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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. Our findings indicate that crypto connectedness reflects important events and oscillates substantially while reaching lower limit values when compared to 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 market downturns spill over substantially faster than comparable market surges. Overall, the connectedness dynamics are driven by a combination of both crypto (momentum, on-chain activity, off-chain activity) and legacy financial and economic (financial and economic uncertainty, and financial market performance) factors, while the asymmetry is more connected to the off-chain crypto activity and the combination of economic, financial, and monetary factors. In both the total connectedness and asymmetry modeling, these can serve as hands-on indicators to be further translated into specific portfolio re-balancing decisions, risk management, and regulatory frameworks.

1. Introduction and motivation

Quantification of volatility and assessment of its transfer is central to financial modeling as well as practical applications (Diebold and Yilmaz, 2015). Volatility spillovers that materialize into connectedness among cryptocurrencies are particularly intriguing since the cryptos are characterized by unprecedented levels of volatility, a rich network structure, and complex connections within asset classes (Corbet et al., 2018).[1] These key features differentiate cryptocurrencies from standard financial assets (Härdle et al., 2020; Guo et al., 2022).

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[1] Because the labels for digital assets vary in the literature, we use crypto assets, cryptocurrencies, or "crypto" as a shorthand for 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).

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As evidenced by Ji et al. (2019) and supported by our results, cryptocurrencies tend to move together more strongly during periods around extreme events compared to traditional assets and experience rather low connectedness during tranquil periods. This applies to both positive and negative extremes.[2] The baseline connectedness of the whole system is weaker but with higher amplitudes and overall volatile interconnections. Even though this might seem almost standard and trivial from the perspective of the traditional financial markets concerning portfolio management and risk diversification, the practical implications for crypto investors are different. As the diversification benefits decrease during the extreme events, and more so during the negative extreme events, the run towards quality often means a run towards Bitcoin (Katsiampa, 2019). However, the diversification benefits during the tranquil periods mostly translate not towards lower risk but towards a higher possible return, as separate crypto coins or tokens tend to surge in a way and magnitude not observed in the traditional markets. The deeper into the list of cryptos we go, the closer to this "jackpotting" behavior we get.

Nevertheless, many questions related to connectedness in the crypto market remain open. How do the connectedness dynamics evolve in a network of key cryptocurrencies? How does it differ for 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 analysis, we answer these questions with a battery of the most recent methodological advances and cover the majority of the crypto market in terms of its capitalization.

Since the seminal papers by Diebold and Yılmaz (2009, 2012, 2014), much of the financial research has been devoted to studying the interdependence of returns or return volatilities with the spillover index. This measure quantifies the directional propagation of shocks through forecast error variance decomposition of the underlying vector autoregressive (VAR) model, a well-known framework estimating interrelationships in multivariate setups (Enders, 2008). A large amount of literature has emerged based on the above-mentioned studies in traditional finance as well as in emerging crypto finance.

Our main research objective is to advance beyond the conventional descriptive assessments of total spillovers and directional analysis prevalent in financial literature or their frequency dynamics (Baruník and Křehlík, 2018). The goal is not only to calculate and describe the spillovers among cryptocurrencies but to fill the research gap and explain their dynamics with the fundamental empirical variables available for the cryptocurrency universe. As we have mentioned earlier, the different states of the market with respect to connectedness represent different implications for market participants. Hence, identifying and assessing these periods through directly observable variables, whether crypto-related or exogenous, can offer valuable real-time insights into approaching the current market situation. This knowledge is particularly relevant for portfolio and risk management, encouraging more risk-seeking behavior during tranquil periods to capitalize on the unpredictable surges of individual coins or tokens.

To identify and assess the market situation, we integrate various technical measures of blockchain activity and off-chain exchange activity, along with external macroeconomic factors, to reveal the key drivers of the qualitatively differing negative and positive connectedness segments. The adopted approach is motivated by Kristoufek (2015) but ventures into the connectedness domain beyond Bitcoin as the single asset of interest. Building upon our findings, we propose a few examples of potential innovative applications to extend and motivate the significance of our research for practitioners. For traders, the identified key empirical drivers of connectedness can be utilized to develop predictive models for significant crypto market events or to create early warning systems to anticipate periods of heightened connectedness. New DeFi or blockchain-based instruments and products that dynamically adjust their risk exposure to good and bad volatility can be developed by financial innovators. Finally, our empirically driven modeling approach based on publicly available data can be integrated by regulatory authorities, especially as cryptocurrencies become more standardized financial products.

The 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 (Antonakakis et al., 2020). Further, as in Baruník et al. (2016) we decompose the measured volatility into its positive and negative components to describe distinct dynamics behind connectedness associated with market surges and downturns. We also qualitatively analyze the impact of exogenous news on connectedness and asymmetry. Exploring the asymmetry connectedness brings additional insights into understanding the underlying dynamics of the network. Good and bad volatility have different transmission mechanisms. Good volatility typically propagates through optimism and positive news, while bad volatility spreads through fear, uncertainty, and negative news, often resulting in contagion. Market participants tend to react differently to positive and negative news. Also, investors and portfolio managers have various strategies with respect to their interest in different types of events and different levels of risk. Focusing solely on the total connectedness might average out the connectedness in the separate volatilities, leading to less efficient portfolio and trading strategies (Chen et al., 2024).

The above approach is even more important for crypto asset portfolios, where dynamic properties are more extreme compared to traditional financial markets. As the crypto assets are on their way to becoming more integrated into the portfolios of various financial institutions, they will become of interest to regulators and stress testing, which emphasizes the understanding of the spillover effects in negative times (Charfeddine et al., 2020).[3] As one recent example, Albrecht and Kočenda (2024) revealed that Cardano and Ripple are the most effective options for optimizing portfolio weights and hedging ratios in cryptocurrency risk management.

[2] Example of a positive extreme can be the New York Stock Exchange (NYSE) launching Bitcoin futures on the Intercontinental Exchange (ICE) or exchange-traded fund (ETF) approval, while the global meltdown of the financial markets at the beginning of the COVID-19 pandemic, the Terra-Luna collapse, or the FTX exchange filing for bankruptcy represent negative extremes.

[3] The argument is supported by the spot Bitcoin and Ethereum ETFs that will likely be, sooner or later, followed by spot ETFs of at least some of the other most capitalized altcoins.

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 influential drivers of crypto-connectedness. The combination of the three contributions clearly separates our study from the preceding ones. We not only describe the connectedness dynamics and possible implications but we explore and describe the dynamics via other factors. One needs to realize that the most used and most recent methodological approaches towards connectedness and spillovers build on kernels, smoothing, and similar techniques. Therefore, connectedness and spillovers are often available only ex-post, with a lag, sometimes a considerable one (Gabauer and Gupta, 2018; Antonakakis et al., 2019b). However, the time lag can be of utmost importance, specifically for the crypto markets with their swift dynamics and abrupt turns of events. Understanding the sources and drivers of connectedness can provide signs and signals of an upcoming change in connectedness that would be quantitatively available only later. Hence, our approach provides some sort of "qualitative nowcasting".

Overall, we show that crypto market connectedness oscillates substantially but reaches lower limit values when compared to traditional financial markets. Most periods of extremely high or low connectedness can be linked to specific historical events of a macroeconomic and monetary nature or to influential events in the history of crypto markets. Furthermore, the study of good and bad volatility spillover asymmetry uncovers that crypto market crashes usually spill over substantially faster than comparable market upturns. Our findings can thus be utilized to dynamically tailor existing risk management strategies within the cryptocurrency segment with respect to the observed asymmetry in connectedness. This would enable the enhancement of portfolio resilience for crypto investors and fund managers, particularly during market downturns. Moreover, our qualitative analysis of the impact of exogenous news contributes to the methodological discussion on price endogeneity in crypto markets (Jiang et al., 2018; Kristoufek, 2018; Mark et al., 2022), as we observe the so-called "excess volatility puzzle" (Shiller, 1981) when large price movements occur without a pertinent flow of news.

From a data-driven point of view, while total connectedness is influenced by a combination of various types of factors, the asymmetry largely depends on the macroeconomic state of the global markets. This knowledge may be essential for future regulatory attempts in the cryptocurrency industry. For portfolio and risk management, it is important to follow the whole set of indicators — crypto market momentum, on-chain activity, off-chain (exchanges) activity, and financial and economic uncertainty — that point towards increasing or decreasing underlying connectedness, with clear implications for diversification and related strategies. For regulators, our results indicate that most care should be directed towards situations when the legacy markets are calm and start falling abruptly. Such events quickly translate into strengthened asymmetry in good and bad volatility connectedness in cryptos, likely leading to large corrections.

The rest of the paper is organized as follows. The next Section 2 reviews the key related literature. Section 3 describes the methodology used to estimate the measure of volatilities and, consequently, their connectedness. We also discuss specific parameters of our setup therein. Section 4 presents the dataset, and we explain the origin of relevant variables. Section 5 provides a qualitative analysis of the events associated with connectedness dynamics. We analyze the determinants of connectedness and its asymmetry in Section 6, and finally, Section 7 concludes.

2. Related literature

The principal research on the financial characteristics of crypto assets can be traced to studies by Barber et al. (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 et al. (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 the impact of news on connectedness, we provide a detailed qualitative analysis of recent historical events pertaining to connectedness dynamics during a relatively long period between 2019 and 2024. This is an important topic in the recent literature where the effect of the news on Bitcoin price is analyzed in depth by Corbet et al. (2020b), who 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 and conclude that Bitcoin might serve as a hedging device against this type of macroeconomic risk. In a companion research, Corbet et al. (2020a) examine the impact of Fed's Federal Open Market Committee macroeconomic announcements regarding the U.S. Federal Fund interest rate and quantitative easing. 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. Using quantile regression, Suleman et al. (2023) analyze the opposite direction of the impact and conclude that the Bitcoin investors' Sentiment Index (BSI) moderates the connectedness due to positive and negative volatility for eleven U.S. industrial sectors.

