DNB Working Paper
No 846/November 2025

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EUROSYSTEEM

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* Views expressed are those of the author and do not necessarily reflect official positions of De Nederlandsche Bank.

Working Paper No. 846

November 2025

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An econometric investigation on the stability of stablecoins: Are these coins stable or is their stability just a flip of the coin?
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October 31, 2025

Abstract

This paper investigates the volatility dynamics of USD-backed stablecoins, challenging the assumption of inherent stability. Using a multi-level econometric framework, including GARCH, SVAR, and TVP-VAR models, we analyze how stablecoins respond to macro-financial shocks such as monetary policy changes, market uncertainty, and crypto volatility. Results show that USDC and TUSD are highly sensitive to external disturbances, while USDT and DAI remain relatively resilient. Stablecoins primarily absorb volatility but become more connected to systemic risk during crises. Frequency-domain analysis reveals short-term spillovers dominate during stress events, with long-term integration increasing post-2021. The findings highlight the heterogeneous nature of stablecoins and their growing ties to traditional finance, underscoring the need for tailored regulation and ongoing monitoring to mitigate systemic vulnerabilities.

Keywords:stablecoins, volatility, financial markets, monetary policy.
JEL classifications: F31, G14, E42, E58.

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1 Introduction

Stablecoins are digital assets designed to maintain a stable value by being pegged to a reserve asset, such as fiat currencies (e.g. USD), commodities (e.g. gold) or other financial instruments (e.g. crypto-assets). Since their inception in 2014, their role in the global financial ecosystem has grown markedly, offering potential benefits such as faster and cheaper cross-border payments, enhanced financial inclusion, and increased transactional efficiency. Unlike traditional cryptocurrencies, which are characterized by high volatility, stablecoins aim to combine the operational efficiency of digital assets with the perceived reliability of sovereign money. Central banks and regulatory authorities play a dual role in the evolving stablecoin ecosystem.[1] First, they serve as financial stewards, seeking to ensure that stablecoin activity does not undermine monetary policy transmission, financial stability, or consumer protection. Second, many central banks are actively exploring or piloting Central Bank Digital Currencies (CBDCs) as a digital evolution of cash, with the aim of preserving monetary sovereignty.

Despite their name, stablecoins are not inherently stable. Functionally, their issuers often operate in a manner analogous to deposit-taking institutions: they issue digital tokens in exchange for fiat currency and hold a portfolio of reserve assets on the other side of their balance sheet. These reserves may include cash, government securities, commercial paper, and in some cases, other digital assets. The viability of a stablecoin's peg is contingent upon the liquidity, credit quality, and transparency of these underlying assets. The structural parallels with traditional banks imply that stablecoins are subject to similar fragility, especially in times of market stress, liquidity constraints, or waning investor confidence.[2]

This fragility is exemplified by the collapse of TerraUSD in May 2022, when the algorithmic stablecoin lost its peg and fell to \$0.35, sparking widespread instability across crypto markets. By contrast, fiat-collateralized stablecoins such as USD Tether (USDT) and USD Coin (USDC) claim to maintain a 1:1 peg to the U.S. dollar through reserves composed of high-quality liquid assets (HQLA). However, questions remain regarding

[1] see e.g. Cengiz (2025) for a view on stablecoins and their regulations. Also the stablecoin Mica regulation plays a role in this new type of asset, see e.g. Nadal (2025).

[2] e.g. Ferreira (2021) look at the risks and rewards in stablecoin.

the composition, transparency, and auditability of these reserves. The failures of Silicon Valley Bank and the forced merger of Credit Suisse in 2023 highlight the potential for even regulated financial institutions to destabilize markets, raising critical questions about whether similarly structured stablecoin issuers could pose systemic risks if left inadequately regulated. It should be noted that the issuers of stablecoins are not limited to Fintech companies but also include a growing number of traditional financial institutions which could see these digital assets become even more widespread across the banking and financial industry. This is clearly illustrated by Table 1, which provides an overview of traditional financial institutions either exploring or issuing a stablecoin.

