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GOOD VS. BAD VOLATILITY IN MAJOR CRYPTOCURRENCIES: THE DICHOTOMY AND DRIVERS OF CONNECTEDNESS

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Good vs. Bad Volatility in Major Cryptocurrencies: The Dichotomy and Drivers of Connectedness

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Abstract:
Cryptocurrencies exhibit unique statistical and dynamic properties compared to those of traditional financial assets, making the study of their volatility crucial for portfolio managers and traders. We investigate the volatility connectedness dynamics of a representative set of eight major crypto assets. Methodologically, we decompose the measured volatility into positive and negative components and employ the time-varying parameters vector autoregression (TVP-VAR) framework to show distinct dynamics associated with market booms and downturns. The results suggest that crypto connectedness reflects important events and exhibits more variable and cyclical dynamics than those of traditional financial markets. Periods of extremely high or low connectedness are clearly linked to specific events in the crypto market and macroeconomic or monetary history. Furthermore, existing asymmetry from good and bad volatility indicates that information about market downturns spills over substantially faster than news about comparable market surges. Overall, the connectedness dynamics are predominantly driven by fundamental crypto factors, while the asymmetry measure also depends on macro factors such as the VIX index and the expected inflation.

JEL: C58, G10, C36
Keywords: Volatility, Dynamic connectedness, Asymmetric effects, Cryptocurrency

1 Introduction

Quantification of volatility and assessment of its transfer is central to financial modeling as well as practical applications (Diebold & Yilmaz, 2015). Volatility spillovers that materialize into connectedness among cryptocurrencies are particularly intriguing since they are characterized by unprecedented levels of volatility, a rich network structure, and complex connections within asset classes. These key features differentiate cryptocurrencies from standard financial assets (Guo, Härdle, & Tao, 2022; Härdle, Harvey, & Reule, 2020). Nevertheless, many questions related to connectedness in the crypto market remain open. How do the connectedness dynamics evolve in a network of the key cryptocurrencies, and how does it differ with respect to negative and positive shocks? How does the nature of key events affect volatility spillovers on the crypto market? What are the key drivers of the qualitatively differing (negative and positive) connectedness segments? In our paper, we answer those questions with a battery of methodological advances and cover most of the crypto market in terms of its capitalization.[1]

Since the seminal papers by Diebold and Yılmaz (2009), Diebold and Yılmaz (2012), and Diebold and Yılmaz (2014), much of the financial research has been devoted to studying the interdependence of returns or return volatilities with the spillover index introduced therein. This measure quantifies the directional propagation of shocks through forecast error variance decomposition of the underlying vector autoregressive model (VAR), which is a well-known model estimating interrelationships in multivariate setups (Enders, 2008). A large amount of literature has emerged based on the abovementioned studies in traditional finance and emerging crypto finance. Our goal is to move beyond the typical reports on total spillovers, directional analysis, or their frequency dynamics (Baruník & Křehlík, 2018). We calculate the spillovers of volatility approximated by several realized variance (RV) measures and explain the spillovers with fundamental variables for crypto assets, such as blockchain activity, exchange activity, and external macroeconomic factors in an approach similar to Kristoufek (2015) but venturing beyond Bitcoin as the single asset of interest.

Our key methodological tool is the time-varying parameters vector autoregression (TVP-VAR) framework, which generalizes the traditional moving-window estimation technique by estimating a full VAR model in each time period of the sample. Furthermore, we decompose the measured volatility into its positive and negative components, and we describe distinct dynamics behind connectedness associated with market surges and downturns. We also qualitatively analyze the impact of exogenous news on connectedness and asymmetry, thus contributing to the discussion on price endogeneity in crypto markets (Jiang, Nie, & Ruan, 2018; Kristoufek, 2018; Mark, Sila, & Weber, 2020), as we observe the so-called "excess volatility puzzle" (Shiller, 1981) when large price movements occur without a pertinent flow of news.

In sum, we (i) analyze the connectedness dynamics of the representative set of crypto assets, (ii) assess how news affects volatility spillovers among them, including their impact on bad and good volatility, and (iii) determine the set of impactful drivers of crypto-connectedness. Along these lines, we review the literature related to our research questions to show our contribution better.

The principal research on the financial characteristics of crypto assets can be traced to studies by Barber, Boyen, Shi, and Uzun (2012), Meiklejohn et al. (2013) or Kristoufek (2013). At that time, most of the research understandably focused on Bitcoin as the original and sole dominant player on the market. With additional crypto assets entering the market, studies covering the structure of linkages in the crypto market have become more frequent. Corbet, Lucey, Urquhart,

[1]Because the labels for digital assets vary in the literature, we use crypto assets, cryptocurrencies, or "crypto" as a shorthand, as terms of interchangeable meaning. Similarly, we use the terms connectedness and spillovers interchangeably, as both have been used in the literature to describe the same phenomenon of volatility connectedness quantifying the dynamic characterization of volatility spillovers among various assets or across markets, modeling them as a network; see Diebold and Yilmaz (2015).

and Yarovaya (2019) or Härdle et al. (2020) provide a comprehensive overview of the relevant crypto literature and its progress from Bitcoin-dominant topics to current research avenues.

Regarding news impact on connectedness, we provide a qualitative analysis of news pertaining to connectedness dynamics. This is an important topic in the recent literature where the effect of the news on Bitcoin price is analyzed in depth by Corbet, Larkin, Lucey, Meegan, and Yarovaya (2020). Corbet et al. (2020) explain Bitcoin's returns with an index of headline sentiment, economic surprises, and the business cycle. They find that Bitcoin's returns react negatively to positive news about unemployment and durable goods. Thus, Corbet et al. (2020) concludes that Bitcoin might serve as a hedging device against this type of macroeconomic risk. Furthermore, Sapkota (2022) assesses the impact of media sentiment on Bitcoin's RV and finds that news tends to have a long-term effect on the volatility of Bitcoin. However, the literature still lacks a similar analysis covering a larger representative set of crypto assets. To the best of our knowledge, there is no analysis that investigates connectedness among crypto assets by disentangling volatility due to positive and negative shocks. Nevertheless, Ji, Bouri, Lau, and Roubaud (2019) calculate return and volatility spillovers among six large cryptos and consider positive and negative returns separately. They find that the net positions of the assets do not depend on their relative sizes and that the connectedness of negative returns is stronger than that of positive returns. We arrive at a roughly similar conclusion based on modeling the interrelation of realized semivariances instead of returns.

The literature on drivers behind connectedness in crypto is still in its infancy. Walther, Klein, and Bouri (2019) identify the Global Financial Stress Index or Chinese Policy Uncertainty Index as good predictors of volatility spillovers in the crypto market. Walther et al. (2019) and Bouri, Lucey, Saeed, and Vo (2021) conclude that crypto assets appear to be driven by the global business cycle and variables pertaining to global financial conditions. Ji et al. (2019) argue that determinants of spillovers stem from trading volume, the Global Financial Stress Index, the CBOE US Implied Volatility Index (VIX), and commodity prices, particularly gold prices. Regarding more specific drivers, Andrada-Félix, Fernandez-Perez, and Sosvilla-Rivero (2020) find that, instead of standard financial market variables, connectedness among crypto assets is driven by crypto-specific variables, such as Wikipedia searches, the market capitalization of the respective assets, and the total trade volume of specific coins. On the other hand, Charfeddine, Benlagha, and Khediri (2022) omit crypto-specific factors, as in Andrada-Félix et al. (2020), and by using the Diebold and Yılmaz (2012, 2014) approach, they find that primarily the volumes of traded coins and the VIX are statistically significant predictors of total connectedness. Finally, Wang, Ma, Bouri, and Guo (2022) analyze drivers that improve forecasting of Bitcoin's volatility from a macroeconomic and technical-analysis perspective. Their results show the general superiority of macro factors, such as the RV of the S&P 500 index, over technical factors. However, they suggest that the momentum and the trading volume stand out among the technical factors. Our results suggest that the total connectedness is driven predominantly by fundamental crypto factors, while the asymmetry measure also depends on macro factors such as VIX and the breakeven inflation rate.

