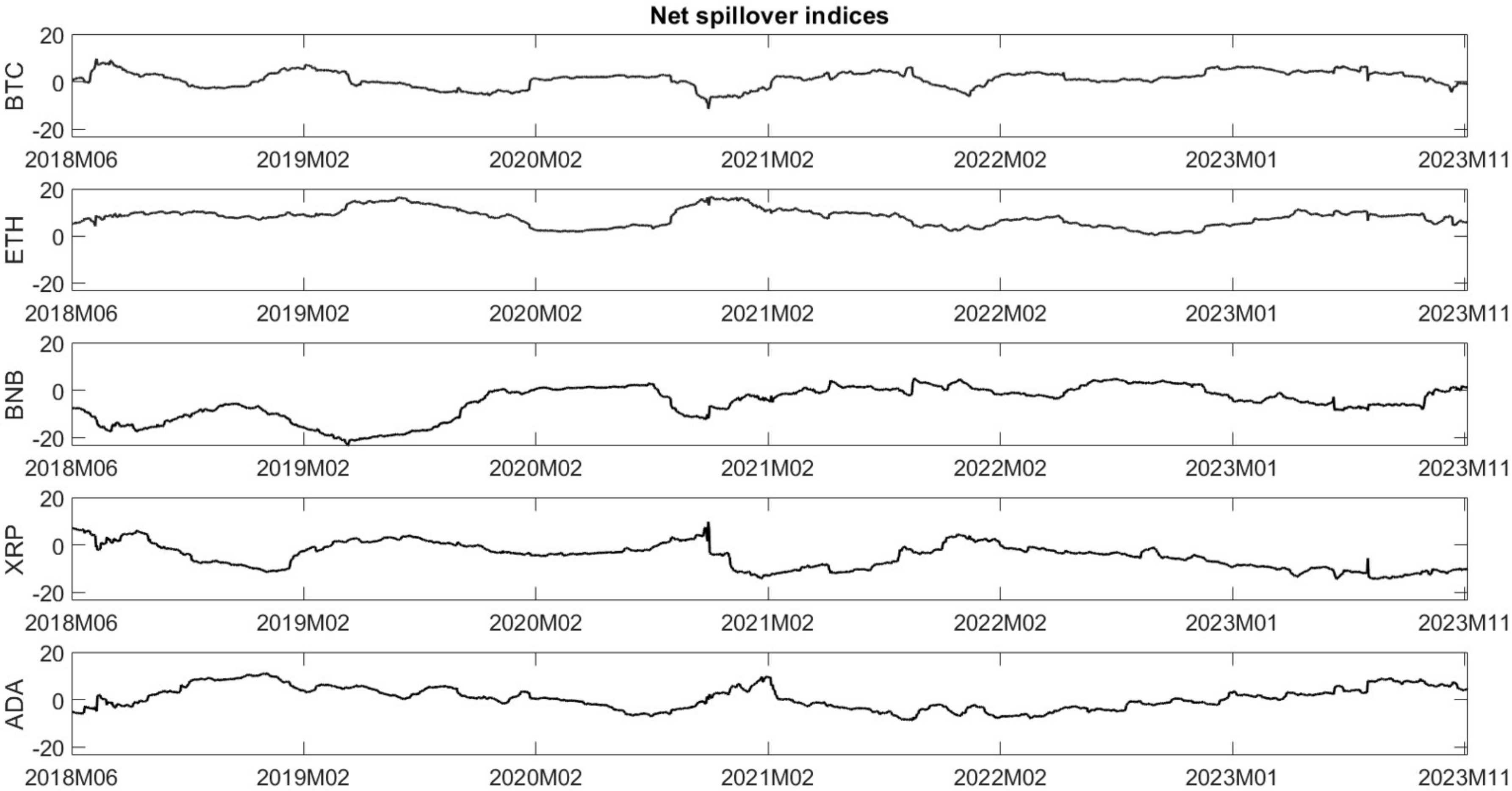

Table 1: Empirical Probability of an Endogenously Detected Increase in Connectedness after Specific Events (in percents)