This paper investigates the key drivers of volatility in major USD-backed stablecoins. To this end, we adopt a multi-level econometric approach that captures both market-driven and policy-driven volatility dynamics. First, we estimate GARCH models to identify volatility clustering and persistence within individual stablecoin returns. Second, to evaluate the impact of U.S. monetary policy shocks on stablecoin dynamics, we employ a structural vector autoregression (SVAR) framework. Our analysis is based on the Crypto Compare Index (CCIX), covering four prominent stablecoins spanning a four-year period sufficient to cover several systemic episodes including the COVID-19 pandemic, rising global interest rates, and multiple stablecoin failures—providing a unique opportunity to assess stablecoin resilience under stress. This paper examines both endogenous drivers of volatility within the crypto ecosystem, using Bitcoin as a proxy for the crypto market, and exogenous drivers arising from broader macroeconomic and policy conditions, such as U.S. and European equity markets, monetary policy rates, and economic policy uncertainty indices.

The academic literature on stablecoins is still nascent. Despite stablecoins having existed since 2014 and their use gaining traction since 2019, the academic literature on stable coins started around 2019 as illustrated in systematic reviews by Moura de Carvalho et al. (2025) and Ante et al. (2023). Moura de Carvalho et al. (2025) provide a comprehensive literature review on stablecoins, highlighting regulatory gaps and the need for clearer governance and transparency to ensure long-term stability. Ante et al. (2023) identified only 22 journal articles dedicated to stablecoins, which they categorized into three primary research clusters: (1) the design, stability, and safe-haven properties

Table 1: Traditional financial institutions exploring or issuing stablecoins.

Institution	Stablecoin Project	Intended Use or Purpose
J.P. Morgan Chase	*JPM Coin*	Permissioned USD-backed token for interbank settlement and institutional client payments on J.P. Morgan's Onyx blockchain network.
Fiserv	*FIUSD*	Stablecoin designed for use by banks, merchants, and financial institutions to enable faster payments and on-chain settlement within regulated networks.
Bank of America, Citigroup, Wells Fargo (U.S. consortium)	*U.S. Bank Stablecoin Initiative*	Proposed consortium-backed dollar stablecoin to streamline large-value interbank transfers and compete with private stablecoins.
Standard Chartered	*HKD Stablecoin JV*	Joint venture in Hong Kong to issue a Hong Kong dollar-backed stablecoin under the city's new licensing regime for tokenized deposits.
European Bank Consortium (ING, Banca Sella, KBC, Danske Bank, DekaBank, UniCredit, SEB, CaixaBank and Raiffeisen Bank International)	*Euro Stablecoin Project*	Euro-denominated stablecoin initiative aligned with the EU's MiCA framework, aimed at cross-border settlement and tokenized deposit interoperability.
Bank of North Dakota	*Roughrider Coin*	State-backed U.S. dollar stablecoin pilot for domestic bank and credit union payments and liquidity management.
Early Warning Services (Zelle Network)	*Zelle Stablecoin (under exploration)*	Retail-focused stablecoin to enhance instant payment functionality within the Zelle network and banking partners.

of various stablecoins; (2) interlinkages between stablecoins and broader crypto markets; and (3) interactions between stablecoins and traditional macroeconomic variables. Kosse et al. (2023) questions the true stability of various stablecoin models and emphasizes the importance of distinguishing between design types when assessing systemic risk. Thanh et al. (2023) find that the price stabilities of major stablecoins are interconnected, suggesting systemic vulnerabilities in the broader crypto ecosystem. Grobys et al. (2021) investigate how collateralization affects stablecoin stability, concluding that overcollateralization improves resilience but does not eliminate volatility. Sood and Feng (2023) explores algorithmic stablecoin designs and identifies key risks such as feedback loop failures and insufficient demand elasticity that can lead to collapse. Our paper is also linked to the depegging risk of stablecoins, see for example Lee et al. (2025) who look at the depegging risk using both econometrics (logistic regression) and machine learning (random forest and XGBoost). Their findings show significant fluctuations in Bitcoin and Ethereum volatility influence the depegging risk of stablecoins

In addition to the academic contribution, this research has important policy implications. By quantifying the volatility spillovers and sensitivities of stablecoins to macro-financial stressors (stock markets, monetary policy and economic policy), our findings can inform future regulatory frameworks such as those outlined by The Office of the Superintendent of Financial Institutions (OSFI) and the Basel Committee. In particular, they provide empirical grounding for risk-based capital treatment, reserve composition standards, and liquidity requirements for institutions exposed to stablecoins either directly or indirectly. As regulators grapple with integrating digital assets into traditional prudential regimes, rigorous empirical analysis remains essential for understanding the stability, or instability, of these emerging instruments.