Regarding the methodological approach, our study relates well to Andrada-Félix et al. (2020), who calculate volatility connectedness within and between blocks of four traditional currencies and four cryptocurrencies. Our sample includes eight of the consistently largest assets and covers an even larger proportion of the market's liquidity. We estimate the linkages in the network by employing the TVP-VAR model similarly to Andrada-Félix et al. (2020). However, their estimation is based on the Kalman filter method of Antonakakis and Gabauer (2017), while we estimate the TVP coefficients with the quasi-Bayesian local likelihood (QBLL) of Petrova (2019) and implemented by Baruník and Ellington (2020, 2023). Hence, unlike in Andrada-Félix et al. (2020), our measures provide confidence intervals, and we can distinguish periods with statistically meaningful differences between the quantified outcomes. Our key contributions show that crypto market connectedness shows more variable and cyclical dynamics than those of the traditional financial markets. Most of the periods of extremely high or low connectedness can be connected to specific events in the crypto markets related to history or the history of macroeconomic or monetary nature. Furthermore, the study of good and bad volatility spillover asymmetry uncovers that information about crypto asset market downturns usually spills over substantially faster than news about comparable market upturns. While the total connectedness is mostly driven by crypto-related factors, the asymmetry is largely affected by macroeconomic drivers as well.

The paper proceeds as follows. We describe the methodology used to estimate the measure of volatilities and, consequently, their connectedness in Section 2, and we also discuss specific parameters of our setup therein. Section 3 presents the dataset, and we explain the origin of relevant variables. Section 4 provides a qualitative analysis of the events associated with connectedness dynamics. We analyze the determinants of connectedness and its asymmetry in Section 5, and finally, Section 6 concludes.

2 Methodology

Volatility connectedness is estimated based on two realized volatility measures defined for a continuous-time stochastic process of log prices, denoted as p_t, which evolves within a time horizon $[0 \leq t \leq T]$. This process consists of a continuous component and a pure jump component, as expressed by the equation:

$$p_t = \int_0^t \mu_s ds + \int_0^t \sigma_s dW_s + J_t, \tag{1}$$

where μ represents a locally bounded predictable drift process, σ denotes a strictly positive volatility process, and J_t represents the jump part. All these components are adapted to a common filtration $\mathcal{F}$. The quadratic variation of p_t is given by:

$$[p_t, p_t] = \int_0^t \sigma_s^2 ds + \sum_{0<s\leq t} (\Delta p_s)^2, \tag{2}$$

where $\Delta p_s = p_s - p_{s-}$ represents the jumps if they occur. The first component in Equation (2) corresponds to integrated variance, while the second term captures jump variation. Andersen and Bollerslev (1998) introduced the concept of RV by proposing an estimator that involves summing squared returns to estimate quadratic variation. This estimator is consistent under the assumption that there is no noise contamination in the price process.

Intraday returns, denoted as r_k, are defined as the difference between intraday log prices p_k and p_{k-1}, which are equally spaced over the interval $[0, t]$. The RV is then defined as the sum of squared intraday returns:

$$RV = \sum_{k=1}^{n} r_k^2. \tag{3}$$

As the number of observations n approaches infinity, the RV converges in probability to the quadratic variation $[p_t, p_t]$.

Furthermore, Barndorff-Nielsen, Kinnebrock, and Shephard (2010) decomposed the RV into two components of realized semivariances (RS), which capture the variation attributed to negative (RS^-) or positive (RS^+) price changes (returns), respectively. This decomposition allows for an interpretation of asymmetries in volatility, following the established terminology by Patton and Sheppard (2015): “bad and good volatility.” The realized semivariances are defined as follows:

$$RS^{-} = \sum_{k=1}^{n} \mathbb{I}(r_k < 0) r_k^2, \tag{4}$$

$$RS^{+} = \sum_{k=1}^{n} \mathbb{I}(r_k \geq 0) r_k^2. \tag{5}$$

The realized semivariance provides a comprehensive breakdown of the RV, resulting in:

$$RV = RS^{-} + RS^{+}. \tag{6}$$

As the number of observations increases, the realized semivariance converges toward two main components: half of the integrated variance, represented by $1/2 \int_0^t \sigma_s^2 ds$, and the sum of jumps related to negative and positive returns (Shephard, 2010). The negative and positive semivariances provide information about the variability linked to extreme movements in the underlying variable's tails, and as such, they offer valuable metrics for assessing the downside and upside risks, respectively.

To estimate the connectedness measures, we consider an N-dimensional vector of (RV), or $(RS^{-},\ RS^{+})$, to follow a locally stationary TVP-VAR of order p. This observed process is approximated around some fixed point $u_0 = t_0/T$ as a stationary process $\tilde{\boldsymbol{X}}_t(u_0)$ under the regularity conditions $|\boldsymbol{X}_{t,T} - \widetilde{\boldsymbol{X}}_t(u_0)| = O_p(|t/T_0 - u_0| + 1/T)$ as follows:

$$\widetilde{\boldsymbol{X}}_t(u_0) = \boldsymbol{\Phi}_1(u_0)\widetilde{\boldsymbol{X}}_{t-1}(u_0) + \ldots + \boldsymbol{\Phi}_p(u_0)\widetilde{\boldsymbol{X}}_{t-p}(u_0) + \boldsymbol{\epsilon}_t, \tag{7}$$

where $\boldsymbol{\epsilon}_t = \Sigma^{-\frac{1}{2}}(u_0)\boldsymbol{\eta}_{u_0}$ and $\boldsymbol{\eta}_{u_0} \approx NID(0, \boldsymbol{I}_M)$ and $\boldsymbol{\Phi}(u_0) = (\boldsymbol{\Phi}_1(u_0), \ldots, \boldsymbol{\Phi}_p(u_0))^T$ are the time-varying autoregressive coefficients.

In parallel with the standard VAR, this TVP-VAR process has a time-varying $VMA(\infty)$ representation due to Dahlhaus (1996) as

$$\boldsymbol{X}_{t,T} = \sum_{h=-\infty}^{\infty} \boldsymbol{\Psi}_{t,T}(h)\boldsymbol{\epsilon}_{t-h}, \tag{8}$$

where $\sum_{h=-\infty}^{\infty} \boldsymbol{\Psi}_{t,T}(h) \approx \boldsymbol{\Psi}(t/T, h)$ is a bounded stochastic process at a finite horizon $h = 1, \ldots H$. Following Baruník and Ellington (2020, 2023), our calculations adapt the generalized identification scheme of Pesaran and Shin (1998) to a locally stationary process $\tilde{\boldsymbol{X}}_t(u_0)$ defined above. Thus, in the underlying TVP-VAR model, the connectedness measures are invariant to variable ordering.

2.1 Total spillovers

We compute the total spillover index, as introduced by Diebold and Yılmaz (2012), by using the H-step-ahead generalized forecast error variance decomposition matrix. This matrix consists of elements denoted by θ_{jk}^H, in which h ranges from 1 to the desired forecast horizon H. The calculation for each element is given by:

$$\theta_{jk}^H = \frac{\sigma_{kk}^{-1} \sum_{h=0}^{H-1} \left(\mathbf{e}_j' \boldsymbol{\Psi}_h \boldsymbol{\Sigma}_\epsilon \mathbf{e}_k\right)^2}{\sum_{h=0}^{H-1} \left(\mathbf{e}_j' \boldsymbol{\Psi}_h \boldsymbol{\Sigma}_\epsilon \boldsymbol{\Psi}_h' \mathbf{e}_k\right)}, \qquad j, k = 1, \ldots, N, \tag{9}$$

where $\boldsymbol{\Psi}_h$ represents the moving average coefficients obtained through the forecast at any time t. The variance matrix for the error vector, denoted as $\boldsymbol{\Sigma}_\epsilon$, encompasses σ_{kk} as its diagonal elements corresponding to the kth positions. The selection vectors, $\mathbf{e}_j$ and $\mathbf{e}_k$, are defined to have a value of one at the jth or kth element, respectively, and zero elsewhere. Diebold and Yılmaz (2012) introduce the concept of total connectedness based on a normalization where the elements are divided by the sum of the row, denoted as $\widetilde{\theta}_{jk}^{H}=\theta_{jk}^{H}/\sum_{k=1}^{N}\theta_{jk}^{H}$. The total connectedness measure quantifies the impact of volatility shocks across variables within the system on the overall forecast error variance:

$$\mathcal{S}^{H}=100\times\frac{1}{N}\sum_{\substack{j,k=1\\ j\neq k}}^{N}\widetilde{\theta}_{jk}^{H}. \tag{10}$$

Since $\sum_{k=1}^{N}\widetilde{\theta}_{jk}^{H}=1$ and $\sum_{j,k=1}^{N}\widetilde{\theta}_{jk}^{H}=N$, the connectedness contributions arising from volatility shocks are standardized by the overall variance of the forecast errors.