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	54.3	55.6	53.9	56.5	82.9	80.1	**90.7**	87.1	**94.9**	**91.2**
2	Rating agency improves tech/adoption grade of Bitcoin	Market	51.5	54.7	53.4	58.5	51.3	56.4	66.6	66.5	**92.3**	88.8
3	PBOC intends to "dispose of" virtual currency business activities	Policy	59.7	62.1	64.4	63.0	65.5	63.4	81.6	80.7	89.6	**92.6**
4	WHO declares COVID-19 a pandemic	Market	47.0	52.3	**95.8**	**93.6**	**98.2**	**96.8**	**99.2**	**98.1**	**99.7**	**99.4**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	42.6	49.6	84.6	85.3	**93.5**	**93.9**	**97.9**	**97.8**	**99.5**	**99.5**
6	Cardano Smart Contracts launch	Market	46.9	49.4	55.3	55.8	60.3	61.1	**94.9**	**96.3**	**98.5**	**98.7**
7	Crypto market-cap reaches $3 trillion	Market	50.5	51.8	61.3	63.6	72.1	71.7	**92.9**	**90.5**	**94.4**	87.7
8	LUNA crashes	Market	66.3	66.6	74.2	75.3	88.3	88.9	**94.9**	**94.9**	**97.3**	**97.8**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	51.0	53.4	52.8	52.3	63.2	56.8	71.9	66.8	**92.8**	88.9
10	FTX downfall	Market	55.2	58.0	56.5	60.7	61.5	64.9	86.7	**91.4**	72.6	76.3

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Appendix A

Table A1: Descriptive statistics

Variables	Obs.	Mean	St. Dev.	Min	Mdn	Max	Skewness	Kurtosis	ADF Test
BTC/USD	2154	20852.00	15431.00	3236.80	16445.00	67567.00	0.92	-0.15	-1.43
ETH/USD	2154	1197.10	1093.30	84.31	837.60	4812.10	1.08	0.31	-1.45
BNB/USD	2154	161.30	171.52	1.51	32.07	672.33	0.74	-0.60	-1.85
XRP/USD	2154	0.51	0.33	0.14	0.42	3.38	2.66	12.46	-4.42^{***}
ADA/USD	2154	0.45	0.56	0.02	0.26	2.97	1.97	3.65	-2.08
BTC/USD log diff	2153	0.00	0.04	-0.46	0.00	0.23	-0.80	12.80	-32.13^{***}
ETH/USD log diff	2153	0.00	0.05	-0.55	0.00	0.23	-0.93	10.67	-16.20^{***}
BNB/USD log diff	2153	0.00	0.06	-0.54	0.00	0.53	0.42	16.75	-8.88^{***}
XRP/USD log diff	2153	0.00	0.06	-0.55	0.00	0.61	1.13	19.33	-13.28^{***}
ADA/USD log diff	2153	0.00	0.06	-0.50	0.00	0.86	2.01	26.48	-8.52^{***}

Note: the dataset encompasses the period from November 7, 2017, to November 30, 2023, and provides descriptive statistics for daily logarithmic returns.

Table A2: Dates of specific endogenously detected events

Event	Description of the shock	Date	Source
1	A contentious Bitcoin Cash (BCH) hard fork	November 15, 2018	https://www.bitira.com/november-2018-in-crypto-monthly-news-roundup/
2	Rating agency improves tech/adoption grade of Bitcoin	March 26, 2019	https://bitcoinist.com/weiss-ratings-bitcoin-best-positioned-to-become-popular-store-of-value/
3	PBOC intends to "dispose of" virtual currency business activities	November 22, 2019	https://www.cryptowisser.com/what-happened-to-crypto-in-november-2019/
4	WHO declares COVID-19 a pandemic	March 11, 2020	https://www.who.int/director-general/speeches/detail/who-director-general-s-opening-remarks-at-the-media-briefing-on-covid-19---11-march-2020
5	China banns financial and payment institutions from providing cryptocurrency services	May 18, 2021	https://www.reuters.com/technology/bitcoin-ethereum-plunge-crypto-market-cap-losses-nearly-1-trillion-2021-05-19/
6	Cardano Smart Contracts launch	September 12, 2021	https://www.crypto-news-flash.com/top-six-crypto-events-in-september-2021-that-may-affect-the-market/
7	Crypto market reaches $3 trillion	November 10, 2021	https://www.analyticsinsight.net/10-most-important-bitcoin-moments-in-2021-to-be-remembered/
8	Terra-LUNA crashes	May 9, 2022	https://cryptonews.net/news/other/18498539/
9	The U.S. Treasury Department cracks down on Tornado Cash platform	August 12, 2022	https://www.wsj.com/articles/tornado-cashs-sanctions-show-shift-in-crypto-regulatory-focus-11660336224
10	FTX downfall	November 1, 2022	https://abcnews.go.com/Business/timeline-cryptocurrency-exchange-ftxs-historic-collapse/story?id=93337035

Note: This table presents sources confirming the dates of specific events. The dates were endogenously chosen by the bootstrap-after-bootstrap procedure created by Greenwood-Nimmo et al. (2024). The dataset encompasses the period from November 7, 2017, to November 30, 2023, and we calculate the daily logarithmic returns of five cryptocurrencies.