The paper is organized in the following way. Section 2 describes the data used and their features. Section 3 provides the econometric models used to explain the volatility drivers of the stablecoins. Section 4 gives the results and section 5 concludes.

2 Data

2.1 Stablecoin and cryptoassets

We use stablecoin data from the CryptoCompare Data Aggregated Index (CCIX), previously known as CCCAGG (CryptoCompare Coin Comparison Aggregated Index), see CCData (2025).[3] This index provides a real-time price benchmark designed to offer the most accurate valuation for cryptocurrency traders and investors at any given time. The

[3]This in contrast to Bewaji et al. (2024) how looked at arbitrage opportunities between exchanges.

CCIX employs a comprehensive and well documented and version-controlled methodology that includes a 24-hour volume-weighted average price, a time-based penalty factor, and an outlier detection mechanism to ensure data reliability. It consolidates trading data from over 250 cryptocurrency exchanges, calculating a volume-weighted average over a 24-hour period. The index is computed individually for each cryptocurrency in all trading pairs and markets in which it is listed (e.g., CCIX BTC-USD). The time stamp of this data set is on the minute basis, which makes it very granular. Although our data sets range from 2013 to May 2024, we only include the period starting at January 2020, given the limited number of active stablecoins before that. The data variables we use from their dataset are: date and time (UNIX timestamp), coin from and to, converted volume trade from and to this coin, and close price per minute (exchange rate of the coins).

The coin pairs we look at are: 1) $\mathrm{USDT-USD}$, $\mathrm{USDC-USD}$, $\mathrm{DAI-USD}$ and $\mathrm{TUSD-USD}$. The choice of coins is based on 1) their market capitalization (USDT, USDC by far the largest) and 2) the availability of a full date set for the whole period ranging from January 2020 to December 2023. We also include Bitcoin ($\mathrm{BTC-USD}$) and Ethereum ($\mathrm{ETH-USD}$) in our analysis to compare with traditional cryptoassets. For the econometric analyses, we focus on the pricing per day and use the closing price of the last minute of the day (23:59). This is consistent with the CCIX time convention which treats Day Close as 12:00 am UTC (CCData, 2025). As a consequence, our closing price data will differ from the daily close price available at other sources of market data such as CoinMarketCap, which for example uses 8:00 pm UTC.

2.2 Macroeconomic

With respect to macroeconomic and financial/capital markets data, we leverage multiple sources. The financial markets data is covered in section 2.2.1. Macroeconomic and US monetary policy rates are covered in section 2.2.2. This enables us to assess the capital markets and real economy drivers of volatility in stablecoins and cryptoassets. This is particularly important because regulators such as the OSFI release guidelines on the on-/off-balance sheet holdings of these assets by banks and insurance companies. It also impacts the cost of funding these holdings through funds transfer pricing and the impact on, among other things, their liquidity stress] testing, liquidity coverage ratio, and net stable funding.

2.2.1 Capital Markets

The following American and European stock markets are included in our analysis.