However, the literature offering a similar analysis while covering a larger and more representative set of crypto assets is still very scarce. Our sample thus includes eight of the consistently largest crypto assets and covers a dominant proportion of the market's liquidity for the last five years. Abubakr Naeem et al. (2022) bring valuable evidence that is conceptually the closest to our contribution and compute volatility spillovers and asymmetries for eight cryptocurrencies between 2018 and 2020. However, their dataset is shorter and covers an earlier period than ours. Further and understandably, they do not cover the full COVID-19 pandemic period and the Russo-Ukrainian War. While being a valuable contribution, their study focuses on quantitative directional network analysis but does not discuss the qualitative impact of specific historical events except for the spread of COVID-19 in 2020 and does not attempt to assess empirical drivers beyond the quantified connectedness measures. Next, Corbet et al. (2018) analyze the volatility spillovers between three major crypto coins and a variety of financial assets, Yi et al. (2018) explore static and dynamic volatility connectedness between eight major cryptocurrencies, and Andrada-Félix et al. (2020) study the total connectedness among the four main cryptocurrencies and four traditional fiat currencies. Finally, Ji et al. (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 the drivers behind connectedness among crypto assets is still in its infancy. Walther et al. (2019) identify the Global Financial Stress Index or Chinese Policy Uncertainty Index as good predictors of volatility spillovers in the crypto market and 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 the trading volume, the Global Financial Stress Index, the U.S. CBOE Implied Volatility Index (VIX), and commodity prices, particularly energy, and gold. Regarding more specific drivers, Andrada-Félix et al. (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 et al. (2022) omit crypto-specific factors and 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 et al. (2023) 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.

3. Methodology

Volatility connectedness is estimated based on realized measures of asset price variation 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 assumed 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 Eq. (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 et al. (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 towards 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 (Barndorff-Nielsen et al., 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, RS^-, or 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 $\widetilde{\boldsymbol{X}}_t(u_0)$ 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:

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

where $\epsilon_t = \Sigma^{-\frac{1}{2}}(u_0)\boldsymbol{\eta}_{u_0}$ and $\boldsymbol{\eta}_{u_0} \approx NID(0, \boldsymbol{I}_M)$ and $\boldsymbol{\Phi}(u_0) = (\boldsymbol{\Phi}_1(u_0), \dots, \boldsymbol{\Phi}_p(u_0))^T$ 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

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

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 $h = 1, \dots, H$. Following Baruník and Ellington (2020, 2024), 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.

3.1. 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:

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

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.

3.2. 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 et al. (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^-.

3.3. Estimation methodology and setup

The choice of methodology is motivated by the increasing interest of the mainstream literature in models that understand economic variables as driven by shocks with heterogeneous responses and persistence. For such dynamics, the TVP methods introduced by Baruník and Ellington (2020, 2024) identify smoothly varying persistence structures stemming from underlying linkages due to volatilities, for instance. Further, assuming that our RV series is locally stationary, we can estimate it with the quasi-Bayesian local likelihood (QBLL) method of Petrova (2019). This has several advantages, such as allowing for estimating larger systems. While our study setup is not challenged by large system size, this feature remains broadly advantageous in such models. On the inference side, QBLL provides a convenient set of metrics about uncertainty from the posterior distribution of connectedness measures. Other studies typically use methods that only give point estimates of the VAR parameters and thus rely on bootstrapping for confidence intervals. Our approach allows us to discern periods of statistically significant differences between connectedness stemming from positive and negative volatility spillovers. Also, the methodology presented in this paper estimates the time-varying persistence of the shocks; we omit the frequency responses, though. Rolling window and inference issues of large systems are discussed by Demirer et al. (2018) and further by Baruník and Ellington (2024).

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 (Diebold and Yılmaz, 2012, 2014; Baruník and Křehlík, 2018). We turn to the more general TVP-VAR process which 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 that can bias the subsequent windows as an outlier is carried through the rolling procedure with constant weight in the regressions. In the TVP-VAR case, the outlier's weight decays depending on the kernel parameters.

We estimate the dynamic network model introduced by Baruník and Ellington (2020, 2024) 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 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 Eq. (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 (2024). 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.

Since QBLL employs a Bayesian framework, it necessitates the assumption of a prior distribution. Following the approach outlined by Baruník and Ellington (2020, 2024), we utilize the Minnesota Normal-Wishart prior as parameterized according to Kadiyala and Karlsson (1997). This prior selection aligns with the QBLL estimation methodology established by Petrova (2019), who derives a time-varying quasi-posterior Normal-Wishart distribution for the drifting parameters in a closed-form expression suitable for Gaussian VAR models. This approach facilitates straightforward and efficient computation. The use of Normal-Wishart priors in the QBLL method ensures that the time-varying covariance matrix remains symmetric and positive definite due to its inverted-Wishart properties, thereby avoiding the need for additional constraints such as triangularization. Consequently, the order of variables in the VAR system does not affect the estimation of the reduced-form covariance matrix. Moreover, the method allows for the direct estimation of the evolving covariance matrix while preserving its properties over time, eliminating the need for diagonalization, thanks to the inverted Wishart posterior density. The application of the QBLL TVP-VAR estimation technique for quantifying volatility connectedness offers significant practical advantages, as highlighted by Baruník and Ellington (2020).

Our study relates methodologically to Andrada-Félix et al. (2020), who calculate volatility connectedness within and between blocks of four traditional currencies and four cryptocurrencies, and Abubakr Naeem et al. (2022), who combine the older methodology by Diebold and Yılmaz (2012) with Baruník et al. (2016) to disentangle volatility due to positive and negative shocks. While the latter paper estimates the underlying VAR model on moving-window subsets of 150, 215, and 250 days, we estimate the linkages in the network by employing the TVP-VAR model in each time period similarly to Andrada-Félix et al. (2020). However, their estimation is based on the Kalman filter method of Antonakakis et al. (2020), while we estimate the TVP coefficients with QBLL.

Hence, unlike in Andrada-Félix et al. (2020) and Abubakr Naeem et al. (2022), our approach directly provides dynamic 95% confidence intervals ready-made for inference. This contrasts with previous attempts to study the asymmetric relationship based on the bootstrapping results of a simulation-based model. Bootstrapping provides a universal static confidence band to distinguish periods with statistically meaningful differences in asymmetry in connectedness due to positive and negative shocks. The dynamic approach based on QBLL confidence intervals allows for a locally focused, more rigorous, transparent, and straightforward statistical evaluation.

We quantitatively assess the dynamics of connectedness and existing asymmetries within good and bad volatility spillovers by employing several 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 6, along with estimation results.

4. Data

We perform our analysis with 5-min Open-High-Low-Close price data downloaded from the Binance exchange by using their official Binance Historical Market Data repository at www.binance.com/en/landing/data. The 5-min returns are calculated by using the Close values of the 5-min period. Our sample period runs from July 5, 2019, to May 31, 2024, i.e., it contains 1793 observations. 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 h, we are not limited by a standard 7- or 8-h trading period in a calendar day. Therefore, we aggregate the RV measures over 24 h daily based on the UTC midnight time.[4]

[4] Table A.2 in the Appendix summarizes basic descriptive statistics, along with the augmented Dickey–Fuller (ADF) test statistics (Dickey and Fuller, 1979) and Zivot-Andrews test (Zivot and Andrews, 2002), which both strongly rejects the unit root in all of the RV series, making the TVP-VAR analysis feasible. Tables A.3 and A.4 then complement Table A.2 with the counterparts of RV series due to negative and positive returns. The basic statistics are heterogeneous across the studied crypto assets.

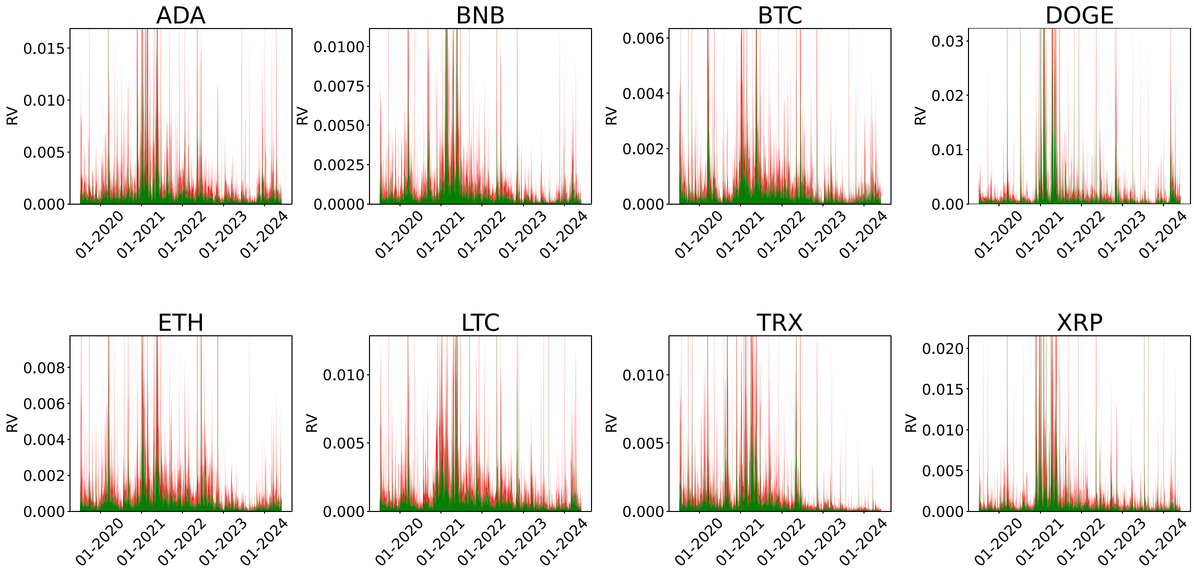

Fig. 1. Time series of realized semivariances for individual crypto assets. Volatility due to positive returns (in green) and volatility due to negative returns (in red) are stacked to allow for an intraday comparison. The specific y-axes are set according to the 97.5th quantile of the respective total RV to avoid occasional spikes that overshadow the dynamics on low-volatility days. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

4.1. Optimal data frequency discussion

For a broad range of traditional financial assets, the 5-min frequency for estimating realized RV represents a standard, as established in the seminal empirical study by Liu et al. (2015). However, due to the unique properties of crypto assets and their varying levels of microstructure noise, using a 5-min frequency may need further examination, as it could introduce more noise. A comparable investigation into the crypto asset market was conducted by Zieba (2022), who finds that variations in the noise-to-signal ratio analysis hinder clear conclusions. The study suggests that the 15-min frequency might be optimal, while the MSE analysis indicates that the 5-min frequency performs similarly to lower, less noisy frequencies like 60 min.