Table A3: Directional return spillovers among cryptocurrencies

	BTC	ETH	BNB	XRP	ADA	FROM Others
BTC	35.75	22.91	15.97	11.48	13.88	64.25
ETH	21.39	33.45	15.14	14.17	15.85	66.55
BNB	17.95	18.23	40.56	10.86	12.40	59.44
XRP	13.20	17.38	10.87	41.34	17.22	58.66
ADA	14.92	18.26	11.60	16.28	38.95	61.05
TO Others	67.46	76.78	53.58	52.79	59.35	61.99
NET SPILLOVER	3.17	10.22	-5.86	-5.87	-1.70	

Note: The values in the table represent the percentage of returns shared between cryptocurrencies. Column "FROM" demonstrates returns received from other cryptocurrencies; row "TO" demonstrates returns transmitted to other cryptocurrencies. In the row "NET SPILLOVER", we compare received and transmitted returns. The dataset encompasses the period from November 7, 2017, to November 30, 2023, and we calculate the daily logarithmic returns of five cryptocurrencies.

Table A4: Robustness of the Empirical Probabilities: 5-day spillover average as a pre-event comparison period

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	43.10	45.60	41.80	45.40	71.90	73.00	83.00	79.00	**93.40**	86.20
2	Rating agency improves tech/adoption grade of Bitcoin	Market	40.50	38.00	38.70	41.40	38.60	37.60	51.00	51.90	85.40	80.10
3	PBOC intends to "dispose of" virtual currency business activities	Policy	60.70	65.70	62.70	67.10	65.20	67.10	82.40	83.00	**90.80**	**94.30**
4	WHO declares COVID-19 a pandemic	Market	56.90	59.50	89.40	**95.20**	**95.60**	**97.40**	**98.00**	**98.70**	**99.10**	**99.40**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	50.20	51.80	80.80	86.70	**93.20**	**94.40**	**95.90**	**98.20**	**98.20**	**99.60**
6	Cardano Smart Contracts launch	Market	63.60	57.90	60.60	64.70	64.10	69.30	**96.00**	**98.30**	**97.70**	**99.70**
7	Crypto market-cap reaches $3 trillion	Market	52.20	51.90	62.40	64.00	74.40	72.00	**92.70**	**90.50**	**95.50**	88.10
8	LUNA crashes	Market	65.90	69.00	69.60	77.30	83.90	**90.00**	**93.20**	**95.70**	**95.80**	**98.00**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	41.80	42.90	39.50	40.20	49.90	47.00	59.80	55.00	86.40	80.80
10	FTX downfall	Market	49.70	51.00	48.60	54.50	55.40	58.20	79.50	88.40	62.70	71.30

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table A5: Correlation between market cap of each cryptocurrency and connectedness index

	TCI correlation
BTC market cap	-0.45
ETH market cap	-0.22
BNB market cap	-0.16
XRP market cap	-0.43
ADA market cap	-0.35

Note: The correlation value denotes the Pearson correlation value between the market cap of each cryptocurrency and the Total return connectedness index.

Table A6: Hedge ratios and portfolio weights – Pre-covid period

	Pre-covid period									
	Hedge ratios					Portfolio weights				
Crypto	Mean	Median	sd	Min	Max	Mean	Median	sd	Min	Max
ADA - ETH	0,980	0,964	0,192	0,511	2,039	0,106	0,057	0,381	-1,126	1,345
XRP - ETH	0,856	0,820	0,227	0,443	2,627	0,499	0,494	0,467	-0,567	1,431
BTC - ETH	0,626	0,625	0,145	0,128	1,147	1,091	1,128	0,374	-0,392	1,68
BNB - ETH	0,731	0,719	0,175	0,378	1,275	0,425	0,414	0,34	-0,928	1,397
ETH - ADA	0,671	0,704	0,191	0,059	1,146					
XRP - ADA	0,696	0,684	0,172	0,187	1,555	0,843	0,938	0,435	-0,412	1,655
BTC - ADA	0,471	0,479	0,140	0,060	0,955	1,133	1,171	0,263	0,058	1,643
BNB - ADA	0,554	0,578	0,181	0,076	0,936	0,671	0,676	0,265	0,048	1,401
ETH - XRP	0,802	0,833	0,224	0,143	1,303					
ADA - XRP	0,979	0,968	0,275	0,367	3,187					
BTC - XRP	0,538	0,561	0,185	0,014	1,001	0,874	0,924	0,281	-0,001	1,345
BNB - XRP	0,616	0,634	0,211	0,101	1,266	0,457	0,446	0,29	-0,172	1,227
ETH - BTC	1,073	1,071	0,262	0,101	1,626					
ADA - BTC	1,202	1,204	0,381	0,477	4,204					
XRP - BTC	0,949	0,927	0,324	0,090	2,957					
BNB - BTC	0,957	0,993	0,253	0,252	1,829	0,056	0,007	0,271	-0,916	1,202
ETH - BNB	0,655	0,652	0,217	0,129	1,308					
ADA - BNB	0,733	0,723	0,244	0,128	1,902					
XRP - BNB	0,590	0,565	0,254	0,083	2,159					
BTC - BNB	0,494	0,493	0,148	0,128	1,047					