- Individual Exchanges:
  - S&P 500: Gauge of large-cap U.S. equities. The index includes 500 leading companies and covers approximately 80% of the available market capitalization.
  - FTSE100: The Financial Times Stock Exchange 100 Index tracks the United Kingdom's top 100 companies
  - CAC40: The CAC 40 is the benchmark French stock market index representing a capitalization-weighted measure of the 40 most significant stocks among the 100 largest market cap companies traded on Euronext Paris
  - DAX: Deutscher Aktienindex is the German stock market index consisting of the 40 major German blue chip companies trading on the Frankfurt Stock Exchange
- Market indices:
  - DXY: Index that measures the value of the US dollar against a weighted basket of six major currencies (EUR, JPY, GBP, CAD, SEK, and CHF). This is typically used as a measure of risk sentiment in the FX markets. An increase in DXY would typically suggest a flight to safety.
  - VIX: Real-time market index that captures the anticipation of volatility in the S&P500 index. It functions as a gauge of risk sentiment in the markets.
  - CDX IG CDSI GEN 5Y Corp: Credit default swap index that tracks investment-grade corporate credit in North America. This functions as a measure of credit risk appetite in the American capital markets

- ITRX EUR CDSI GEN 5Y Corp: iTraxx Europe Credit Default Swap Index for investment-grade European corporate debt, with 5-year maturity denominated in Euros, which basically captures the overall market stability. This functions as a measure of credit risk appetite in European capital markets.

We obtain these from the S&P Capital IQ Pro service, which is a financial industry platform for comprehensive financial data, analytics, and market intelligence, used to support informed decision making and strategy formulation in capital markets. These data are used to assess the impact of market sentiment, market stress, and risk appetite on the volatility of stablecoins. All macroeconomic and financial market data are obtained at daily frequency and aligned with the cryptoasset data using forward fill in case of missing data. No further transformations are applied unless otherwise specified in the model descriptions.

2.2.2 US monetary policy rates

Besides the pricing information on stablecoins, cryptoassets, and capital market activity, we also use macroeconomic data to assess the influence of monetary policy on the volatility of stablecoins. We include data on the monetary policy rates of the United States, as we look at US dollar backed stablecoins. This enables us to capture the impact of the real economy and economic policy on the volatility of the price of stablecoins.

- CBOT 30-day federal funds futures: Futures contracts traded on the Chicago Board of Trade (CBOT) by investors looking to hedge against or speculate on changes in short-term interest rates. This captures market expectations of interest rates and cost of raising liquidity

- DFF Index: The Federal Funds Effective Rate (DFF) is a key macroeconomic index that represents the interest rate at which depository institutions lend federal funds to each other overnight, It can be considered the risk free rate and the minimum cost of liquidity in the financial sector.

- Economic Policy Uncertainty Index (EPU): An economic uncertainty index developed by Baker et al. (2016), is based on the frequency of newspaper coverage that proxies the movements in policy-related economic uncertainty. The index captures expectations of outcomes in stock price volatility, investment, and employment rates in policy-sensitive sectors like defense, healthcare, and infrastructure construction.

2.3 Data preparation and statistics

Figure 1 presents the correlation structure among the key macro-financial and market variables included in the analysis. The matrix reveals strong positive correlations among major equity indices (CAC40, DAX, DJI, FTSE, and S&P 500), indicating that global equity markets tend to move together and share substantial common risk factors. This pattern reflects the high degree of international market integration and the tendency for volatility shocks to propagate quickly across equity benchmarks.