The cryptocurrency literature still lacks a consensus on the use of specific high-frequencies for various analyses. For instance, Katsiampa et al. (2022) utilize hourly data to assess co-movements and correlations among a wide array of highly tradable crypto assets using a Diagonal-BEKK model. Conversely, Yarovaya and Zieba (2022) employ 5- and 20-min frequencies, noting that results for 5-, 10-, and 15-min frequencies are very similar. Sensoy (2019) examine Bitcoin's weak-form efficiency using 15- to 45-min frequencies, concluding that as the frequency increases, pricing efficiency diminishes. Additionally, Zargar and Kumar (2019) explore the informational efficiency and martingale hypothesis of Bitcoin returns with 15- to 120-min and daily data, finding statistical evidence of inefficiency at the highest frequencies, namely 15- and 30-min intervals. Lastly, Vo and Yost-Bremm (2020) develop high-frequency trading strategies for Bitcoin at the 5-, 15-, and 360-min frequencies, determining that the 15-min frequency yields the highest profits, followed by the 5-min frequency.

Due to these inconclusive results, we initially experimented with various return granularities, specifically 5-, 15-, 30-, and 60-min frequencies, with a particular focus on the commonly preferred 5- and 15-min frequencies. When the total connectedness measure $\mathcal{S}^H$, defined in Eq. (10), is computed based on 5- and 15-min frequencies, the correlation between the two time series reaches 98%, indicating nearly identical dynamics. Naturally, the similarity decreases with longer intervals, but the lowest correlation between 5- and 60-min intervals still exceeds 93%. Based on these results, we conservatively adhere to the default 5-min frequency, which is generally supported by Zieba (2022). Additionally, we analyzed the correlations of daily RV time series, defined in Eq. (3), based on the granularity of the underlying log returns for individual crypto assets. The correlation coefficients reported in Table A.6 rarely fall below 90%, indicating they convey very similar information. For 5-min and 15-min returns, the minimum value is 92% for ETH, while reaching 98% for BTC and DOGE. This strong similarity further supports the robustness of our results based on 5-min price data.

4.2. Realized volatilities

In Fig. 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, including 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 spot Bitcoin ETF. Another spike in volatility is observed around the middle of 2022, corresponding to the collapse of the stablecoin TerraUSD below its 1 USD peg. At the end of the dataset, the most recent period of heightened volatility occurred in the first quarter of 2024, coinciding with the U.S. Securities and Exchange Commission's January approval to launch the first Bitcoin spot ETFs in the United States.

Among the eight coins, the high volatility of Dogecoin stands out, driven by Elon Musk's tweets (Shahzad et al., 2022) in January 2021. Musk's Twitter activity sparked an interest in Dogecoin, producing unprecedented volatility in the following months. 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, Fig. 1 highlights the dynamic and rapidly evolving nature of the cryptocurrency market, along with rapid changes in crypto market volatility.

4.3. Explanatory variables

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 (Nguyen et al., 2019; Kukacka and Kristoufek, 2023). 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: www.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 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,[5] the velocity of BTC and ETH (what proportion of coins "changed hands" on the given blockchain, ticker NVTAdj), and BTC hash rate (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: www.fred.stlouisfed.org. 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). Commodities are represented by the Gold bouillon index as in Ji et al. (2019) downloaded from www.investing.com and the S&P GSCI commodity index downloaded from www.spglobal.com. Global economic activity is proxied by the Baltic Dry index also downloaded from www.investing.com, and lastly, we include Economic Policy Uncertainty downloaded from the official website www.policyuncertainty.com. All the time series are available on a daily basis. Weekends and other nontrading days take the value of the last available observation.[6]

5. 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 structure of the connectedness origin, which we leave for Section 6. 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.

5.1. Total dynamic network connectedness

In Fig. 2, we present the total dynamic network connectedness over the whole period under research.[7] The total volatility connectedness oscillates in a remarkably wide interval between 17 and 87, 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, particularly in periods characterized by very narrow confidence intervals.

[5] 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).

[6] We report on descriptive statistics of the variables in Table A.5.

[7] Table A.7 reports on its descriptive statistics in the first row.

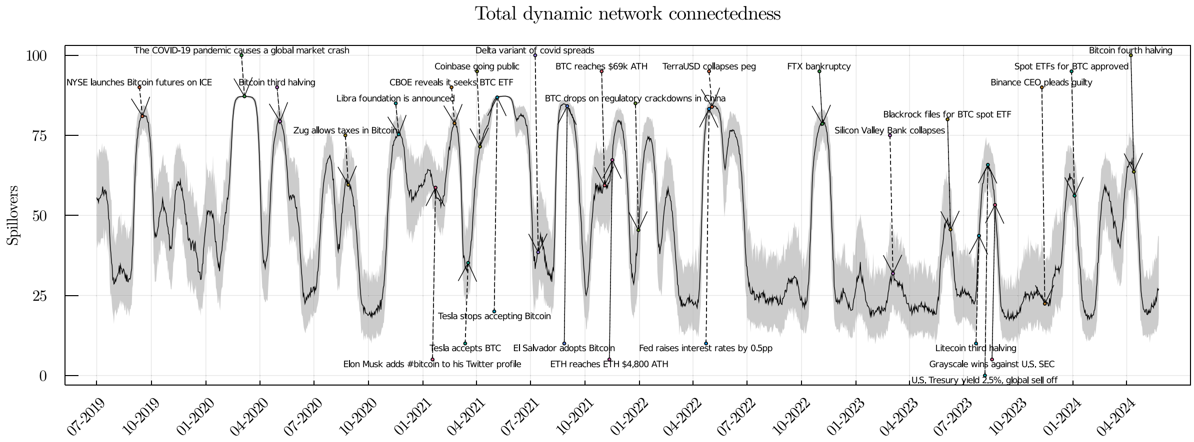

Fig. 2. Total dynamic network connectedness defined by Eq. (10). The shaded area represents 95% confidence intervals, and the solid line represents the median of the simulated distribution.

The reported range between 17 and 87 contrasts with the results for the connectedness of stocks or volatility spillovers between various standard financial markets that often do not drop below 50 (Diebold and Yılmaz, 2014; Baruník et al., 2016; Baruník and Křehlík, 2018; Baruník and Kočenda, 2019). Nevertheless, they seldom go below 40 (Diebold and Yılmaz, 2009; Baruník and Ellington, 2020; Baruník et al., 2022). Conversely, the upper bound corresponds to values reported for standard financial markets in the above-mentioned studies, usually surpassing 85 and even reaching 90. This comparison suggests that the lower limit is markedly edged off in the cryptocurrency segment when compared to those of the standard financial markets. Importantly, it also contrasts with the results for the connectedness in crypto by Abubakr Naeem et al. (2022), who, using the well-established methodology by Diebold and Yılmaz (2012) based on a VAR model moving-window estimation, report markedly less oscillating dynamics in an interval between roughly 70 and 90. On the other hand, the total connectedness dynamics among four cryptocurrencies presented in Andrada-Félix et al. (2020), using the Kalman filter method of Antonakakis and Gabauer (2017), reveal dynamics roughly comparable to our results, while the oscillation ranges approximately from 10 to 70.

The other pattern that characterizes the total connectedness dynamics is its considerable smoothness when compared to 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 used the static estimation approach of the past dynamics from an approximating rolling window; associated drawbacks are discussed in the previous section.

5.2. 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. For clarity of interpretation, we marked in Fig. 2 the key events impacting the volatility connectedness of the crypto market (Rognone et al., 2020; Corbet et al., 2020b; Sapkota, 2022; Albrecht and Kočenda, 2024).

The first 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 crypto player, generally supported 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 framed by the global outbreak of the COVID-19 pandemic at the turn of February and March 2020, 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 quickly decreased during April as the crypto segment 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, driven by the increasing popularity of DeFi and NFTs. Finally, Bitcoin reached its then all-time-high price of over 69 thousand USD, 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, the sharpest increase since 2000. This step was followed by the TerraUSD May collapse below its 1 USD peg and the Chapter 11 bankruptcy procedure launched for the cryptocurrency exchange FTX in November 2022, dropping the Bitcoin price below 16 thousand USD. Although the volatile period for the crypto segment persisted for several months, including the collapse of Silicon Valley Bank in March 2023, total connectedness remained relatively low until two spikes during the summer of 2023. In mid-June, BlackRock and Grayscale, along with nine other companies, applied for spot Bitcoin ETFs. However, the favorable market impact of this event and of the Litecoin halving at the beginning of August was overshadowed by an unexpectedly high U.S. Fed inflation reading. This led to a rise in the U.S. Treasury yield to its highest level in over two years, reaching 2.5%, which discouraged investments in risky assets and triggered a crypto market crash on August 17, 2023. By the end of the month, Grayscale's victory against the U.S. Securities and Exchange Commission, which was forced to review its initial denial of the Bitcoin ETF applications, brought renewed optimism. This positive development likely restored interest in the cryptocurrency market, as prices steadily rose until December 2023.

The growing cryptocurrency market experienced a significant interruption due to a money-laundering scandal involving Binance, the world's largest cryptocurrency exchange, halting market momentum for approximately two months. Binance's founder, Changpeng Zhao, resigned in November 2023 after admitting to being guilty of money laundering violations. However, interest in the market surged again with the final approval and launch of Bitcoin ETFs in January 2024, marking a new period of heightened connectedness. In February, daily net inflows into the U.S.-listed spot Bitcoin ETFs strongly outpaced new supply before the halving, leading to a new all-time-high price of over 73.7 thousand USD on March 14. This demand-supply imbalance, combined with halving expectations, likely led to the Bitcoin Flash Crash on April 15. The following Bitcoin fourth halving event on April 19 reduced the block reward for miners by half and concluded the last observed period of elevated connectedness. The dataset span also covers the U.S. Securities and Exchange Commission's approval of eight Ethereum ETFs for listing and trading in May 2024.