2.2 Measuring asymmetries in spillovers

We employ the realized semivariances defined above and account for spillovers from volatility due to negative returns ($\mathcal{S}^{-}$) and positive returns ($\mathcal{S}^{+}$). If the contributions of RS^{-} and RS^{+} are equal, the spillovers are symmetric, and we expect the spillovers to be of the same magnitude as spillovers from RV. On the other hand, the differences in the realized semivariances result in asymmetric spillovers.

Baruník, Kočenda, and Vácha (2016) quantify the extent of asymmetries in volatility spillovers based on the spillover asymmetry measure ($\mathcal{SAM}$), defined as the difference between positive and negative spillovers:

$$\mathcal{SAM}=\mathcal{S}^{+}-\mathcal{S}^{-}, \tag{11}$$

where $\mathcal{S}^{+}$ and $\mathcal{S}^{-}$ represent volatility transmission indices resulting from positive and negative semivariances, denoted as RS^{+} and RS^{-}, with an H-step-ahead forecast at time t. The measure $\mathcal{SAM}$ reflects the degree of asymmetry in spillovers caused by RS^{-} and RS^{+}. As demonstrated by Baruník et al. (2016), a $\mathcal{SAM}$ value of zero indicates that the spillovers from RS^{-} and RS^{+} are equal. Conversely, a positive (negative) value of $\mathcal{SAM}$ indicates that the spillovers from RS^{+} are greater (smaller) than those from RS^{-}.

2.3 Estimation methodology and setup

Typically, dynamic connectedness is calculated with a moving window approach that slides over the dataset and calculates a static model while adding the next observation and dropping the oldest one (Baruník & Křehlík, 2018; Diebold & Yılmaz, 2012, 2014). We turn to the more general TVP-VAR process, which is estimated with the QBLL method of Petrova (2019). The method provides a distribution of parameters that defines a confidence interval in each period. Therefore, unlike in the traditional connectedness and spillover methodology, we can describe the statistical significance of the connectedness measures and the meaningful differences between connectedness due to good and bad volatility. Additionally, we can discuss specific events that determine the observed dynamics since the connectedness is localized. Compared to estimating dynamic connectedness with a moving-window VAR, TVP-VAR eliminates the arbitrary selection of window length and the omission of observations. TVP-VAR also does not suffer from sensitivity to outliers, which can bias the subsequent windows.

We estimate the dynamic network model introduced by Baruník and Ellington (2020, 2023) with the autoregressive lag parameter of 2 periods since it is commonly used in similar applications, and the value was also suggested by the Bayesian information criterion (BIC) for a static VAR over the whole sample. Another crucial parameter is the bandwidth of the kernel, which determines the weights of the observations around the fixed point u_0 from Equation 7 for each point in the sample. Typically, a larger kernel bandwidth smooths and increases the connectedness since more observations are considered in the simulation step. Having evaluated several bandwidths, we selected the width of 7 days, particularly due to stronger inference in $\mathcal{SAM}$

and as it is the length of the crypto trading week. A more detailed discussion on the estimation parameters for various data-generating processes can be found in Baruník and Ellington (2023). Finally, we truncate the moving-average process representation at horizon $H = 30$, as we note that varying this parameter does not produce materially different results.

Our further analysis quantitatively assesses the dynamics of connectedness and existing asymmetries within good and bad volatility spillovers by employing a number of potential drivers within crypto markets as well as external financial and macroeconomic factors. For ease of exposition and interpretation, the model specifications are introduced later in Section 5, along with estimation results.

3 Data

We perform our analysis with 5-minute open-high-low-close price data downloaded from the Binance exchange by using their official data repository. Our sample period runs from July 5, 2019, to February 28, 2023, and we cover eight assets that consistently represent the majority of the overall market capitalization and liquidity in the crypto market. Specifically, we employ high-frequency price data for Bitcoin (BTC), Ethereum (ETH), Binance Coin (BNB), Litecoin (LTC), Cardano (ADA), XRP (formerly Ripple), Tron (TRX), and Dogecoin (DOGE). Since crypto coins are traded 24 hours, we are not limited by a standard 7- or 8-hour trading period in a calendar day. Therefore, we aggregate the RV measures over 24 hours daily based on the UTC midnight time. Table 3 in the Appendix summarizes basic descriptive statistics, along with the augmented Dickey-Fuller (ADF) test statistics (Dickey & Fuller, 1979), which strongly rejects the unit root in all of the RV series, making the TVP-VAR analysis feasible. The basic statistics are heterogeneous across the studied crypto assets. BTC is the most stable, with the lowest maximum value and the lowest standard deviation of the volatility process across the set. DOGE, on the other hand, is by far the most erratic and unstable.

In Figure 1, we individually present positive and negative RV for each asset. In 2019 and early 2020, most cryptos appeared to have relatively low volatility, with occasional spikes and dips. This changed with the onset of the COVID-19 pandemic in March 2020, when higher volatility in the cryptocurrency market corresponded to a global market panic. In contrast, we see a massive surge of interest in cryptocurrencies during 2021, which led to a substantial increase in volatility, with frequent and large price movements for all eight assets. The surge in volatility can likely be attributed to a number of factors that include increased investments by institutional investors and the growing mainstream acceptance of cryptocurrencies as a legitimate asset class, e.g., speculation about the introduction of the Bitcoin ETF.

Among the eight coins, the high volatility of Dogecoin stands out, driven by Elon Musk's tweets (Shahzad, Anas, & Bouri, 2022). Musk's Twitter activity sparked an interest in Dogecoin, producing unprecedented volatility. Even when compared to the pandemic crash in 2020, Dogecoin's RV magnitude is approximately eight times as large as that recorded for Bitcoin during the pandemic 2020 crash. Overall, Figure 1 highlights the dynamic and rapidly evolving nature of the cryptocurrency market, along with rapid changes in crypto market volatility.

Our analysis also explains the dynamics of connectedness and existing asymmetries between good and bad volatility spillovers. In that sense, we search for drivers within crypto markets as well as for external factors since cryptocurrencies have become more intertwined with traditional financial markets and reflect macroeconomic, mostly monetary, indicators (Kukacka & Kristoufek, 2023; Nguyen, Nguyen, Nguyen, & Pham, 2019). For crypto-related potential drivers, we combine two data sources.

First, for BTC, ETH, and the other coins in the aggregate, we use the momentum measure defined as the logarithmic deviation (ratio) of the current market capitalization from the previous seven days. Next, from CoinMetrics.io, we utilize the blockchain structural data on the number of active addresses for BTC and ETH (activity on the blockchains, ticker AdrActCnt), the sum