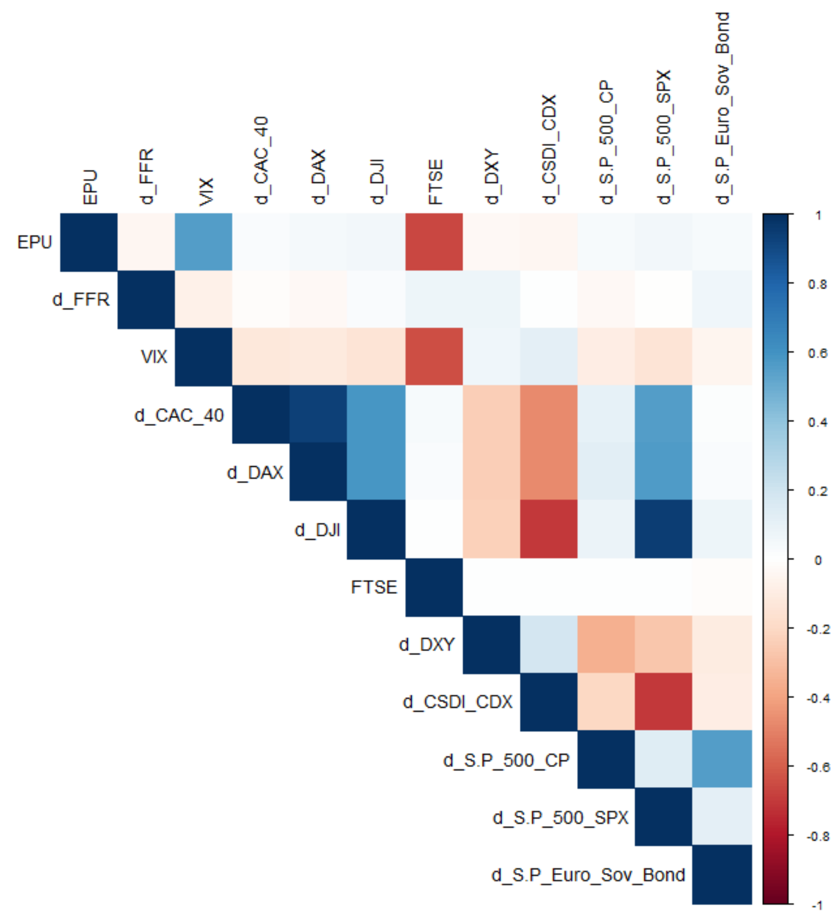


Figure 1: Data correlation matrix.

In contrast, volatility and risk-aversion measures such as the VIX, the U.S. Dollar Index

(DXY), and the Economic Policy Uncertainty (EPU) index exhibit negative correlations with equities, consistent with their roles as indicators of financial stress. When market uncertainty rises or risk aversion increases, equity prices typically fall while safe-haven assets appreciate. Similarly, the S&P Euro Sovereign Bond Index shows mild negative correlations with equities and positive associations with volatility and uncertainty measures, reflecting its defensive characteristics during periods of market turmoil.

The correlations of policy-related variables such as the Federal Funds Rate (FFR) and EPU with asset returns are generally weaker, suggesting that these variables operate through distinct channels that may not be fully reflected in contemporaneous market movements. This distinction underscores their importance for analyzing stablecoin price volatility, as policy uncertainty and interest rate changes can affect funding costs, investor sentiment, and liquidity conditions even when traditional market indexes remain stable.

Overall, the correlation structure indicates that global risk factors–captured by broad equity and volatility indexes–explain a significant portion of the co-movement across financial markets. However, the relatively modest correlations of policy and credit-related variables imply that relying solely on market indexes would overlook important sources of variation relevant to stablecoin volatility. Incorporating measures such as the FFR, EPU, and sovereign bond returns therefore provides a more comprehensive view of how both market and policy shocks transmit to the stability of USD-backed digital assets.

In essence, given the high collinearity among equity indices and the more independent behavior of risk and policy variables, focusing on measures such as the VIX, DXY, EPU, and FFR yield greater insight into the structural drivers of stablecoin volatility than relying solely on traditional market indexes.

3 Methodology

This study employs a multi-level econometric framework to capture the volatility dynamics of USD-backed stablecoins in response to market and policy shocks. The approach integrates volatility modeling, time-varying correlation analysis, and structural causal inference to examine the interplay between stablecoins, major cryptocurrencies, and macro-financial variables. By combining univariate, multivariate, and time-varying models, we ensure that both asset-specific features and systemic interactions are appropriately captured.

3.1 Structural vector autoregression (SVAR)

To identify the effect of macro-financial shocks on stablecoin markets, we estimate a Structural VAR (Sims, 1980; Christiano et al., 1999) under two identification schemes: (i) recursive Cholesky ordering, and (ii) heteroskedasticity-based identification using GARCH errors (Normadin and Phaneuf, 2004; Lanne and Saikkonen, 2007). The reduced form is given by:

$$y_t = \sum_{i=1}^{p} \Phi_i y_{t-i} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma_\varepsilon), \tag{1}$$

while the structural form is:

$$A_0 y_t = \sum_{i=1}^{p} A_i y_{t-i} + u_t, \quad u_t \sim \mathcal{N}(0, I), \tag{2}$$

with $B = A_0^{-1}$ mapping reduced-form residuals to orthogonal shocks.