5.3. 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). Fig. 3 represents the time series graphically[8] and reveals that spillovers due to negative and positive volatility are 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 Fig. 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 95% confidence level, and even more importantly, this difference practically never materializes during a period of considerable economic importance.[9]

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

8 Table A.7 reports on descriptive statistics of spillovers due to negative and positive volatility.

9 A rare exception appears in March 2023 around the collapse of Silicon Valley Bank.

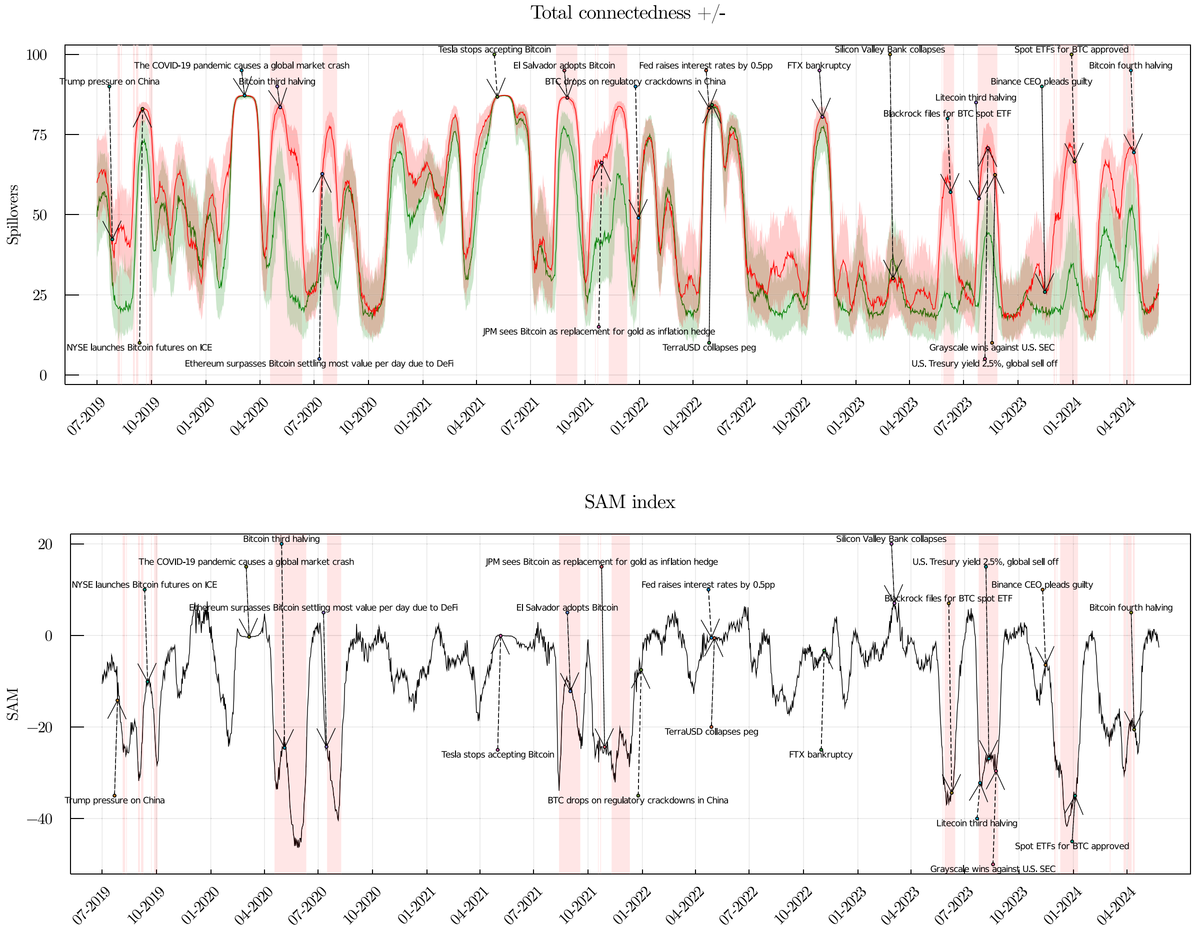

Fig. 3. Estimates of total negative (in red) and positive (in green) connectedness in the upper panel and $\mathcal{SAM}$ in the bottom panel. $\mathcal{SAM}$ is defined by Eq. (11) and measures the asymmetry between the two sources of connectedness. Simulated 95% confidence bands allow for directly identifying periods of significant differences between the two sources of connectedness represented by shaded areas of non-overlapping confidence intervals. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

dominance of the positive connectedness. Again, the observed dynamics are markedly richer compared to Abubakr Naeem et al. (2022), who report $\mathcal{SAM}$ in their cryptocurrency network to oscillate between roughly minus 15 and 0, supporting our results for dominantly negative $\mathcal{SAM}$.

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 5.2 is also linked with a statistically distinct positive and negative connectedness quantified by $\mathcal{SAM}$ (see Fig. 3).

More detailed observations indicate ten 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 boosted cryptocurrency prices again after the bull run in the first half of 2019. Most of the other cases coincide with the events important for total connectedness and relate to: (i) the period around September 2019 (Bitcoin futures on NYSE), (ii) May to June 2020 (Bitcoin's third halving), (iii) August to September 2021 (El Salvador adopting Bitcoin), (iv) August 2023 (U.S. Treasury yield reaching 2.5%, crypto market crash on August 17, but also the Grayscale's victory against U.S. SEC), (v) January 2024 (spot Bitcoin ETFs approved and launched), and (vi) April 2024 (Bitcoin's fourth halving). The following three cases are mostly linked to asymmetries rather than to 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), (ii) in November 2021, JPMorgan Chase & Co. supported Bitcoin as an inflation hedge that might replace gold, a move leading to a new all-time-high of Bitcoin as well as Ethereum, and (iii) the turn of May and June 2023, associated with spot Bitcoin ETFs applications. Finally, negative dips of $\mathcal{SAM}$ might not be fundamentally important *per se*. However, they often approximate the boundaries of the periods when significant differences in connectedness occur.

When looking at the ten specific 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 market crashes framed others. However, overall, important structural changes in the cryptocurrency market (Bitcoin futures, Bitcoin and Litecoin halvings, the popularity of DeFi, Bitcoin as legal tender, Bitcoin as an inflation hedge by JPMorgan, spot Bitcoin ETFs applications and approvals) were often linked to asymmetries. This finding goes against the intuition that positive volatility is connected to price increases and negative volatility is connected to market crashes. For instance, even during the crypto rallies in April 2020 or February to March 2024, 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 within the first half of the analyzed period can be recognized for 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).[10]

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, eliminating 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.

6. Explaining the connectedness and asymmetry

Linking the connectedness and existing asymmetries to specific 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 attributed to specific characteristics and changes in the underlying processes of the examined blockchains. Additionally, we consider external macroeconomic and monetary drivers. This way, we try to understand the underlying dynamics of connectedness within the analyzed system and provide both a qualitative and quantitative basis for the identification of changes in connectedness before they become visible in the measures that are estimated ex-post.

6.1. Baseline model

Our subsequent analysis rests on estimating the baseline model specified in daily frequency represented by Eq. (12) below. In addition to examining the total connectedness $\mathcal{S}^H$ defined in Eq. (10),[11] we use the same model specification to explore drivers of the asymmetries existing in connectedness. In such a case, the dependent variable is $\mathcal{SAM}$ defined in Eq. (11).[12]

$$\begin{aligned}
Connectedness_t &= \beta_0 + \beta_1 Momentum_{BTC,t} + \beta_2 Momentum_{ETH,t} + \beta_3 Momentum_{Alts,t} \\
&+\beta_4 \log(Addresses)_{BTC,t} + \beta_5 \log(Addresses)_{ETH,t} + \beta_6 \log(Fees)_{BTC+ETH,t} \\
&+\beta_7 \log(Inflow)_{BTC+ETH,t} + \beta_8 \log(Outflow)_{BTC+ETH,t} \\
&+\beta_9 \log(Velocity)_{BTC,t} + \beta_{10} \log(Velocity)_{ETH,t} + \beta_{11} \log(HashRate)_t \\
&+\beta_{12} \log(Volume)_{BTC,t} + \beta_{13} \log(Volume)_{ETH,t} + \beta_{14} \log(Volume)_{Alts,t} \\
&+\beta_{15} \log(Trades)_{BTC,t} + \beta_{16} \log(Trades)_{ETH_t} + \beta_{17} \log(Trades)_{Alts,t} \\
&+\beta_{18} \log(SP500)_t + \beta_{19} \log(VIX)_t + \beta_{20} BEInflation_t + \beta_{21} IR_t + \beta_{22} \log(EPU)_t \\
&+\beta_{23} \log(BalticDry)_t + \beta_{24} \log(Gold)_t + \beta_{25} \log(GSCI)_t + \varepsilon_t
\end{aligned} \tag{12}$$

[10] Moreover, Fig. B.4 provides a detailed picture of the net connectedness of the cryptoassets of interest; they provide a split into the total net connectedness and the net connectedness in the good and bad volatilities and Table A.8 provides respective descriptive statistics. No crypto could be labeled as a dominant giver or a dominant receiver in any of the metrics. The role of leader and follower of each analyzed crypto asset possesses strong dynamics. However, there are several interesting findings. First, Bitcoin cannot be identified as a strong and clear leader in the market, even though its net position remains positive at most times. The same holds for the overall net connectedness and the bad and good volatility connectedness. Second, Dogecoin is a clear follower of the group as the main transmitter and a leader. This holds specifically at the beginning of 2021, i.e., during one of the main DOGE-related hypes. The period is characterized by a strong leadership of both Bitcoin and Dogecoin, while other crypto assets mostly followed. Additionally, Dogecoin's net connectedness produces a relatively stable negative pattern. Finally, although there is no dominant giver over the analyzed period, Bitcoin, Ethereum, and Litecoin report a clear positive mean net position of the directional spillover index. Litecoin shows the highest uncertainty in the metrics across the three, and thus, the expected leadership of Bitcoin and Ethereum is identified. The most prominent receivers are Dogecoin, as already mentioned, and XRP and BNB, although their levels are much lower than those of Dogecoin. Cardano and Tron remain close to zero on average.