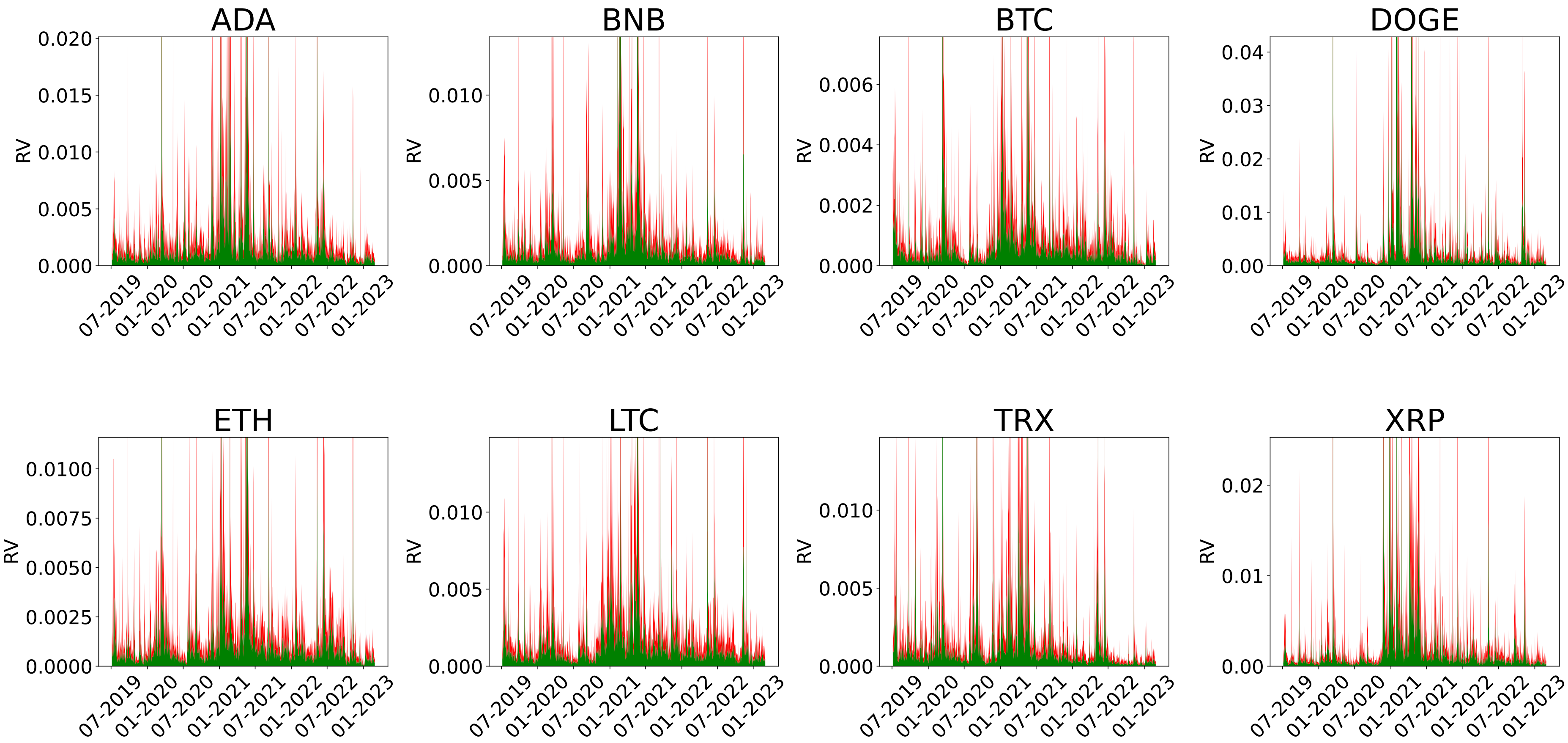

Figure 1: Time series of realized semivariances for individual crypto assets. Volatility due to positive returns (in green) and volatility due to negative returns (in red) are stacked to allow for an intraday comparison. The specific y-axes are set according to the 97.5th quantile of the respective total RV to avoid occasional spikes that overshadow the dynamics on low-volatility days.

of the fees on the BTC and ETH blockchains (measure of the blockchain load and possible congestion, ticker FeeMeanUSD), inflows and outflows to the centralized exchanges for all coins where available,[2] the velocity of BTC and ETH (what proportion of coins "changed hands" on the given blockchain, ticker NVTAdj), and BTC hashrate (as the measure of the network security, ticker HashRate). Finally, from the Binance data repository, we collect exchange (off-chain) trading volumes for BTC and ETH separately and aggregate for the remaining coins, as well as the number of trades in the same structure.

Second, the traditional financial market and macroeconomic indicators are collected from the St. Louis Federal Reserve database. Specifically, we include the S&P 500 index and the VIX index as proxies for the value and uncertainty of the traditional financial markets, respectively. The macroeconomic indicators are represented by the break-even inflation (10-year break-even inflation rate, ticker T10YIE, representing the expected inflation derived from 10-year treasury constant maturity securities and 10-year treasury inflation-indexed constant maturity securities) and the short-term interest rate (market yield on U.S. treasury securities at 1-year constant maturity, ticker DGS1). All the time series are available on a daily basis. Weekends and other nontrading days take the value of the last available observation.

4 Qualitative analysis and timing of events

We begin reporting the results of our analysis with a qualitative description related to the overall measure of aggregate volatility spillovers among the analyzed crypto assets. As in Diebold and Yılmaz (2012), in this section, we do not assume any underlying causal structure of the connectedness origin, which we leave for Section 5. Instead, we consider the underlying structure as given and describe its main properties and general patterns while also focusing on linking the dynamics of the total connectedness to the key historical events and major economic conditions throughout the analyzed period. We also compare and contrast the overall connectedness dynamics of the crypto assets to the patterns revealed in earlier studies that focused on standard financial markets.

Second, we study the decomposition of the total connectedness due to good and bad volatilities. The interaction between these two components is reflected by $\mathcal{SAM}$ (defined as the difference between positive and negative connectedness), which quantitatively captures the asymmetric reaction due to positive and negative shocks. The adopted estimation methodology directly provides dynamic 95% confidence intervals of the two components ready-made for inference. This contrasts with previous attempts to study the asymmetric relationship based on bootstrapping results of a simulation-based model, which provides a universal static confidence band for $\mathcal{SAM}$ (Baruník et al., 2016). The dynamic approach based on QBLL confidence intervals allows for a locally focused, more rigorous, transparent, and straightforward statistical evaluation of the difference between the behavior of the two sources of connectedness that reflect positive and negative shocks on the market.

4.1 Total dynamic network connectedness

In Figure 2, we present the total dynamic network connectedness over the whole period under research. The total connectedness oscillates between 20 and 80, with clearly identified periods of high connectedness corresponding to crucial events affecting the cryptocurrency market in the recent past. Generally, a high proportion of the connectedness is driven by contemporaneous correlations, which we observe particularly in periods characterized by very narrow confidence intervals.

[2] We study connectedness on the largest centralized exchange so the capital inflows and outflows represent the willingness to trade or store the gains, respectively (tickers FlowInExUSD and FlowOutExUSD).

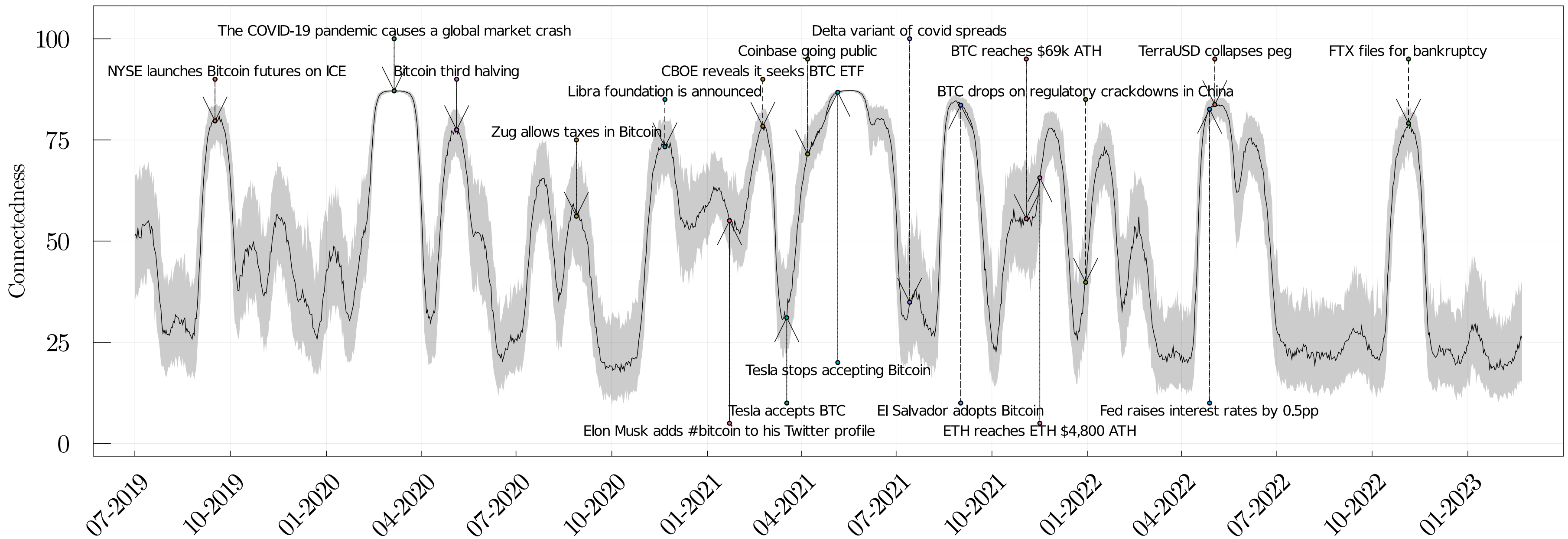

Figure 2: Total dynamic network connectedness defined by Equation 10. The shaded area represents 95% confidence intervals, and the solid line represents the median of the simulated distribution.