The vector $\mathbf{y}_t$ is specified in stationary form: return series and macro variables are included in levels where appropriate, while the federal funds rate is differenced to ensure stationarity.

Under GARCH identification, structural shocks are assumed to follow independent GARCH(1,1) processes:

$$\sigma_{k,t}^2 = (1 - \gamma_k - g_k) + \gamma_k \varepsilon_{k,t-1}^2 + g_k \sigma_{k,t-1}^2, \quad k = 1, \ldots, K,$$

yielding a diagonal conditional covariance matrix $\Lambda_t = \mathrm{diag}(\sigma_{1,t}^2, \ldots, \sigma_{K,t}^2)$. The reduced-form covariance evolves as $\Sigma_t = B \Lambda_t B^\top$, allowing identification of B via maximum likelihood. Identification is feasible when Λ_t exhibits sufficient cross-series heterogeneity, ensuring at least $K - 1$ linearly independent volatility paths (Sentana and Fiorentini, 2001).

3.2 Time-varying parameter VAR

To capture evolving spillovers and structural breaks more flexibly, we estimate a TVP-VAR (Primiceri, 2005). Unlike the SVAR, the TVP-VAR allows coefficients and error variances to evolve smoothly over time, enabling the model to track shifts in spillover intensity during crises. The specification is:

$$y_t = A_t z_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, \Sigma_t), \tag{3}$$

$$\text{vec}(A_t) = \text{vec}(A_{t-1}) + \xi_t, \quad \xi_t \sim \mathcal{N}(0, \Xi_t), \tag{4}$$

where parameters evolve via a Kalman filter with forgetting factors, a technique which recursively updates estimates by combining prior beliefs with new observations, allowing smooth adaptation to structural changes. This approach is particularly well-suited for high-volatility environments like crypto currencies, where structural change is the rule rather than the exception.

3.3 Connectedness measures

From the TVP-VAR, we derive generalized forecast error variance decompositions (GFEVDs) (Diebold and Yilmaz, 2014) and connectedness indices (Diebold and Yilmaz, 2012). These measures quantify how much of each variable's forecast error variance can be explained by shocks to other variables, thereby mapping the direction and intensity of spillovers. The generalized impulse response is:

$$\text{GIRF}_{j,t}(H) = \mathbb{E}[y_{t+H}|\varepsilon_{j,t} = \delta_{j,t}, \Omega_{t-1}] - \mathbb{E}[y_{t+H}|\Omega_{t-1}], \tag{5}$$

with

$$\Psi_{j,t}(H) = \Sigma_{jj,t}^{-1/2} B_{H,t} \Sigma_t e_j. \tag{6}$$

The normalized GFEVD is:

$$\tilde{\varphi}_{ij,t}(H) = \frac{\sum_{h=0}^{H-1} \Psi_{ij,t}^2(h)}{\sum_{k=1}^{m} \sum_{h=0}^{H-1} \Psi_{ik,t}^2(h)}, \quad \sum_{j=1}^{m} \tilde{\varphi}_{ij,t}(H) = 1, \tag{7}$$

leading to the Total Connectedness Index:

$$C_t(H) = \frac{1}{m} \sum_{\substack{i,j=1 \\ i \neq j}}^{m} \tilde{\varphi}_{ij,t}(H) \times 100. \tag{8}$$

Directional and net connectedness measures are also computed:

$$C_{i,t} = C_{i\rightarrow\cdot,t}(H) - C_{i\leftarrow\cdot,t}(H), \tag{9}$$

$$C_{i\rightarrow\cdot,t}(H) = \sum_{j\neq i} \tilde{\varphi}_{ji,t}(H), \tag{10}$$

$$C_{i\leftarrow\cdot,t}(H) = \sum_{j\neq i} \tilde{\varphi}_{ij,t}(H), \tag{11}$$

$$\mathrm{NPDC}_{ij,t}(H) = \big(\tilde{\varphi}_{ji,t}(H) - \tilde{\varphi}_{ij,t}(H)\big) \times 100. \tag{12}$$

The TCI thus reflects overall systemic connectedness, while directional measures reveal which assets act as net transmitters or receivers of shocks, providing a detailed map of systemic risk flows.