[11] Descriptive statistics of the empirical variable $\mathcal{S}^H$ can be found in the first row of Table A.7.

[12] Descriptive statistics of the components of the empirical variable $\mathcal{SAM}$ can be found in the second and third rows of Table A.7.

We look at a set of potential drivers of connectedness among the whole system of 8 crypto assets[13] with the aim of covering various perspectives—momentum, blockchain activity, exchange activity, and external macroeconomic factors, including different market conditions (Antonakakis et al., 2019a; Bouri et al., 2021). As there are 8 crypto assets in our dataset, we need to select and aggregate most of the measures to avoid overfitting and collinearity. 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. The rest of the coins are treated jointly as altcoins.

The selection of variables is based on previous research into structural aspects of different types of dynamics in the crypto markets, which still remain rather scarce. We mostly build on our previous results in Kukacka and Kristoufek (2023), Kristoufek (2023), Kubal and Kristoufek (2022) and Kristoufek and Bouri (2023) as well as the results in Demir et al. (2018), Shaikh (2020), Corbet et al. (2020b), Pyo and Lee (2020), Lyócsa et al. (2020) and Wang et al. (2023). The reasoning for the final choice of the baseline model, i.e., the starting set of variables and thus parameters to estimate, is as follows. The momentum effect is separated into Bitcoin, Ethereum, and the rest of the market, as the momentum of these entities is expected to have different effects. Bitcoin is perceived as the first mover in the market, and its initial momentum is thus expected to be detached from the rest of the market that follows later. The Bitcoin momentum is thus expected to have a negative effect on total connectedness. The effects of Ethereum and the rest of the altcoins are less clear as the reactions can vary. However, Ethereum is regarded as the second most significant asset behind Bitcoin. The aggregate altcoins' momentum is expected to be positive as altcoins tend to move together. The active addresses and fees are closely related to the momentum factors. However, they represent a more stable or long-term measure of the market activity and are more connected to network development rather than prices. The logic and the expected effects for the total connectedness are the same as for the momentum. The remaining factors connected to the network and exchange activity mostly control the market specifics. In general, a possible Bitcoin leadership is expected to push the connectedness down. Conversely, Ethereum is expected to lead the rest of the market, catching up to Bitcoin, and hence pushing the connectedness up (Ji et al., 2019). The macroeconomic variables are included as mostly control variables for the external factors of the traditional markets. Given that these external factors have demonstrated an impact on Bitcoin returns and volatility, it is reasonable to assume that they may similarly influence the dynamic properties of other crypto assets and, consequently, the overall dynamics of the cryptocurrency markets (Umar et al., 2021). The starting set of variables is the same for the model of asymmetry, which puts together the logic of their selection for the total connectedness and the evidence of asymmetric volatility in cryptoassets (Troster et al., 2019; Ardia et al., 2019; Fakhfekh and Jeribi, 2020; Cheikh et al., 2020; Fung et al., 2022).

The paper's primary empirical contribution lies in identifying this rich collection of 25 potential drivers of connectedness in crypto.[14] The selection of variables is primarily motivated by sound economic justification, which is supported by the latest discoveries in empirical studies on cryptocurrencies. As already discussed in the Introduction, Walther et al. (2019), Corbet et al. (2020b,a) and Charfeddine et al. (2022) support the impact of macroeconomic news, represented by the dynamics of break-even inflation and the short-term interest rate, and the importance of the global economic business cycle (Walther et al., 2019; Andrada-Félix et al., 2020; Wang et al., 2023) proxied by the development of the Baltic Dry Index (Kilian, 2009), a leading economic indicator tracking the cost of shipping major dry raw materials. Monetary policy aspects such as inflation protection or the impact of the U.S. interest rate are also highlighted, e.g., by Li and Wang (2017), Saiedi et al. (2021), Pagnotta (2021) and Bouri and Jalkh (2023). Financial sentiment or financial market variables suggested by Corbet et al. (2018), Ji et al. (2019), Andrada-Félix et al. (2020), Sapkota (2022), Charfeddine et al. (2022) and Suleman et al. (2023) are proxied by two broad financial market indicators: the S&P 500 and VIX indices, while the inclusion of the latter also follows the findings of Walther et al. (2019), Bouri and Jalkh (2023) and Chowdhury and Damianov (2024). Further literature containing inclusion of S&P 500 comprises (Rudkin et al., 2023; BenMabrouk et al., 2024). As represented by the U.S. EPU Index, policy uncertainty is associated with cryptocurrency prices and their volatility (Demir et al., 2018; Ji et al., 2019; Yen and Cheng, 2021; Umar et al., 2023). Due to its suggested "safe haven" property, the relationship between cryptocurrency and gold prices has been explored in numerous studies, including Klein et al. (2018), Ji et al. (2019), Bouri and Jalkh (2023), Yousaf et al. (2023), BenMabrouk and Khalifa (2024) and Narayan and Kumar (2024). The "proof-of-work" protocol of many cryptocurrencies and its linkage to oil and gas prices also warrants the inclusion of variable tracking developments in energy commodity markets, as recommended by Ji et al. (2019), Joo and Park (2023), BenMabrouk and Khalifa (2024) and Narayan and Kumar (2024). Next, trading volume has been found among the main drivers in Ji et al. (2019), Charfeddine et al. (2022) and Andrada-Félix et al. (2020), and its inclusion also follows the results of Balcilar et al. (2017), Li and Wang (2017), Zhang and Zhao (2023) and Bouri and Jalkh (2023). Finally, momentum is motivated by empirical research by Zhang and Zhao (2023), who examine the determinants of realized volatility measures in a cross-section of more than 50 cryptocurrencies.

Pagnotta (2021) further brings attention to the fundamentals of cryptocurrency empirical pricing: the basic aspects of mining and the role of security. These concepts are related to cryptocurrency users' basic needs and the incentives for miners that we proxy with the number of active addresses, transaction fees, money coming into and going out of centralized exchanges, the speed of circulation (called velocity), and the BTC hash rate, all in line with empirical findings of Kukacka and Kristoufek (2023). Finally, addresses serve as a measure of transaction demand (Parino et al., 2018) and mining difficulty (Li and Wang, 2017).

[13] Descriptive statistics of the associated realized measures can be found in Tables A.2, A.3, and A.4.

[14] Descriptive statistics of all 25 explanatory variables can be found in Table A.5.

Table 1
Estimated models for total connectedness and for asymmetry in connectedness for good and bad volatility. Based on a daily dataset of 25 explanatory variables covering the period from July 7, 2019, to May 31, 2024, i.e., 1791 observations. The models always start with the baseline model in Eq. (12), and then the variables with the overfitting risk (VIF over 10) are eliminated step-by-step, resulting in the "full" versions of the models. The "final" versions of the models are obtained after step-wise eliminating the statistically insignificant variables (at the 90% confidence level). The heteroskedasticity and autocorrelation consistent (HAC) standard errors according to Stock and Watson (2003) are reported in parentheses.

Variable/Model:	Connectedness $\mathcal{S}^H$: full			Connectedness $\mathcal{S}^H$: final			$\mathcal{SAM}$: full			$\mathcal{SAM}$: final		
const	581.58	(165.16)	***	656.71	(147.44)	***	−237.61	(103.20)	**	−232.69	(26.13)	***
Momentum_{BTC}	−29.66	(22.12)					25.31	(13.26)	*			
Momentum_{ETH}	4.19	(18.97)					−13.38	(10.65)				
Momentum_{Alts}	−21.63	(14.64)		−32.50	(11.41)	***	1.27	(7.21)				
$\log(Addresses)_{BTC}$	−22.91	(6.64)	***	−26.12	(6.36)	***	0.14	(4.38)				
$\log(Addresses)_{ETH}$	9.39	(6.17)		11.38	(6.25)	*	−3.13	(4.11)				
$\log(Fees)_{BTC+ETH}$	5.81	(1.84)	***	5.85	(1.70)	***	−4.94	(1.07)	***	−5.05	(0.73)	***
$\log(Velocity)_{BTC}$	−0.11	(2.41)					7.38	(1.28)	***	6.97	(1.13)	***
$\log(Velocity)_{ETH}$	2.28	(3.16)					−8.26	(1.73)	***	−8.56	(1.37)	***
$\log(Volume)_{ETH}$	10.82	(3.14)	***	10.51	(2.16)	***	0.57	(1.38)				
$\log(Volume)_{Alts}$	7.68	(1.97)	***	8.07	(1.87)	***	0.78	(0.93)				
$\log(Trades)_{BTC}$	−8.30	(2.11)	***	−9.42	(1.60)	***	−0.44	(1.36)				
$\log(VIX)$	6.53	(4.59)		7.57	(4.21)	*	9.55	(2.34)	***	8.16	(2.07)	***
IR	−0.55	(1.10)					−1.53	(0.62)	**	−1.50	(0.43)	***
$\log(EPU)$	−2.73	(1.27)	**	−2.49	(1.27)	**	−0.83	(0.67)				
$\log(BalticDry)$	−4.69	(2.96)		−5.21	(2.78)	*	−0.34	(2.07)				
$\log(Gold)$	−67.68	(18.40)	***	−75.13	(13.81)	***	2.09	(11.28)				
$\log(GSCI)$	−2.70	(8.78)					36.01	(4.38)	***	34.51	(4.35)	***
Adjusted R^2	0.42			0.42			0.27			0.26		
White test	692.15	***		421.06	***		734.92	***		312.62	***	
LM test	1250.84	***		1225.53	***		1373.67	***		1398.52	***	
ADF test	−6.33	***		−6.39	***		−8.18	***		−8.00	***	
KPSS test	0.09			0.09			0.08			0.08		

* For the test, statistical significance at the 90% confidence level.
** For the test, statistical significance at the 95% confidence level.
*** For the test, statistical significance at the 99% confidence level.