The volatility connectedness oscillates in a remarkably wide interval between 20 and 80. As such, it contrasts with the results for the connectedness of stocks or volatility spillovers between various standard financial markets that often do not drop below 50 (Baruník & Kočenda, 2019; Baruník et al., 2016; Baruník & Křehlík, 2018; Diebold & Yılmaz, 2014). Nevertheless, they seldom go below 40 (Baruník, Bevilacqua, & Tunaru, 2022; Baruník & Ellington, 2020; Diebold & Yılmaz, 2009). Conversely, the upper bound of the connectedness on standard financial markets reported in the above studies normally surpasses 85 and even reaches 90. The comparison suggests that both extremes are rather edged off in the cryptocurrency segment when compared to those of the standard financial markets.

The other pattern that characterizes the total connectedness dynamics is its considerable smoothness when compared to that of the resulting plots of earlier applications of the Diebold and Yılmaz (2014) and Baruník and Křehlík (2018) methodologies. This phenomenon is fully in accord with outcomes reported by Baruník and Ellington (2020). It results from the dynamic 'continuous' approach to estimating parameters of the underlying locally stationary TVP-VAR at each point in time. The reason is that the QBLL estimation procedure is essentially based on a Gaussian kernel weighting function that puts greater weights on observations surrounding each estimated period relative to distant observations to estimate the connectedness measure for the given day. Conversely, earlier studies typically have used the static estimation approach of the past dynamics from an approximating rolling window; associated drawbacks are discussed in the previous section.

4.2 Timing and impact of crucial events

We now focus in detail on cyclical increases in the total connectedness dynamics. The connectedness is high during several prolonged periods, and for clarity of interpretation, we marked in Figure 2 the key events impacting the volatility connectedness of the crypto market (Corbet et al., 2020; Rognone, Hyde, & Zhang, 2020; Sapkota, 2022).

The first clearly observable period of markedly high connectedness appeared around September 2019. It is linked to the Bitcoin bull run when its price more than tripled in the first half of the year, reaching almost 14 thousand USD. The NYSE owner, Intercontinental Exchange, Inc. (ICE), launched Bitcoin deliverable futures contracts on September 22. In addition, China, a crucial global player, was generally supportive of the development of blockchain technology around this period. Interestingly, these steps were met with a weak immediate reaction on the spot markets. However, the apparently unfulfilled expectations of the cryptocurrency investors led to Bitcoin prices dropping by almost 18% in the following days.

The next high connectedness period is clearly framed by the global outbreak of the COVID-19 pandemic at the turn of February and March 2020, which was followed by government-enforced lockdowns leading to a coordinated crash of global financial markets. Bitcoin dropped by more than 50% in one month and even fell below 5 thousand USD in its deepest downturn. Interestingly, the connectedness rather quickly decreased during April as the crypto segment quickly regained its market capitalization while establishing an attractive speculative environment for the later bull run in the second half of 2020, when Bitcoin rose to 28 thousand USD in December 2020. These observations align with Divakaruni and Zimmerman (2021), who find a robust link between the COVID-induced Economic Impact Payment (EIP) relief program and Bitcoin investment in the USA. Although they estimate that only 0.02% of the EIP program was spent on Bitcoin, they report a significant increase of almost 4% in the traded volume between April and June in the modal EIP amount of 1.2 thousand USD. Several other events logically connected to cryptocurrency segment dynamics are further associated with hump-shaped periods of high total connectedness in 2020. They are, specifically, Bitcoin's third halving that reduced the block reward to 6.25 BTC in May, Switzerland canton Zug allowing paying taxes in Bitcoin in September, and the November announcement of the stablecoin payment system formerly known as Libra by Facebook (now Meta Platforms, Inc.).

Early 2021 is marked by Bitcoin's (then) all-time high price of over 40 thousand USD and a prolonged period of high connectedness around the value of 60. The high connectedness is framed by surging prices in the whole crypto market and several important events forming the overall bull run dynamic of the first quarter of 2021. The most prominent ones were Elon Musk's Tweets supporting Bitcoin and Dogecoin and the filing for Bitcoin ETF by the Chicago Board Options Exchange (CBOE) in March. Another high connectedness period between April and June 2021 possibly originates in the commitment of Tesla's owner, Elon Musk, to accept payments in Bitcoin while holding a considerable number of Bitcoins in the company's balance sheet. In addition, the first cryptocurrency exchange, Coinbase Global, Inc., went public on NASDAQ during the period as well. The irony of fate is that many consider Elon Musk's tweet that Tesla no longer accepts Bitcoin as the trigger for the May crash, while the connectedness remains very high over almost the whole period of the price drop from above 63 thousand USD to below 30 thousand USD reached in July. The sell-off of the whole segment ended with the rapid outbreak of the new Delta variant of COVID-19, spreading a new wave of worries over the worldwide markets and leading to the new crypto bull run during the second half of 2021. Similar to the second half of 2020, the hump-shaped periods of large volatility spillovers among crypto markets in the second half of 2021 are associated with well-known events. Namely, with the adoption of Bitcoin as a legal tender in El Salvador in September 2021, Ethereum reached a price of 4.8 thousand USD, which was driven by the increasing popularity of DeFi and NFTs, and finally, Bitcoin reached its current all-time-high price of over 69 thousand USD, which was mainly due to institutional investors' demand in November 2021.

Global concerns about intensifying inflation pressures and rising interest rates frame the overall decline of cryptocurrency markets, together with global financial markets, and its steep decline supported by several crashes during the entire first half of 2022. In June, Bitcoin went down below the 20 thousand USD barrier and has fluctuated between 16 and 29 thousand USD since then. The four periods of high connectedness observed during 2022 are linked to crucial events related to the crypto assets market. There were strong fears about regulatory crackdowns in China and the U.S. in January, forcing the Bitcoin price to tumble below 40 thousand USD for the first time since August 2021. Furthermore, the Fed increased its key interest rate by 50 basis points in May, which was the sharpest increase since 2000; this step was followed by the TerraUSD collapse below its 1 USD peg in May. Finally, the Chapter 11 bankruptcy procedure was launched for the cryptocurrency exchange FTX in November 2022. Interestingly, although the wild period for the crypto segment continued until the end of our research time span, the total connectedness remained at a very low level.

4.3 Asymmetries due to good and bad volatility

We now analyze the dynamic asymmetries due to good and bad volatility as introduced by Baruník et al. (2016). Figure 3 reveals that spillovers due to negative and positive volatility are very often similar in terms of their magnitudes. This observation is in stark contrast to existing connectedness studies covering standard financial markets, typically documenting periods clearly dominated interchangeably by either negative or positive spillovers. We show in the top panel of Figure 3 that periods of significant difference between the two sources of connectedness are *always* dominated by negative volatility. In contrast, in periods of large overlap of the two measures and their confidence intervals, the spillovers due to positive volatility occasionally become larger. Nevertheless, this difference is *never* statistically significant at the 5% level, and even more importantly, this difference never materializes during a period of considerable economic importance.