Table A7: Hedge ratios and portfolio weights – Covid period

	Pre-covid period									
	Hedge ratios					Portfolio weights				
Crypto	**Mean**	**Median**	**sd**	**Min**	**Max**	**Mean**	**Median**	**sd**	**Min**	**Max**
ADA - ETH	0,984	0,981	0,225	0,519	1,609	0,062	0,035	0,275	-0,735	0,977
XRP - ETH	0,938	0,750	0,698	0,258	7,406	0,383	0,359	0,423	-0,374	1,279
BTC - ETH	0,597	0,584	0,126	0,338	0,909	1,019	0,992	0,291	0,357	2,006
BNB - ETH	0,787	0,717	0,290	0,382	2,596	0,553	0,568	0,494	-0,715	1,386
ETH - ADA	0,556	0,532	0,152	0,277	0,994					
XRP - ADA	0,620	0,476	0,537	0,166	5,714	0,638	0,71	0,397	-0,329	1,237
BTC - ADA	0,360	0,327	0,135	0,129	0,787	1,037	1,030	0,157	0,658	1,591
BNB - ADA	0,562	0,477	0,247	0,262	2,413	0,804	0,945	0,418	-0,171	1,340
ETH - XRP	0,616	0,608	0,289	0,046	1,423					
ADA - XRP	0,726	0,700	0,363	0,041	1,752					
BTC - XRP	0,439	0,400	0,227	0,030	1,141	0,837	0,913	0,304	-0,161	1,368
BNB - XRP	0,568	0,529	0,293	0,029	1,584	0,607	0,653	0,404	-0,256	1,341
ETH - BTC	1,004	0,991	0,154	0,670	1,488					
ADA - BTC	1,068	1,048	0,285	0,519	1,763					
XRP - BTC	1,104	0,888	0,765	0,358	7,584					
BNB - BTC	0,950	0,839	0,380	0,347	2,664	0,206	0,153	0,395	-0,724	1,115
ETH - BNB	0,760	0,803	0,290	0,114	1,331					
ADA - BNB	0,953	0,943	0,387	0,142	1,923					
XRP - BNB	0,831	0,687	0,730	0,113	8,606					
BTC - BNB	0,533	0,501	0,228	0,108	1,064					

Table A8: Hedge ratios and portfolio weights – Chinese ban period

	Pre-covid period									
	Hedge ratios					Portfolio weights				
Crypto	**Mean**	**Median**	**sd**	**Min**	**Max**	**Mean**	**Median**	**sd**	**Min**	**Max**
ADA - ETH	0,924	0,905	0,133	0,651	1,401	0,182	0,189	0,277	-1,11	0,877
XRP - ETH	0,952	0,926	0,155	0,615	1,472	0,172	0,174	0,382	-1,583	1,370
BTC - ETH	0,712	0,716	0,054	0,488	0,801	1,172	1,156	0,266	0,579	2,036
BNB - ETH	0,859	0,845	0,117	0,576	1,573	0,452	0,526	0,376	-1,380	1,083
ETH - ADA	0,675	0,692	0,110	0,371	0,936					
XRP - ADA	0,796	0,795	0,117	0,375	1,091	0,528	0,524	0,307	-0,306	1,316
BTC - ADA	0,532	0,539	0,081	0,293	0,711	1,068	1,074	0,173	0,572	1,560
BNB - ADA	0,676	0,675	0,137	0,344	1,221	0,756	0,787	0,315	-1,116	1,318
ETH - XRP	0,722	0,718	0,120	0,346	1,078					
ADA - XRP	0,825	0,821	0,116	0,518	1,257					
BTC - XRP	0,567	0,583	0,094	0,260	0,759	1,094	1,093	0,197	0,575	1,661
BNB - XRP	0,710	0,707	0,146	0,312	1,206	0,737	0,812	0,376	-1,595	1,448
ETH - BTC	1,071	1,054	0,125	0,845	1,838					
ADA - BTC	1,101	1,065	0,209	0,767	2,331					
XRP - BTC	1,126	1,061	0,228	0,776	2,328					
BNB - BTC	0,999	0,942	0,239	0,714	2,881	0,063	0,101	0,260	-0,718	0,572
ETH - BNB	0,849	0,856	0,072	0,606	1,040					
ADA - BNB	0,916	0,886	0,160	0,687	1,735					
XRP - BNB	0,924	0,905	0,165	0,628	1,805					
BTC - BNB	0,653	0,662	0,076	0,295	0,788					