6.2. Model for total connectedness

The model for total connectedness is estimated based on our daily dataset of 25 explanatory variables covering the period from July 7, 2019, to May 31, 2024, i.e., 1791 observations.[15] Starting with the full set of variables in Eq. (12), we first eliminate the factors with a high risk of collinearity 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 VIF 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. After the variable selection procedure, the final specification of the estimated model for total connectedness takes the following form:

$$\begin{aligned}
&\mathcal{S}^H_t = \beta_0 + \beta_3 Momentum_{Alts,t} \\
&+\beta_4 \log(Addresses)_{BTC,t} + \beta_5 \log(Addresses)_{ETH,t} + \beta_6 \log(Fees)_{BTC+ETH,t} \\
&+\beta_{13} \log(Volume)_{ETH,t} + \beta_{14} \log(Volume)_{Alts,t} + \beta_{15} \log(Trades)_{BTC,t} \\
&+\beta_{19} \log(VIX)_t + \beta_{22} \log(EPU)_t + \beta_{23} \log(BalticDry)_t + \beta_{24} \log(Gold)_t + \epsilon_t
\end{aligned} \quad (13)$$

The results for the total connectedness dynamics and its driving factors are summarized in Table 1. As the residuals are serially correlated and heteroskedastic, we report the heteroskedasticity and autocorrelation consistent (HAC) standard errors.[16] We present both the full model and the final model. The former includes all variables from Eq. (13), except those eliminated due to collinearity, while the latter comprises the variables remaining after step-by-step significance elimination. In the final model, the effects of significant variables have the same direction as the ones of the full model and their effects are mostly more pronounced. As there are no radical differences between the full and the final model and the adjusted coefficients of determination are not distinguishable after rounding, we interpret the final model only.

From the most general perspective, the total connectedness dynamics can be explained through a combination of both crypto markets-related effects as well as the influence of the traditional market, building on the previously documented interplay between cryptocurrency market dynamics and traditional financial markets (Zeng et al., 2020).

[15] This dataset is two observations shorter than the underlying dataset of log returns used to compute the realized volatility measures because the dynamic network model employed to calculate the dependent variables $\mathcal{S}^H$ and $\mathcal{SAM}$ is of autoregressive order 2.

[16] The lag length selection procedure to obtain HAC standard errors follows the standard formula $0.75 \times T^{1/3}$ as recommended by Stock and Watson (2003).

Starting from the crypto-related ones, we find that Bitcoin often goes against the total connectedness of the market. The effects of both on-chain (active addresses) and off-chain (trades on Binance) have negative effects on connectedness. This relates to Bitcoin often surging first, only being followed by the rest of the market. When the number of active addresses on the Bitcoin blockchain goes up by 1%, the expected decrease in connectedness is around 0.26. This is a huge effect. However, it will be at least partially mitigated by the positive effect in Ethereum as one expects the active addresses to grow for ETH also (when the active addresses go up for BTC) and the joint effect of BTC and ETH fees which will likely go up when the activity on both networks goes up. Nevertheless, the effect of the on-chain activity in Bitcoin is considerate and is well in hand with our previous research (Kukacka and Kristoufek, 2023). Also, note that a 1% change in active addresses is almost a σ-event. We see similar interactions in the off-chain interactions as the effects of Ethereum and altcoins volumes boost connectedness while Bitcoin trades push it down. The role of trading volume in affecting market connectedness is documented by Kurka (2019). In contrast to the on-chain activity, the off-chain activity of ETH and altcoins overpowers the negative push of BTC on total connectedness. Previous studies have indicated that off-chain activities, such as trading volumes (Charfeddine et al., 2022; Ji et al., 2019; Andrada-Félix et al., 2020; Balcilar et al., 2017), are crucial drivers of total connectedness and significantly influence market dynamics, often outweighing on-chain activities (Hasan et al., 2021). As volume and trades are more volatile than the active addresses, the variability in the off-chain trading activity is worth following more for a practitioner as the 1% events are more likely there and the effects of similar albeit lower magnitude. Therefore, following a trading (off-chain, exchange) activity of these three baskets can give valuable insights into the (at that time) latent connectedness evolution, similar to the on-chain (transactional) activity but with a slightly lower importance. The momentum of altcoins stands alone and plainly says that when altcoins shoot up, they detach from the dynamics of the rest, i.e., Bitcoin and Ethereum, which is what we often observe in the crypto markets.

Moving to the factors outside of the crypto sphere, we find VIX, EPU, Baltic Dry, and Gold to be significant, which corroborates the results of Walther et al. (2019) and Balli et al. (2020) but goes partially against Sapkota (2022), Ji et al. (2019), Charfeddine et al. (2022) or Andrada-Félix et al. (2020), who also represented financial market by including the S&P500 index. It is thus evident that information, or rather uncertainty, from the traditional and macro markets transmits to the crypto markets. Interestingly, none of the direct monetary measures (interest rates and break-even inflation) are part of the final model. Starting from the financial uncertainty represented by VIX and EPU, we see that the effects of the two are partially offset, as these are quite highly correlated (0.53). However, they do not offset completely, highlighting the complex relationship between financial uncertainty measures and market connectedness, emphasizing the nuanced impact of these variables (Wang et al., 2021). The increasing uncertainty in the traditional financial markets thus comes together with connectedness moving upwards, pushing the crypto markets together. The global economic activity, measured by the Baltic Dry index, is tied with loosening connectedness, making space for diversification in crypto. However, all three of these uncertainty measures are on the edge of statistical significance, and following them for qualitative expectations about the underlying connectedness dynamics certainly has some reliability questions attached. On the other side, the price of gold has a strong, clearly significant effect on the connectedness. In magnitude, the effect is massive, underlying the results of many previous studies on the relationship between crypto assets and gold (Shahzad et al., 2019; Bouri et al., 2020; Zeng et al., 2020). A 1% change in the price of gold has an expected opposite change of 0.75 in connectedness. However, the price of gold is also remarkably stable, and such a 1% change is, in fact, around a 1.35σ event. Gold is only weakly correlated with other significant macro and financial variables, and its effect is thus not marginalized much by such factors. It is also very mildly correlated with all momentum metrics, thus partially overtaking mostly the Bitcoin momentum effect from the full model. Lastly, gold is highly correlated (0.74) with the S&P500 index, which had been eliminated due to collinearity in the early stages of modeling. Gold thus likely carries at least part of the information about dynamics of the overall capital market as well, maybe even more so than being a measure of uncertainty in the system as it is not correlated, or only weakly, with the other factors connected to such type uncertainty. Either way, gold is evidently a crucial factor to follow.

Overall, the final model clearly shows that the connectedness can be explained by a palette of factors. The $\bar{R}^2$ of 0.42 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. The results offer clear sets of variables to follow for an interested party, which in our case comprises mostly portfolio managers but also regulators. As connectedness is observable mostly ex-post, the identified clusters of variables provide valid indicators of changes in the underlying connectedness mechanism. Importantly, we identified that most of the variable baskets are relevant—momentum, on-chain activity, off-chain (exchanges) activity, financial uncertainty, and economic uncertainty (and the financial market performance only indirectly via gold). Following these groups and interactions within can serve as hands-on indicators that can be further translated into specific portfolio re-balancing decisions. For regulators, it is more important to follow the asymmetries, and we continue with the results there forth.

6.3. Model for asymmetry in connectedness

Section 5.3 shows that there is a strong asymmetry present between the connectedness of good and bad volatility. This is evidenced by mostly negative $\mathcal{SAM}$. The dataset and the variable selection procedure for this model are the same as for the total connectedness model above. The final estimated model specification for the asymmetry in connectedness for good and bad volatility after variable selection has the following form:

$$\mathcal{SAM}_t = \beta_0 + \beta_6 \log(Fees)_{BTC+ETH,t} + \beta_9 \log(Velocity)_{BTC,t} + \beta_{10} \log(Velocity)_{ETH,t} + \beta_{19} \log(VIX)_t + \beta_{21} IR_t + \beta_{25} \log(GSCI)_t + \varepsilon_t \tag{14}$$

Table 1 summarizes the results from the estimated model, covering the factors driving such asymmetry. The asymmetry towards higher connectedness in bad volatility is represented by negative values of $\mathcal{SAM}$. Also, the asymmetry is mostly negative, and we must interpret the results accordingly. Note that this is a contradiction with the previous results of Baur et al. (2018), who report that positive shocks increase volatility more than negative shocks, which contrasts with traditional financial markets. Our newer dataset thus provides new insights even at this very basic level. Back to the interpretation of the estimated model, the negative estimated partial effects need to be read as amplifying the asymmetry, while the positive estimated partial effects represent pushing towards symmetry in the connectedness of good and bad volatility.

Starting with the crypto-related factors, we find the fees and velocities of Bitcoin and Ethereum to be significant. The increasing fees, as a measure of transactional activity on-chain and thus also a measure of congestion of the network(s), are linked with increasing asymmetry in connectedness. When fees on BTC and ETH increase by 1%, it is expected that the asymmetry increases (gets more negative) by 0.05. In its amplitude, this seems like a tiny effect, but note that the fees are highly variable, with a mean value of 1.96 and a standard deviation of 1.23. Putting this together with the estimated effect of fees on the total connectedness being positive, it means that the increasing on-chain activity is connected to the market moving together. Still, this joint movement is more pronounced with respect to the negative volatility. Therefore, if the market is highly congested, it will tend to fall more together than in the case of upward volatility and connected market congestion, supporting the results of Cheikh et al. (2020) who found that increased on-chain activity correlates with higher market connectedness, particularly during periods of market downturns. Following fees is thus more important for regulators who are more interested in the negative events than the portfolio managers. The estimates on the effects of velocity tell an additional detail that an increased on-chain activity on the Ethereum blockchain pushes the connectedness further towards asymmetry, at least compared to Bitcoin goes against it but does not compensate for it completely (with the estimated effects of 6.97 and −8.56 for BTC and ETH, respectively, and correlation between the two at 0.54). Even though the Ethereum velocity is insignificant for the total connectedness model, its estimated effect is still positive. This aligns with Katsiampa (2019), who found significant effects of past shocks and volatility on the connectedness of major cryptocurrencies, highlighting the distinct behaviors of Bitcoin and Ethereum in response to market conditions. This leads to a similar interpretation of the network fees in terms of total connectedness and asymmetry.