The above patterns are then transposed into $\mathcal{SAM}$, whose dynamics are plotted in the bottom panel of Figure 3. $\mathcal{SAM}$ is negative most of the time, with several clearly observable

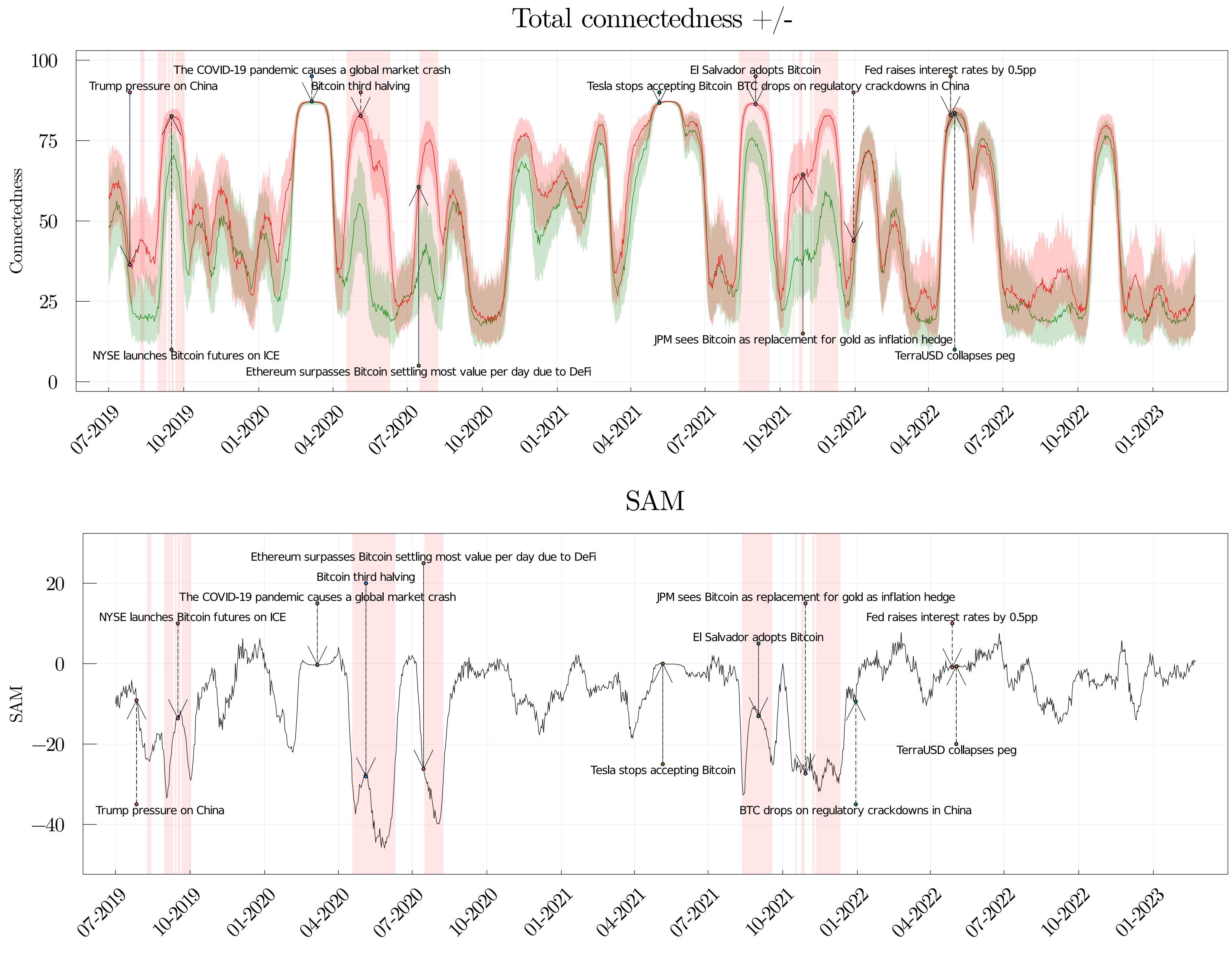

Figure 3: Estimates of total negative (in red) and positive (in green) connectedness in the upper panel and $\mathcal{SAM}$ in the bottom panel. $\mathcal{SAM}$ is defined by Equation 11 and measures the asymmetry between the two sources of connectedness. Simulated 95% confidence bands allow for directly identifying periods of significant differences between the two sources of connectedness represented by shaded areas of disjunct confidence intervals.

drops reaching values below minus 40 and prolonged periods of large and statistically significant dominance of the negative connectedness. The observed pattern is occasionally broken only by short periods of marginal dominance of the positive connectedness.

In sum, we provide evidence of strong unilateral asymmetry effects embedded in the risk spillovers in the crypto asset market. The positive and negative connectedness thus statistically significantly differs in certain periods, and this asymmetry prevails for consecutive days or even weeks, implying that the market operates in different regimes. Based on the discussion linking high spillovers with information flow on the markets (Baruník et al., 2016), our results suggest that information about crypto asset market downturns usually spills over substantially faster than news about comparable market upturns.

We further discuss the impact of the key events related to the crypto assets market and potentially associated with asymmetries in connectedness. The first observation is that only a subset of those events affecting the total connectedness and discussed in detail in Section 4.2 is also linked with a statistically distinct positive and negative connectedness quantified by $\mathcal{SAM}$ (see Figure 3).

More detailed observations indicate six prolonged periods with 95% statistical confidence that are prominent concerning the dynamics in connectedness due to good and bad volatility asymmetries. The first period occurred during a period of low connectedness in August 2019 after U.S. President Donald Trump's trade war pressures on China reboosted cryptocurrency prices again after the bull run in the first half of 2019. The three cases coincide with the events important for total connectedness and relate to the period around September 2019 (Bitcoin futures on NYSE), May to June 2020 (Bitcoin's third halving), and August to September 2021 (El Salvador adopting Bitcoin). The other two cases are solely linked to asymmetries while not with the total connectedness: (i) in August 2020, the increasing popularity of the DeFi segment has led to Ethereum surpassing Bitcoin in terms of the value settlement per day (pattern beginning already in July), and (ii) in November 2021 JPMorgan Chase & Co. supported Bitcoin as an inflation hedge that might replace gold, a move leading to all-time-high of the Bitcoin as well as Ethereum. Finally, negative dips of $\mathcal{SAM}$ might not be fundamentally important *per se*. However, the negative dips often approximate the boundaries of the periods when significant differences in connectedness occur.

When looking at six specific time periods, there is no clear relationship between the asymmetries in connectedness and the price trends of the crypto market. Some periods experienced booms or recoveries, while others were framed by market crashes. However, overall, important structural changes in the cryptocurrency market (Bitcoin futures, Bitcoin halving, the popularity of DeFi, Bitcoin as legal tender, Bitcoin as an inflation hedge by JPMorgan) were often linked to asymmetries. This finding goes against the intuition that positive volatility is connected to price increases and that negative volatility is connected to market crashes. For instance, even during the crypto rally in April 2020, negative volatility had a stronger impact on the market, indicating that the market reacted more strongly to negative news. Regardless of positive or negative market sentiment, bad volatility always has a stronger impact on the market.

A further existing pattern can be recognized for the periods of high total connectedness unrelated to statistically distinguishable asymmetries due to good and bad volatility. These are primarily the period around the COVID-19 crash in 2020, the period around the crash of 2021 (Tesla refusing Bitcoin), and the period around the crashes in 2022 (inflation pressures in January and regulatory crackdowns in China and the U.S., Fed hike, and TerraUSD collapse in May, FTX bankruptcy in November).

Hence, it seems that structural developments shaping the crypto market do induce asymmetric reactions due to positive and negative shocks to volatility. On the other hand, a high contemporaneous correlation stemming from a panic reaction and herding, which characterizes the overall market during crashes, generally leads to very narrow but overlapping confidence intervals, which eliminates the significant differences between the effects of good and bad volatility.

Ultimately, our evidence shows that constructive structural changes are reflected in asymmetries, while destructive panic and herding are not.