3.4 Diagnostics and robustness

Finally, we ensure validity through standard diagnostics. Stationarity, structural breaks, and conditional heteroskedasticity are tested using ADF, KPSS, Bai-Perron, and ARCH-LM tests. Robustness checks include varying lag orders, prior choices, and rolling windows. Together, these confirm that our results are not artifacts of specific model assumptions but reflect persistent features of stablecoin-macro-financial interactions.

4 Results

This result section first conducts the impulse response to the investigated stablecoins to different types of shocks, see section 4.1. This section is followed by a dynamic connectedness analysis (section 4.2). Section 4.3 conducts a sensitivity analysis.

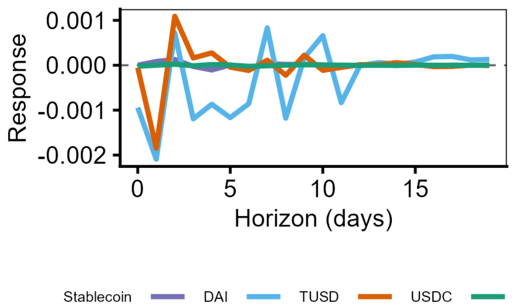
4.1 Impulse response analysis

Figure 2 presents the impulse responses of the USDT, USDC, DAI, and TUSD, to: (1) a monetary policy shock, represented by the FFR (Figure 2a and 2b), (2) economic uncertainty shock, represented by EPU (Figure 2c and 2d), (3) a financial market shock, represented by VIX and (4) shock in the crypto market, represented by Bitcoin (Figure 2e and 2f). Impulse responses are defined as the effect of an unexpected one-standard-deviation increase the respective rate, index, or price. Results are presented under the two structural identification strategies adopted: the benchmark recursive Cholesky decomposition (figures on the left hand side) and GARCH-based heteroskedasticity identification (figures on the right hand side). The recursive ordering reflects assumed contemporaneous priority, with macro-financial variables placed before crypto assets, and Bitcoin preceding stablecoins based on its dominant market role and empirical lead-lag dynamics.

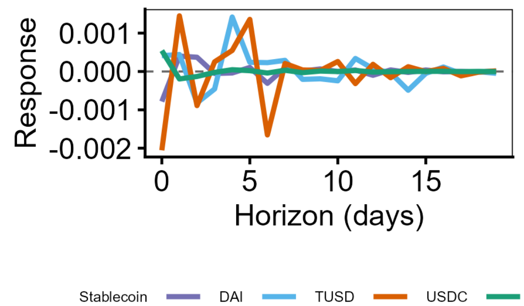
Across all four shock scenarios stablecoins exhibit heterogeneous yet short-lived impulse response patterns. USDC and TUSD consistently show the largest and most pronounced reactions in the immediate aftermath of each shock, whereas USDT remains effectively flat and DAI's movements are modest and transient. For example, a monetary policy tightening provokes an instantaneous drop in TUSD and USDC returns followed by a rapid rebound, indicating high short-run sensitivity, while USDT stays near zero and DAI registers only a mild, brief deviation. Similarly, a sudden increase in market risk (whether policy-related or equity-market volatility) causes TUSD and USDC to exhibit noticeable but short-lived spikes or oscillations, whereas USDT is essentially unresponsive and DAI shows only minor fluctuations. Importantly, these disturbances dissipate quickly: any statistically significant deviations are confined to the first few days post-shock, with stablecoin returns reverting toward baseline thereafter. These short-lived responses are consistent with the use of return-based specifications, which capture transitory deviations rather than persistent level shifts.