Moving on to the non-crypto variables, we find that VIX, the interest rate, and the GSCI index are the only statistically significant variables. Note that none of the macroeconomic variables has been found significant for the total connectedness model. Starting with the energy index, this one mostly overtakes the role of gold in the full model (correlation of 0.38 with gold and 0.75 with S&P500), and with its strong positive effect on the asymmetry, it relates to the situations when the connectedness in good and bad volatility are closer to the balance. As the index majorly represents the overall financial economy growth (due to its high correlation with the stock index), its positive effect on the asymmetry indicates that when the financial markets grow, there is no additional risk towards the negative volatility in crypto. In other words, as a regulator or someone interested mainly in the negative events and their implications, seeing the global financial market grow does not signify an additional risk in a more pronounced downturn in crypto. The risks become closer to symmetric. The effect of VIX provides an additional layer to the story. Its positive estimated effect indicates that the connectedness tends to have symmetric effects when the uncertainty in the traditional financial markets is high. This challenges the results of Balli et al. (2020), who claim that the higher economic uncertainty comes together with lower connectedness in crypto assets but is in hand with (Hasan et al., 2021), who report that financial uncertainty, as captured by VIX, plays a critical role in the dynamics of connectedness, particularly in enhancing symmetry during periods of high market volatility. The market apparently evolves but our extensive analysis also stresses how important it is to control for a large set of variables, covering various aspects in the complex network of connections between economic, financial, and crypto markets. Putting this together with the GSCI effect, the most critical situations for the policymakers and regulators in crypto come when the traditional markets are tranquil, and an unexpected negative shock comes. This will translate into pronounced asymmetry in the crypto connectedness and might lead to a plunge in the broader crypto market. This emphasizes the need to understand the dynamics and asymmetries specifically under different economic conditions and varying market environments (Mensi et al., 2020), and it represents just one of the exemplary scenarios that come from our analysis, contributing to the practice of regulators that will be becoming more important in the coming years with crypto assets penetrating into the legacy financial markets. We identify interest rate among the dominant variables associated with the asymmetry, which generally follows the findings by Corbet et al. (2020a); however, it does not correspond entirely to Corbet et al. (2020b,a), Walther et al. (2019) and Charfeddine et al. (2022), who also detect inflation among important drivers. The negative estimated effect of the interest rate suggests when the interest rates are high, and thus the monetary policy is tight, the crypto market is more sensitive and more likely to correct downwards rather than surge. Finally, the adjusted coefficient of determination of 0.26 for the asymmetry regression indicates a good fit but also that much of the variation remains unexplained. As our starting set of variables is rather broad, we attribute that unexpected events and shocks in the system remain major moving forces.

7. Conclusion

Cryptocurrencies form a special set of assets with unique statistical and dynamic properties compared to those of traditional financial assets such as stocks or Forex rates. Studying how the volatilities of different crypto assets in a portfolio interact, specifically through volatility spillovers, is crucial for portfolio managers and other market participants due to the unprecedented levels of risk and uncertainty involved. Traders, especially those focused on different market phases, are keenly interested in volatility spillovers during market upturns and downturns. We analyze this phenomenon by examining the connectedness between good and bad volatility.

The crypto market, represented by the set of 8 large crypto assets, shows an evolution of connectedness that is unseen in traditional financial markets. 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-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 upward and downward swings. Evidence points towards the domination of higher connectedness due to bad volatility. This suggests that crypto market downturns usually spill over substantially faster than comparable market surges.

While specific historical events can account for periods of both high and low connectedness, as well as pronounced asymmetry, the overall dynamics are effectively explained by a combination of factors such as blockchain activity, market momentum, macroeconomic conditions, and monetary policy. We show that it is essential to follow a rich set of variables of various types to assess the underlying dynamics of connectedness that are not readily observable. Momentum, on-chain activity, off-chain activity, and financial and economic factors of the non-crypto nature all play their role in explaining the connectedness dynamics. Our findings can thus be utilized, e.g., to dynamically tailor existing risk management strategies to enhance portfolio resilience for crypto investors and fund managers. Furthermore, the identified key empirical factors of connectedness can be utilized by traders to develop predictive models for significant crypto market events or to create early warning systems. Next, new DeFi or blockchain-based instruments that dynamically adjust their risk exposure to good and bad volatility can be developed by financial innovators.

In addition, we propose a somewhat unconventional approach to understanding and explaining connectedness and its asymmetry in the crypto market. The conventional method involves identifying factors influencing returns and risk premiums. We concentrate on explaining connectedness and its asymmetry, aiming to uncover and clarify the drivers behind it 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 empirically driven modeling approach can be integrated by regulatory authorities once cryptocurrencies become more standardized financial products, which now seems to be only a matter of time. Moreover, our main results may offer a valuable approximation for understanding the deeper dynamics of traditional assets. The aggressive policies of the U.S. Securities and Exchange Commission 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 aspect is particularly intriguing within the emerging asset pricing literature in the cryptocurrency domain, especially in the context of calculating risk premia. However, we leave the exploration of this application as a potential avenue for future research.

CRediT authorship contribution statement

Jan Sila: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Evzen Kocenda:** Writing – review & editing, Writing – original draft, Validation, Supervision, Methodology, Investigation, Conceptualization. **Ladislav Kristoufek:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Jiri Kukacka:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Baruník and Ellington (2020) and Baruník and Ellington (2024) provide a package `DynamicNets.jl` in `Julia` used in this study to estimate dynamic horizon-specific networks. The package is available at https://github.com/barunik/DynamicNets.jl. The empirical dataset collected and analyzed during the current study was downloaded from the Binance Historical Market Data repository at www.binance.com/en/landing/data, from CoinMetrics: www.coinmetrics.io, from the St. Louis Federal Reserve database: www.fred.stlouisfed.org, from www.investing.com, from www.spglobal.com, and from www.policyuncertainty.com as specified in Section 4. All the data is publicly available.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the authors used the paraphrasing tool QuillBot and the generative AI system ChatGPT-3.5 in order to improve readability and language. After using this tool/service, the authors reviewed and edited the content as needed and took full responsibility for the content of the publication.

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Appendix A. Descriptive statistics

See Tables A.2–A.8.

Table A.2
Descriptive statistics of the RV time series for individual crypto assets. Based on a daily dataset covering the period from July 5, 2019, to May 31, 2024, i.e., 1793 observations. For the ADF tests, we report test statistics, and in all cases, the null hypothesis of unit root presence in the series is rejected at the 99% confidence level. We also report test statistics for the Zivot-Andrew test with a null hypothesis of series having a unit root with a single structural break in the last row, and the null hypothesis is also always rejected at the 99% confidence level.

	mean	std	max	min	skewness	kurtosis	median	ADF test	ZA test
ADA	0.003	0.010	0.32	0.0	21.91	665.71	0.0	−11.65	−12.52
BNB	0.002	0.007	0.17	0.0	14.78	302.66	0.0	−11.03	−11.75
BTC	0.001	0.004	0.11	0.0	18.34	455.61	0.0	−11.43	−12.96
DOGE	0.006	0.028	0.88	0.0	20.69	578.21	0.0	−5.27	−6.06
ETH	0.002	0.006	0.16	0.0	18.08	443.41	0.0	−10.54	−11.24
LTC	0.003	0.007	0.17	0.0	14.99	322.73	0.0	−11.49	−12.47
TRX	0.002	0.007	0.15	0.0	13.71	260.41	0.0	−12.01	−13.18
XRP	0.004	0.010	0.21	0.0	10.55	164.60	0.0	−5.55	−7.30

Table A.3
Descriptive statistics of the positive realized semivariances (RS^{+}) from Eq. (4). Based on a daily dataset covering the period from July 5, 2019, to May 31, 2024, i.e., 1793 observations. For the ADF tests, we report test statistics, and in all cases, the null hypothesis of unit root presence in the series is rejected at the 99% confidence level. We also report test statistics for the Zivot-Andrew test with a null hypothesis of series having a unit root with a single structural break in the last row, and the null hypothesis is also always rejected at the 99% confidence level.

	mean	std	max	min	skewness	kurtosis	median	ADF test	ZA test
ADA	0.002	0.005	0.16	0.0	22.17	664.94	0.0	−11.50	−12.39
BNB	0.001	0.003	0.10	0.0	16.76	384.72	0.0	−11.09	−11.79
BTC	0.001	0.002	0.07	0.0	22.78	687.17	0.0	−11.50	−12.13
DOGE	0.003	0.015	0.47	0.0	21.09	591.62	0.0	−5.31	−6.12
ETH	0.001	0.003	0.08	0.0	19.67	496.06	0.0	−10.48	−11.18
LTC	0.001	0.003	0.08	0.0	15.62	345.54	0.0	−11.32	−12.44
TRX	0.001	0.003	0.08	0.0	14.71	290.47	0.0	−12.48	−16.32
XRP	0.002	0.005	0.10	0.0	10.79	172.75	0.0	−5.15	−6.87

Table A.4
Descriptive statistics of the negative realized semivariances (RS^{-}) from Eq. (5). Based on a daily dataset covering the period from July 5, 2019, to May 31, 2024, i.e., 1793 observations. For the ADF tests, we report test statistics, and in all cases, the null hypothesis of unit root presence in the series is rejected at the 99% confidence level. We also report test statistics for the Zivot-Andrew test with a null hypothesis of series having a unit root with a single structural break in the last row, and the null hypothesis is also always rejected at the 99% confidence level.

	mean	std	max	min	skewness	kurtosis	median	ADF test	ZA test
ADA	0.002	0.005	0.16	0.0	20.90	625.71	0.0	−12.81	−13.65
BNB	0.001	0.003	0.07	0.0	13.03	234.01	0.0	−11.07	−11.79
BTC	0.001	0.002	0.04	0.0	14.91	290.70	0.0	−12.22	−12.82
DOGE	0.003	0.013	0.41	0.0	19.87	541.79	0.0	−5.25	−6.02
ETH	0.001	0.003	0.08	0.0	16.20	374.00	0.0	−10.71	−11.41
LTC	0.002	0.004	0.11	0.0	15.90	375.23	0.0	−9.90	−10.76
TRX	0.001	0.003	0.09	0.0	14.28	292.16	0.0	−11.89	−13.08
XRP	0.002	0.005	0.11	0.0	11.08	177.13	0.0	−5.66	−7.35