5 Explaining the connectedness and asymmetry

Linking the connectedness and existing asymmetries to specific, often external, events provides one angle to explain their dynamics. We now look into their possible internal drivers, i.e., if and how much of the dynamics can be explained and attributed to specific characteristics and changes in the underlying processes of the examined blockchains and external macroeconomic and monetary drivers. Our subsequent analysis rests on estimating the baseline model:

$$\begin{aligned}\mathcal{S}^H = \beta_0 + \beta_1 Momentum_{BTC} + \beta_2 Momentum_{ETH} + \beta_3 Momentum_{Alts} + \\ \beta_4 \log(Adr)_{BTC} + \beta_5 \log(Adr)_{ETH} + \beta_6 \log(Fees)_{BTC+ETH} + \\ \beta_7 \log(Inflow)_{BTC+ETH} + \beta_8 \log(Outflow)_{BTC+ETH} + \\ \beta_9 \log(Velocity)_{BTC} + \beta_{10} \log(Velocity)_{ETH} + \beta_{11} \log(HashRate) + \\ \beta_{12} \log(Volume)_{BTC} + \beta_{13} \log(Volume)_{ETH} + \beta_{14} \log(Volume)_{Alts} + \\ \beta_{15} \log(Trades)_{BTC} + \beta_{16} \log(Trades)_{ETH} + \beta_{17} \log(Trades)_{Alts} + \\ \beta_{18} \log(SP500) + \beta_{19} \log(VIX) + \beta_{20} BEInflation + \beta_{21} IR + \varepsilon\end{aligned} \tag{12}$$

We look at a set of potential drivers of connectedness among the whole system of 8 crypto assets with the aim of covering various perspectives—momentum, blockchain activity, exchange activity, and external macroeconomic factors. As there are 8 crypto assets in our dataset, we need to select and aggregate most of the measures to avoid overfitting and colinearity, as many of the variables would be highly correlated and thus lead to unreliable results. We tackle this issue by mostly focusing on Bitcoin (BTC) and Ethereum (ETH) as the major players within the system, and the rest of the coins are treated jointly as altcoins. In our model, the explanatory variables are represented by time vectors to make the representation easier to read. In addition to examining the total connectedness $\mathcal{S}^H$, we also use the same model specification to explore drivers of the asymmetries existing in connectedness; in such cases, the dependent variable $\mathcal{S}^H$ in Equation 12 is replaced by the $\mathcal{SAM}$ that quantifies asymmetries.

Starting with the full set of variables in Equation 12, we first eliminate the factors with a high risk of colinearity and overfitting. Specifically, we estimate the model and step-by-step eliminate the variables with the highest variance inflation factor (VIF) until no variable has a metric above 10 (Dodge, 2008). After that, we step-by-step eliminate the statistically insignificant variables (at the 90% confidence level) until all variables are significant. As the residuals are serially correlated and heteroskedastic, we report the heteroskedasticity and autocorrelation consistent (HAC) standard errors. The results for the total connectedness dynamics and its driving factors are summarized in Table 1.

The results show that Bitcoin is quite detached from the rest of the cryptocurrency market, as Bitcoin-related variables negatively affect total connectedness. The higher the momentum of BTC is, the lower the total connectedness of the system. The same holds for active Bitcoin addresses and its volume on Binance. Therefore, when Bitcoin gains momentum and there is more activity in the Bitcoin market, the rest of the crypto market does not follow immediately. The rest of the crypto market and its increased activity apparently lead to a tighter interconnection of the whole network. Of the macroeconomic factors, only break-even inflation remains in the model. The external financial markets' factors represented by the S&P500 index and the VIX index thus do not drive the total connectedness. In addition, neither do the short-term interest rates. As the break-even inflation reflects the inflation expectations in 10 years, its estimated negative effect on the total connectedness suggests further detachment of Bitcoin as a reaction

	estimate	SE	t-stat	p-value
constant	12.38	113.71	0.19	0.9100
Momentum_{BTC}	-59.19	12.85	-4.60	$\ll 0.0001$
$\log(Adr)_{BTC}$	-32.13	9.11	-3.53	0.0004
$\log(Inflow)$	13.64	2.963	4.60	$\ll 0.0001$
$\log(Velocity)_{ETH}$	7.30	3.57	2.05	0.0409
$\log(Volume)_{BTC}$	-7.09	2.08	-3.40	0.0007
$\log(Volume)_{ETH}$	10.90	3.41	3.20	0.0014
$\log(Volume)_{Alts}$	6.70	1.93	3.46	0.0006
BEInflation	-19.60	4.86	-4.04	$\ll 0.0001$
R^2	0.377			
$\bar{R}^2$	0.373			
White's test	36.75^{***}			
LM test	1077.82^{***}			
ADF test	-6.17^{***}			
KPSS test	0.085			

Table 1: Estimated model for total connectedness. The model starts with the baseline model in Equation 12, then the variables with the overfitting risk (VIF over 10) are step-by-step eliminated, and the final model is obtained after eliminating the statistically insignificant variables (at the 90% confidence level). For the tests, *** marks statistical significance at the 99% confidence level.

to the expectations of higher long-term inflation, which sets Bitcoin apart from the rest of the top coins.

The key message is that the connectedness of the whole system is clearly not driven solely by external shocks but by a mix of factors—momentum, blockchain-related, exchange-related, and macroeconomic factors. The R^2 of 0.377 validates the results with respect to the quality of the fit. There are no autoregressive components in the model, as we are interested in explaining the driving factors rather than simply modeling the serial correlation of the series. As the model residuals are stationary (based on the results of the ADF and KPSS tests), the autoregressive components are not needed, as there is no strong serial correlation that would invalidate the results.

Section 4.3 shows that there is a strong asymmetry present between the connectedness of good and bad volatility. This is evidenced by mostly negative $\mathcal{SAM}$. Table 2 summarizes the results from the estimated model, covering the factors driving such asymmetry. The asymmetry toward higher connectedness in bad volatility is represented by negative values of $\mathcal{SAM}$, and we must interpret the results accordingly. The variable selection process was the same as for the total connectedness model.

Beginning now with the structural factors, we find that the blockchain activity, namely, the number of active addresses on BTC, the total fees on BTC and ETH, and the centralized exchanges inflows, all lead to lower $\mathcal{SAM}$ and thus higher asymmetry toward connectedness in the bad volatility. Such increased blockchain activity represents medium- to long-term effects, as we use the level or log-level variables (not their first differences). The effects show that the markets tend to fall together more and in a more intertwined manner. In other cryptocurrency-related metrics, BTC and ETH effects mostly go against each other, further supporting the detachment of BTC from the other crypto assets. This is mostly interesting for the momentum metrics, as the short-term boosts in BTC have a more pronounced effect on the asymmetry than that of such boosts in ETH. Therefore, when BTC rallies more than the rest of the market, the asymmetry decreases, whereas when ETH (and likely altcoins in general) rallies more than BTC, the asymmetry increases. The implication is that the markets fall together more strongly after the altcoins catch up with Bitcoin, and we document this through a complex model of the

	estimate	SE	t-stat	p-value
constant	106.90	62.11	1.72	0.0854
Momentum$_{BTC}$	29.47	13.99	2.11	0.0354
Momentum$_{ETH}$	-18.74	10.64	-1.76	0.0783
$\log(Adr)_{BTC}$	-7.83	4.27	-1.84	0.0668
$\log(Fees)_{BTC+ETH}$	-4.74	1.15	-4.13	$\ll$ 0.0001
$\log(Inflow)$	-3.60	1.69	-2.13	0.0335
$\log(Velocity)_{BTC}$	3.16	1.204	2.63	0.0088
$\log(Velocity)_{ETH}$	-10.03	1.84	-5.45	$\ll$ 0.0001
$\log(Volume)_{Alts}$	1.31	0.77	1.70	0.0902
$\log(VIX)$	8.62	2.27	3.80	0.0002
BEInflation	21.34	2.89	7.39	$\ll$ 0.0001
R^2	0.314			
$\bar{R}^2$	0.308			
White's test	418.57***			
LM test	1420.36***			
ADF test	-5.77***			
KPSS test	0.137			

Table 2: Estimated model for asymmetry in connectedness for good and bad volatility. The model starts with the baseline model in Equation 12, then the variables with the overfitting risk (VIF over 10) are step-by-step eliminated, and the final model is obtained after eliminating the statistically insignificant variables (at the 90% confidence level). For the tests, *** marks statistical significance at the 99% confidence level.

crypto assets' interactions. The model delivers R^2 above 0.3 with no autoregressive components again while keeping the residuals stationary.

Furthermore, we present Figure 4 to better illustrate how well the models fit the connectedness and asymmetry dynamics. We stress that no autoregressive terms are being used in the model specification. Nevertheless, the model-fitted values visibly follow the basic trends of the connectedness and asymmetry dynamics. Importantly, the humps and bumps of the total connectedness as well as those of the asymmetry are well captured by the fitted dynamics in the majority of cases. This evidence implies that most of such changes in the connectedness structure are either caused by the identified driving factors or such changes transfer into the driving factors and thus the overall blockchain structure and dynamics. Thus, we can conclude that the volatility connectedness and existing asymmetries due to good and bad volatility are clearly driven by structural factors.