Table A9: Hedge ratios and portfolio weights – LUNA crash period

	Pre-covid period									
	Hedge ratios					Portfolio weights				
Crypto	Mean	Median	sd	Min	Max	Mean	Median	sd	Min	Max
ADA - ETH	0,883	0,881	0,219	0,508	2,636	0,329	0,234	0,406	-0,433	1,231
XRP - ETH	0,883	0,423	0,322	0,207	2,445	0,634	0,698	0,328	-0,133	1,091
BTC - ETH	0,705	0,691	0,184	0,381	1,812	1,024	1,173	0,514	-0,741	1,718
BNB - ETH	0,645	0,626	0,159	0,306	1,680	0,769	0,831	0,331	-0,385	1,326
ETH - ADA	0,725	0,688	0,173	0,252	1,222					
XRP - ADA	0,404	0,475	0,307	0,223	2,045	0,737	0,862	0,374	-0,222	1,150
BTC - ADA	0,548	0,533	0,134	0,197	1,236	0,967	1,043	0,266	-0,232	1,393
BNB - ADA	0,562	0,549	0,128	0,237	1,284	0,874	0,946	0,254	-0,244	1,259
ETH - XRP	0,678	0,650	0,295	0,000	2,067					
ADA - XRP	0,872	0,849	0,352	0,000	2,340					
BTC - XRP	0,480	0,471	0,199	0,000	1,304	0,544	0,523	0,291	-0,048	1,105
BNB - XRP	0,455	0,454	0,180	0,000	1,070	0,499	0,468	0,280	-0,009	1,096
ETH - BTC	1,120	1,068	0,281	0,452	2,029					
ADA - BTC	1,060	1,036	0,244	0,421	2,317					
XRP - BTC	0,634	0,484	0,306	0,115	2,060					
BNB - BTC	0,803	0,756	0,200	0,275	1,753	0,412	0,432	0,343	-0,303	1,267
ETH - BNB	0,898	0,888	0,199	0,318	1,511					
ADA - BNB	0,951	0,957	0,187	0,434	1,736					
XRP - BNB	0,484	0,418	0,258	0,152	1,677					
BTC - BNB	0,705	0,706	0,173	0,323	1,692					

Note: The Tables A5-A9 display key statistical measures for the optimal portfolio weights and hedging ratios, including median, standard deviation (sd), minimum (min), and maximum (max) values. These metrics are presented for distinct time periods, as detailed in the Data section. Sub-periods are identified in Figure 2. Additionally, the dataset in question shows no evidence of the Autoregressive Conditional Heteroskedasticity (ARCH) effect, precluding the possibility of executing Asymmetric Dynamic Conditional Correlation (ADCC) analysis.

Appendix B

Table B1: Empirical Probability of an Endogenously Detected Increase in Connectedness after Selected Events (in percents); <u>Forecast horizon = 8</u>

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	54.3	55.6	53.9	56.5	82.9	80.1	**90.7**	87.1	**94.9**	**91.2**
2	Rating agency improves tech/adoption grade of Bitcoin	Market	51.5	54.7	53.4	58.5	51.3	56.4	66.6	66.5	**92.3**	88.8
3	PBOC intends to "dispose of" virtual currency business activities	Policy	59.7	62.1	64.4	63.0	65.5	63.4	81.6	80.7	89.6	**92.6**
4	WHO declares COVID-19 a pandemic	Market	47.0	52.3	**95.8**	**93.6**	**98.2**	**96.8**	**99.2**	**98.1**	**99.7**	**99.4**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	42.6	49.6	84.6	85.3	**93.5**	**93.9**	**97.9**	**97.8**	**99.5**	**99.5**
6	Cardano Smart Contracts launch	Market	46.9	49.4	55.3	55.8	60.3	61.1	**94.9**	**96.3**	**98.5**	**98.7**
7	Crypto market-cap reaches $3 trillion	Market	50.5	51.8	61.3	63.6	72.1	71.7	**92.9**	**90.5**	**94.4**	87.7
8	LUNA crashes	Market	66.3	66.6	74.2	75.3	88.3	88.9	**94.9**	**94.9**	**97.3**	**97.8**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	51.0	53.4	52.8	52.3	63.2	56.8	71.9	66.8	**92.8**	88.9
10	FTX downfall	Market	55.2	58.0	56.5	60.7	61.5	64.9	86.7	**91.4**	72.6	76.3

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B2: Empirical Probability of an Endogenously Detected Increase in Connectedness after Selected Events (in percents); <u>Forecast horizon = 12</u>