Table A.5
Descriptive statistics of the explanatory variables for Eq. (12). Based on a daily dataset covering the period from July 7, 2019, to May 31, 2024, i.e., 1791 observations. ZA test is the test statistic for the Zivot-Andrews test with a null hypothesis of series having a unit root with a single structural break, and ZA_{pval} is the p-value of the respective test.

	mean	std	min	median	max	ZA test	ZA_{pval}
$Momentum_{BTC}$	0.00	0.06	−0.53	0.00	0.22	−11.99	0.00
$Momentum_{ETH}$	0.00	0.08	−0.67	0.01	0.32	−12.19	0.00
$Momentum_{Alts}$	0.00	0.07	−0.45	0.00	0.47	−11.27	0.00
$\log(Addresses)_{BTC}$	13.70	0.16	13.14	13.73	14.13	−3.63	0.60
$\log(Addresses)_{ETH}$	13.10	0.26	12.18	13.15	14.22	−3.70	0.54
$\log(Fees)_{BTC+ETH}$	1.96	1.23	−1.01	1.99	5.31	−4.57	0.10
$\log(Inflow)_{BTC+ETH}$	20.56	0.90	18.09	20.65	22.90	−4.21	0.23
$\log(Outflow)_{BTC+ETH}$	20.63	0.90	18.10	20.72	22.91	−4.21	0.23
$\log(Velocity)_{BTC}$	4.49	0.54	2.72	4.46	6.07	−6.05	0.00
$\log(Velocity)_{ETH}$	3.99	0.57	1.42	4.03	5.52	−5.42	0.01
$\log(HashRate)$	19.09	0.60	17.79	18.98	20.40	−5.97	0.00
$\log(Volume)_{BTC}$	11.03	0.77	9.10	10.91	13.54	−5.12	0.02
$\log(Volume)_{ETH}$	13.16	0.66	10.98	13.15	15.36	−4.55	0.11
$\log(Volume)_{Alts}$	21.61	0.82	19.49	21.51	25.56	−5.30	0.01
$\log(Trades)_{BTC}$	14.08	0.85	12.16	14.01	16.54	−5.96	0.00
$\log(Trades)_{ETH}$	13.24	0.82	11.08	13.38	15.53	−4.51	0.12
$\log(Trades)_{Alts}$	13.82	0.99	11.34	13.80	17.01	−4.71	0.07
$\log(SP500)$	8.27	0.17	7.71	8.31	8.58	−4.58	0.10
$\log(VIX)$	2.99	0.33	2.45	2.97	4.42	−4.69	0.07
$BEInflation$	2.12	0.44	0.50	2.28	3.02	−4.19	0.24
IR	−0.11	1.70	−3.22	0.48	1.70	−4.02	0.34
$\log(EPU)$	4.92	0.61	2.39	4.87	6.93	−3.96	0.38
$\log(BalticDry)$	7.39	0.50	5.97	7.43	8.64	−4.11	0.29
$\log(Gold)$	7.50	0.10	7.24	7.51	7.79	−3.39	0.75
$\log(GSCI)$	6.22	0.26	5.43	6.30	6.71	−3.13	0.87

Table A.6
Correlations of the daily RV time series based on the granularity of the underlying log returns for individual crypto assets. Based on a daily dataset covering the period from July 5, 2019, to May 31, 2024, i.e., 1793 observations.

ADA	5-min	15-min	30-min	60-min	BNB	5-min	15-min	30-min	60-min
5-min	1.00	0.94	0.89	0.91	5-min	1.00	0.97	0.96	0.92
15-min	0.94	1.00	0.97	0.93	15-min	0.97	1.00	0.95	0.89
30-min	0.89	0.97	1.00	0.95	30-min	0.96	0.95	1.00	0.97
60-min	0.91	0.93	0.95	1.00	60-min	0.92	0.89	0.97	1.00
BTC	5-min	15-min	30-min	60-min	DOGE	5-min	15-min	30-min	60-min
5-min	1.00	0.98	0.93	0.88	5-min	1.00	0.98	0.96	0.97
15-min	0.98	1.00	0.95	0.91	15-min	0.98	1.00	0.98	0.98
30-min	0.93	0.95	1.00	0.97	30-min	0.96	0.98	1.00	0.99
60-min	0.88	0.91	0.97	1.00	60-min	0.97	0.98	0.99	1.00
ETH	5-min	15-min	30-min	60-min	LTC	5-min	15-min	30-min	60-min
5-min	1.00	0.92	0.88	0.84	5-min	1.00	0.95	0.95	0.93
15-min	0.92	1.00	0.96	0.92	15-min	0.95	1.00	0.96	0.94
30-min	0.88	0.96	1.00	0.97	30-min	0.95	0.96	1.00	0.96
60-min	0.84	0.92	0.97	1.00	60-min	0.93	0.94	0.96	1.00
TRX	5-min	15-min	30-min	60-min	XRP	5-min	15-min	30-min	60-min
5-min	1.00	0.93	0.91	0.89	5-min	1.00	0.93	0.90	0.89
15-min	0.93	1.00	0.92	0.88	15-min	0.93	1.00	0.94	0.91
30-min	0.91	0.92	1.00	0.96	30-min	0.90	0.94	1.00	0.95
60-min	0.89	0.88	0.96	1.00	60-min	0.89	0.91	0.95	1.00

Appendix B. Net spillover positions and fitted models

See Fig. B.4.

Table A.7
Descriptive statistics of the total connectedness (S^H), spillovers from volatility due to positive returns (S^+) and spillovers from volatility due to negative returns (S^-). Based on a daily dataset covering the period from July 7, 2019, to May 31, 2024, i.e., 1791 observations. For the ADF tests, we report test statistics, and in all cases, the null hypothesis of unit root presence in the series is rejected at the 99% confidence level. We also report test statistics for the Zivot-Andrew test with a null hypothesis of series having a unit root with a single structural break in the last row, and the null hypothesis is also always rejected at the 99% confidence level.

	mean	std	max	min	skewness	kurtosis	median	ADF test	ZA test
S^H	47.37	21.49	87.26	17.37	0.30	1.76	45.71	−5.80	−7.41
S^+	41.71	20.70	87.16	17.23	0.67	2.24	36.54	−5.17	−6.62
S^-	51.43	21.45	87.25	17.15	0.08	1.65	52.04	−6.09	−7.53

Table A.8
Descriptive statistics of the net position of the directional spillover index (S^H), that is the top panel from Fig. B.4. Based on a daily dataset covering the period from July 7, 2019, to May 31, 2024, i.e., 1791 observations. For the ADF tests, we report test statistics, and in all cases, the null hypothesis of unit root presence in the series is rejected at the 99% confidence level. We also report test statistics for the Zivot-Andrew test with a null hypothesis of series having a unit root with a single structural break in the last row, and the null hypothesis is also always rejected at the 99% confidence level.

	mean	std	max	min	skewness	kurtosis	median	ADF	ZA test
ADA	0.10	0.77	2.70	−2.07	0.53	3.79	−0.05	−5.63	−6.57
BNB	−0.18	0.70	1.55	−2.73	−0.66	4.67	−0.13	−7.10	−7.59
BTC	0.24	0.75	2.97	−2.65	0.27	4.35	0.06	−6.46	−7.01
DOGE	−0.83	1.07	3.79	−4.56	−0.43	5.15	−0.51	−8.14	−9.08
ETH	0.28	0.83	2.84	−2.31	0.26	3.98	0.08	−6.10	−7.18
LTC	0.36	1.00	3.47	−4.27	−0.54	6.27	0.14	−6.44	−6.63
TRX	−0.07	0.88	2.99	−2.72	0.59	3.82	−0.15	−6.11	−8.72
XRP	−0.10	0.96	2.77	−4.75	−0.42	6.02	−0.10	−5.98	−6.61

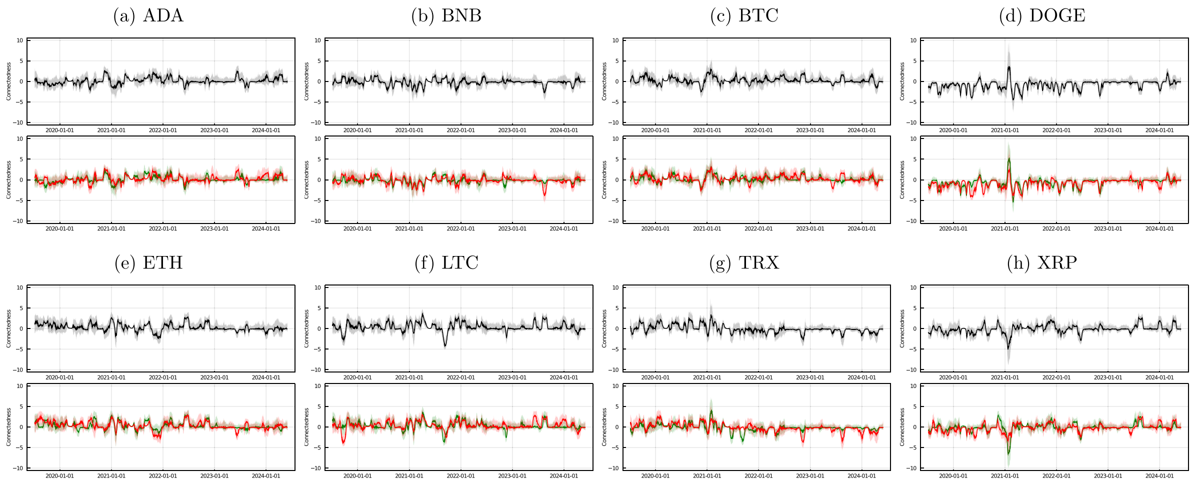

Fig. B.4. Net spillover positions of individual crypto assets.The top panels show the net directional spillover index and the bottom panels show the net directional position for the positive and negative spillover index.

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