6 Conclusion

Cryptocurrencies form a special set of assets with unique statistical and dynamic properties when compared to those of the traditional financial assets such as stocks or Forex rates. Considering their unprecedented levels of risk and uncertainty, studying the joint dynamics of volatilities in a portfolio of crypto assets, represented by volatility spillovers, becomes of interest to portfolio managers and traders. The latter group is specifically interested in volatility spillovers in different market phases that we analyze through the connectedness of good and bad volatility, representing volatility during market upturns and downturns, respectively.

The crypto market, represented by the set of 8 large crypto assets, shows the connectedness evolution unseen for the traditional financial markets presented in previous studies. The measure oscillates in a much wider range, repeatedly phasing between the times of high and low connectedness. Most of these periods can be linked to historical events, both crypto market-

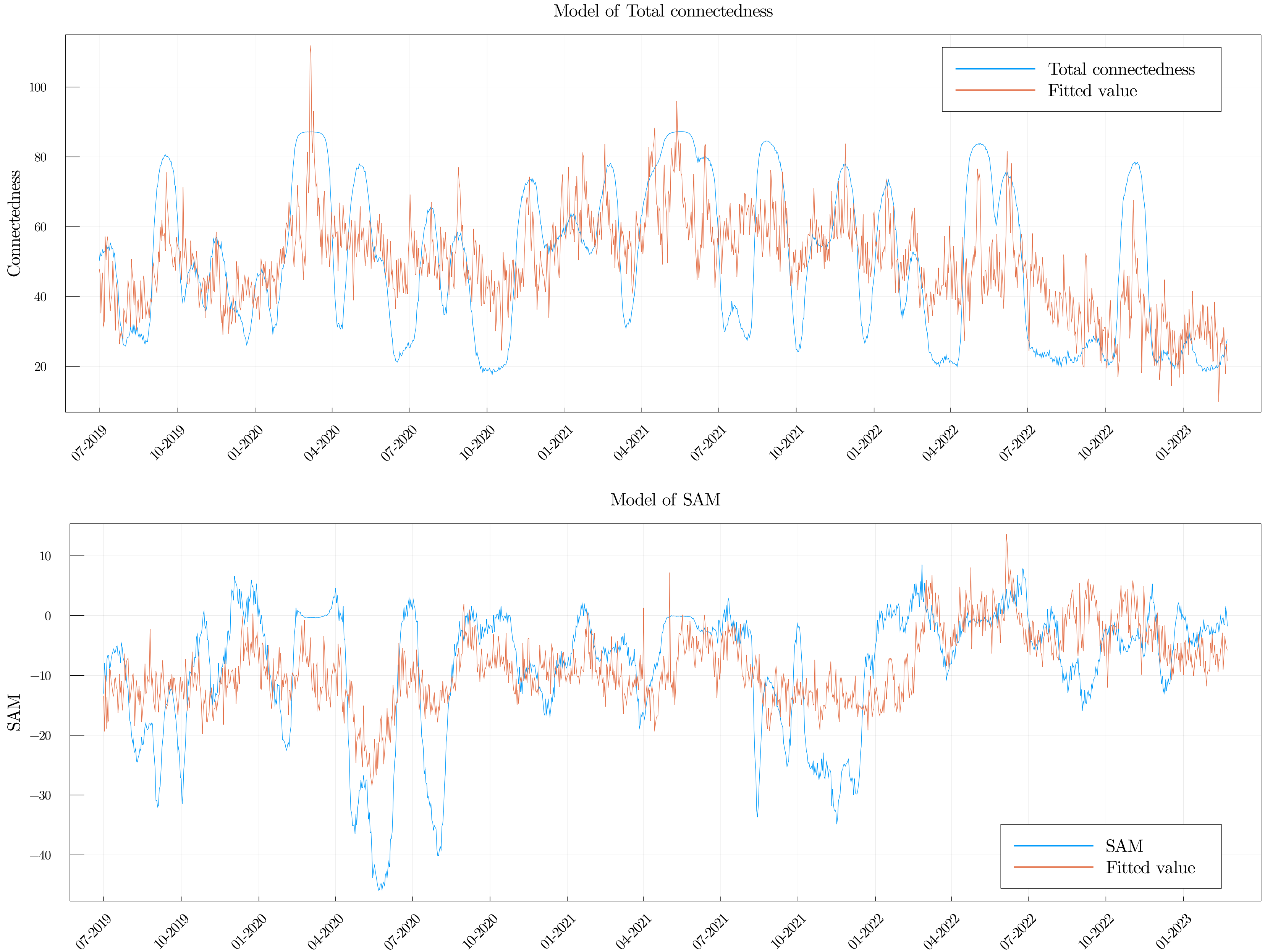

Figure 4: Models of total connectedness and $\mathcal{SAM}$.

related and standard macroeconomic or monetary policy events. The market also shows a high degree of asymmetry in the connectedness between good and bad volatility, representing large swings upward and downward, respectively. Evidence points toward domination of the higher connectedness due to bad volatility. This suggests that information about crypto asset market downturns usually spills over substantially faster than news about comparable market upturns.

Even though the periods of high and low connectedness and the pronounced asymmetry can be attributed to specific historical events, their overall dynamics can be well explained by the set of factors covering blockchain activity, market momentum, macroeconomic situation, and monetary policy. We show that Bitcoin is mostly detached from the overall dynamics, as its momentum and blockchain activity push the whole network connectedness down, while Ethereum and the rest of the altcoins do otherwise. Expected long-term inflation (represented by break-even inflation) also makes the network less connected, highlighting the possible position of Bitcoin as an inflation hedge. The asymmetry is more strongly driven by factors outside of the crypto markets as the VIX index is added to the break-even inflation. The traditional financial market stress materializing in a higher VIX leads to lower asymmetry. From the crypto market factors, the on-chain activity, as well as the activity on the centralized exchanges, lead to higher asymmetry and faster spillovers during market downturns.

In addition to the specific results and implications arising from our exploration of connectedness and its asymmetry in the crypto market, we propose a somewhat unconventional approach to understanding and explaining these phenomena. While the standard approach is to identify potential factors driving the returns and/or risk premiums, we consider the connectedness and its asymmetry and strive to uncover and elucidate the drivers behind this specific factor and dive deeper into its underlying dynamics. This endeavor would be challenging with traditional financial assets that lack the rich data structures of blockchain-based assets. We are aware that the current riskiness, regulatory uncertainty, and other specifics prevent our results from conveying generalizations concerning the connectedness, asymmetry, and their drivers to traditional financial assets. However, our findings may offer a valuable approximation for understanding the deeper dynamics of traditional assets once cryptocurrencies become more standardized financial products. The aggressive policies of the U.S. Securities and Exchange Commission (SEC) in 2022 and 2023, and the active regulatory approach in the EU through their markets in crypto-assets (MiCA) regulation, could indeed diverge. However, if the regulatory stance continues to outweigh dismissive attitudes, the unprecedented data depth of blockchain-based assets may play a vital role in many aspects of modern financial research.

The connectedness measures presented in this paper can generally be used to model a common factor stemming from network connections between asset returns or volatilities. This is particularly interesting to the emerging asset pricing literature in crypto, for example, to calculate risk premia, yet we leave this application as a potential future research avenue.

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There has been no use of AI tools above the standard grammar, spelling, and language support.

Competing interests

The authors have no competing interests to declare.

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7 Appendix

	ADA	BNB	BTC	DOGE	ETH	LTC	TRX	XRP
mean	0.0041	0.0029	0.0017	0.0072	0.0026	0.0035	0.0030	0.0042
std	0.0110	0.0078	0.0044	0.0320	0.0066	0.0076	0.0074	0.0109
max	0.3175	0.1678	0.1106	0.8793	0.1640	0.1743	0.1452	0.2055
min	0.0001	0.0001	0.0000	0.0002	0.0000	0.0001	0.0001	0.0001
skewness	19.52	13.04	16.29	18.07	16.04	13.89	12.17	9.79
kurtosis	519.28	233.56	353.96	438.50	344.11	269.35	203.17	140.59
median	0.002	0.0013	0.0009	0.002	0.0014	0.0018	0.0013	0.0015
ADF test	-10.22^{***}	-11.25^{***}	-12.72^{***}	-10.54^{***}	-10.04^{***}	-10.04^{***}	-10.85^{***}	-6.63^{***}

Table 3: Descriptive statistics of the RV time series for individual crypto assets. For the ADF tests, *** marks the null hypothesis of the presence of unit root rejected at the 99% confidence level.

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