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	54.3	55.6	53.9	56.5	82.9	80.1	**90.7**	87.1	**94.9**	**91.2**
2	Rating agency improves tech/adoption grade of Bitcoin	Market	51.5	54.7	53.4	58.5	51.3	56.4	66.6	66.5	**92.3**	88.8
3	PBOC intends to "dispose of" virtual currency business activities	Policy	59.7	62.1	64.4	63.0	65.5	63.4	81.6	80.7	89.6	**92.6**
4	WHO declares COVID-19 a pandemic	Market	47.0	52.3	**95.8**	**93.6**	**98.2**	**96.8**	**99.2**	**98.1**	**99.7**	**99.4**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	42.6	49.6	84.6	85.3	**93.5**	**93.9**	**97.9**	**97.8**	**99.5**	**99.5**
6	Cardano Smart Contracts launch	Market	46.9	49.4	55.3	55.8	60.3	61.1	**94.9**	**96.3**	**98.5**	**98.7**
7	Crypto market-cap reaches $3 trillion	Market	50.5	51.8	61.3	63.6	72.1	71.7	**92.9**	**90.5**	**94.4**	87.7
8	LUNA crashes	Market	66.3	66.6	74.2	75.3	88.3	88.9	**94.9**	**94.9**	**97.3**	**97.8**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	51.0	53.4	52.8	52.3	63.2	56.8	71.9	66.8	**92.8**	88.9
10	FTX downfall	Market	55.2	58.0	56.5	60.7	61.5	64.9	86.7	**91.4**	72.6	76.3

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B3: Empirical Probability of an Endogenously Detected Increase in Connectedness after Selected Events (in percents); VAR length = 1

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	45.3	47.3	41.2	48.0	77.4	75.8	87.7	81.8	**90.3**	86.4
2	Rating agency improves tech/adoption grade of Bitcoin	Market	42.1	43.8	42.0	44.0	36.5	38.8	53.6	49.2	87.9	78.0
3	PBOC intends to "dispose of" virtual currency business activities	Policy	54.5	58.2	60.4	60.4	70.9	71.8	73.1	79.7	**92.3**	**94.6**
4	WHO declares COVID-19 a pandemic	Market	51.6	53.8	**96.6**	**95.2**	**98.6**	**97.4**	**99.4**	**98.9**	**99.9**	**99.8**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	52.1	55.1	83.1	84.7	**93.6**	**94.1**	**97.0**	**97.7**	**99.2**	**98.9**
6	Cardano Smart Contracts launch	Market	52.3	54.8	54.0	53.7	59.3	59.9	**97.0**	**97.2**	**97.3**	**97.5**
7	Crypto market-cap reaches $3 trillion	Market	54.7	56.8	47.4	48.7	71.0	72.0	**91.0**	87.8	**95.7**	**91.1**
8	LUNA crashes	Market	68.6	68.9	66.8	69.8	84.6	87.3	**94.4**	**95.6**	**96.7**	**98.1**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	35.3	37.1	33.5	37.3	36.5	36.7	53.6	55.0	82.3	78.6
10	FTX downfall	Market	51.1	52.8	58.8	60.0	62.9	62.3	85.2	88.8	73.3	79.6

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified re+j days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B4: Empirical Probability of an Endogenously Detected Increase in Connectedness after Selected Events (in percents); VAR length = 3

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	55.4	55.6	54.4	53.2	89.6	82.0	**91.8**	84.3	**95.2**	88.3
2	Rating agency improves tech/adoption grade of Bitcoin	Market	49.7	53.2	47.2	50.1	54.6	55.7	64.2	59.9	**93.2**	87.2
3	PBOC intends to "dispose of" virtual currency business activities	Policy	53.8	58.2	53.8	58.7	55.6	58.4	76.1	71.7	86.4	89.0
4	WHO declares COVID-19 a pandemic	Market	48.4	51.7	**97.9**	**95.2**	**99.5**	**97.7**	**99.9**	**99.2**	**100.0**	**99.6**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	50.3	49.0	82.8	85.4	**94.8**	**96.6**	**97.4**	**98.4**	**99.5**	**99.6**
6	Cardano Smart Contracts launch	Market	52.0	51.4	53.8	52.2	59.3	58.7	**96.0**	**97.2**	**98.7**	**98.7**
7	Crypto market-cap reaches $3 trillion	Market	62.3	64.0	64.8	65.5	87.5	85.0	**92.9**	**91.6**	**97.5**	**92.0**
8	LUNA crashes	Market	78.9	76.2	78.3	78.5	**91.7**	**90.9**	**96.0**	**96.9**	**98.3**	**99.0**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	54.3	52.1	54.7	51.4	67.8	56.9	73.1	64.3	**90.1**	79.4
10	FTX downfall	Market	48.2	55.6	49.3	54.9	56.1	56.4	76.3	88.5	60.7	75.4

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B5: Robustness of the Empirical Probabilities: 5-day spillover average as a pre-event comparison period; Forecast horizon = 8

Event	**Description of the shock**	**Type of the shock**	**r_e+0**		**r_e+1**		**r_e+5**		**r_e+10**		**r_e+22**	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	43.10	45.60	41.80	45.40	71.90	73.00	83.00	79.00	**93.40**	86.20
2	Rating agency improves tech/adoption grade of Bitcoin	Market	40.50	38.00	38.70	41.40	38.60	37.60	51.00	51.90	85.40	80.10
3	PBOC intends to "dispose of" virtual currency business activities	Policy	60.70	65.70	62.70	67.10	65.20	67.10	82.40	83.00	**90.80**	**94.30**
4	WHO declares COVID-19 a pandemic	Market	56.90	59.50	89.40	**95.20**	**95.60**	**97.40**	**98.00**	**98.70**	**99.10**	**99.40**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	50.20	51.80	80.80	86.70	**93.20**	**94.40**	**95.90**	**98.20**	**98.20**	**99.60**
6	Cardano Smart Contracts launch	Market	63.60	57.90	60.60	64.70	64.10	69.30	**96.00**	**98.30**	**97.70**	**99.70**
7	Crypto market-cap reaches $3 trillion	Market	52.20	51.90	62.40	64.00	74.40	72.00	**92.70**	**90.50**	**95.50**	88.10
8	LUNA crashes	Market	65.90	69.00	69.60	77.30	83.90	**90.00**	**93.20**	**95.70**	**95.80**	**98.00**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	41.80	42.90	39.50	40.20	49.90	47.00	59.80	55.00	86.40	80.80
10	FTX downfall	Market	49.70	51.00	48.60	54.50	55.40	58.20	79.50	88.40	62.70	71.30

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified re+j days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B6: Robustness of the Empirical Probabilities: 5-day spillover average as a pre-event comparison period; Forecast horizon = 12

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	43.10	45.60	41.80	45.40	71.90	73.00	83.00	79.00	**93.40**	86.20
2	Rating agency improves tech/adoption grade of Bitcoin	Market	40.50	38.00	38.70	41.40	38.60	37.60	51.00	51.90	85.40	80.10
3	PBOC intends to "dispose of" virtual currency business activities	Policy	60.70	65.70	62.70	67.10	65.20	67.10	82.40	83.00	**90.80**	**94.30**
4	WHO declares COVID-19 a pandemic	Market	56.90	59.50	89.40	**95.20**	**95.60**	**97.40**	**98.00**	**98.70**	**99.10**	**99.40**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	50.20	51.80	80.80	86.70	**93.20**	**94.40**	**95.90**	**98.20**	**98.20**	**99.60**
6	Cardano Smart Contracts launch	Market	63.60	57.90	60.60	64.70	64.10	69.30	**96.00**	**98.30**	**97.70**	**99.70**
7	Crypto market-cap reaches $3 trillion	Market	52.20	51.90	62.40	64.00	74.40	72.00	**92.70**	**90.50**	**95.50**	88.10
8	LUNA crashes	Market	65.90	69.00	69.60	77.30	83.90	**90.00**	**93.20**	**95.70**	**95.80**	**98.00**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	41.80	42.90	39.50	40.20	49.90	47.00	59.80	55.00	86.40	80.80
10	FTX downfall	Market	49.70	51.00	48.60	54.50	55.40	58.20	79.50	88.40	62.70	71.30

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified re+j days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B7: Robustness of the Empirical Probabilities: 5-day spillover average as a pre-event comparison period; VAR length = 1

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	27.2	31.4	26.4	33.3	66.5	63.9	76.5	71.0	82.7	76.3
2	Rating agency improves tech/adoption grade of Bitcoin	Market	29.0	32.8	29.5	32.0	23.7	26.8	41.4	36.3	79.3	65.9
3	PBOC intends to "dispose of" virtual currency business activities	Policy	56.4	59.9	62.7	63.0	73.0	74.3	74.3	81.6	**93.5**	**95.5**
4	WHO declares COVID-19 a pandemic	Market	68.7	69.7	**98.8**	**97.6**	**99.7**	**98.8**	**99.7**	**99.6**	**100.0**	**100.0**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	41.4	44.9	75.6	78.7	**90.6**	**91.7**	**95.0**	**96.0**	**98.1**	**97.8**
6	Cardano Smart Contracts launch	Market	65.1	65.9	66.7	67.6	72.7	72.9	**99.2**	**99.1**	**99.0**	**98.8**
7	Crypto market-cap reaches $3 trillion	Market	56.4	56.7	48.5	48.6	72.5	71.8	**91.5**	87.7	**96.1**	**91.1**
8	LUNA crashes	Market	67.2	68.9	65.7	69.7	84.0	87.3	**94.2**	**95.6**	**96.5**	**98.1**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	45.0	55.1	44.2	53.5	47.7	55.5	63.5	69.8	89.3	89.3
10	FTX downfall	Market	35.7	40.7	44.1	47.7	48.0	51.1	74.6	82.9	59.2	69.8

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified re+j days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B8: Robustness of the Empirical Probabilities: 5-day spillover average as a pre-event comparison period; VAR length = 3

Event	**Description of the shock**	**Type of the shock**	**r_e+0**		**r_e+1**		**r_e+5**		**r_e+10**		**r_e+22**	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	35.2	37.5	36.2	37.7	76.4	69.3	81.0	71.1	87.3	79.0
2	Rating agency improves tech/adoption grade of Bitcoin	Market	28.9	29.0	27.0	28.8	31.2	31.1	43.0	37.3	82.4	67.9
3	PBOC intends to "dispose of" virtual currency business activities	Policy	63.2	61.2	61.3	61.4	64.0	61.2	81.8	74.4	**90.1**	**90.3**
4	WHO declares COVID-19 a pandemic	Market	64.7	67.8	**99.5**	**97.7**	**99.7**	**99.3**	**100.0**	**99.9**	**100.0**	**99.8**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	39.6	44.1	77.7	82.8	**92.1**	**95.9**	**95.7**	**97.7**	**98.7**	**99.5**
6	Cardano Smart Contracts launch	Market	62.8	64.1	65.3	65.5	69.4	68.2	**98.3**	**99.2**	**99.7**	**99.4**
7	Crypto market-cap reaches $3 trillion	Market	64.8	65.5	67.4	66.7	89.0	86.2	**94.8**	**92.0**	**98.1**	**92.4**
8	LUNA crashes	Market	72.1	76.3	73.5	78.6	88.5	**90.9**	**94.2**	**96.9**	**97.8**	**99.0**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	41.0	41.5	41.9	38.1	57.4	45.5	62.5	52.2	83.8	69.2
10	FTX downfall	Market	47.7	51.4	48.5	52.3	54.8	54.3	75.8	87.0	59.6	73.4

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified re+j days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.

Table B9: Empirical Probability of an Endogenously Detected Increase in Connectedness after Selected Events (in percents); Window = 100

Event	Description of the shock	Type of the shock	r_e+0		r_e+1		r_e+5		r_e+10		r_e+22	
			OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD	OVD	GVD
1	A contentious Bitcoin Cash (BCH) hard fork	Market	47.8	55.1	48.4	57.2	69.0	76.6	67.9	72.8	25.7	33.5
2	Rating agency improves tech/adoption grade of Bitcoin	Market	52.4	54.4	43.1	44.9	33.8	30.1	47.2	41.9	18.9	11.90
3	PBOC intends to "dispose of" virtual currency business activities	Policy	47.9	51.1	43.4	50.9	45.8	65.6	34.8	61.4	48.5	75.5
4	WHO declares COVID-19 a pandemic	Market	53.8	56.2	**99.7**	**97.6**	**99.8**	**98.1**	**99.8**	**99.2**	**99.6**	**98.4**
5	China banns financial and payment institutions from providing cryptocurrency services	Policy	66.8	66.6	**94.7**	**95.9**	**99.4**	**99.8**	**100.0**	**100.0**	**100.0**	**100.0**
6	Cardano Smart Contracts launch	Market	44.3	49.6	46.4	51.1	50.6	53.4	79.3	77.4	30.5	42.1
7	Crypto market-cap reaches $3 trillion	Market	56.6	57.0	44.1	46.1	64.1	60.1	75.2	70.1	**91.1**	86.3
8	LUNA crashes	Market	83.8	79.6	78.7	77.1	88.7	81.3	**99.1**	**97.7**	**99.8**	**99.0**
9	The U.S. Treasury Department cracks down on Tornado Cash platform	Policy	50.0	48.4	48.9	49.8	28.2	24.0	28.3	34.1	16.7	25.4
10	FTX downfall	Market	34.3	43.3	36.5	44.1	47.7	56.2	**96.7**	**99.3**	**97.9**	**99.6**

Note: the table reports the empirical probability that the connectedness index's value exceeds the connectedness index's mean during the specified *re+j* days using bootstrap samples in a rolling sample. The "OVD" and "GVD" headings' results denote the connectedness indices' calculated probabilities using the orthogonalized and generalized forecast error variance decompositions. The results follow the process used by Greenwood-Nimmo et al. (2024); we performed 1000 bootstrap-after-bootstrap nonparametric replications. These results are for the cryptocurrencies BTC/USD, ETH/USD, BNB/USD, XRP/USD, and ADA/USD.