Notably, these relative patterns hold under both identification approaches (a standard Cholesky decomposition and a GARCH-based identification), although the GARCH-based model tends to amplify the magnitude of the initial responses without altering their direction or ordering. In both cases, USDC and TUSD emerge as the most shock sensitive coins, exhibiting the highest volatility in response to external disturbances, while USDT (and to a lesser extent DAI) remains far more resilient, showing little to no significant response. This suggests that stablecoins with lower market depth or less flexible backing structures (like TUSD and USDC) are more susceptible to abrupt economic and financial shocks, whereas the largest stablecoin, USDT, maintains a remarkably stable profile even amid substantial macroeconomic and crypto-market volatility. [4] Bootstrapped confidence intervals confirm that the statistically significant responses of TUSD and USDC are concentrated in the early days following each shock, while USDT and DAI remain within insignificance bands throughout. This reinforces the interpretation that volatility spillovers into stablecoins are transitory and coin-specific, with implications for their reliability under stress.

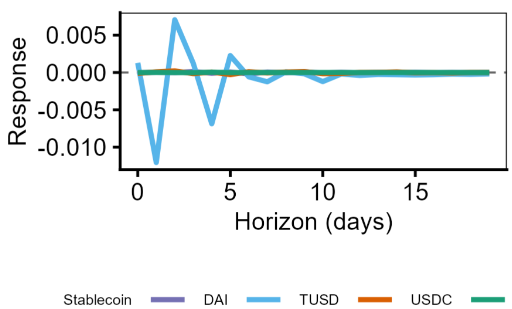
[4] Approximate 24-hour trading volumes as of October 2025: USDC $\approx$ \$9-20 billion, TUSD (TrueUSD) $\approx$ \$17-46 million, USDT (Tether) $\approx$ \$60-140 billion, and DAI $\approx$ \$150-180 million. Source: *CoinGecko* and *CoinMarketCap*, accessed October 2025.



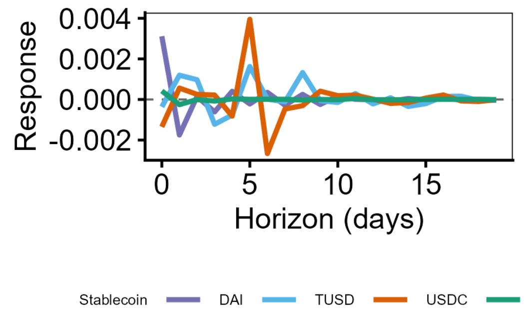
(a) IRFs to FFR (Cholesky).



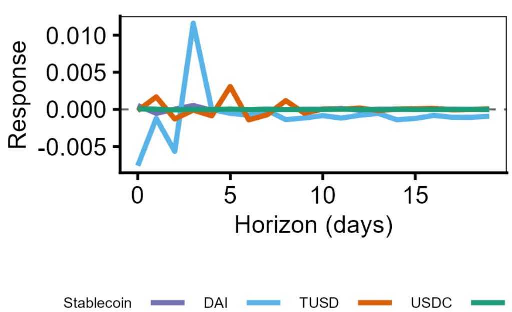
(b) IRFs to FFR (GARCH).



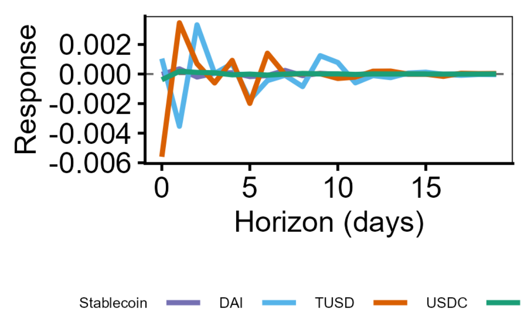
(c) IRFs to EPU (Cholesky).



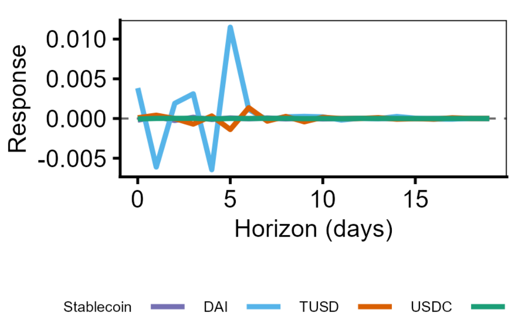
(d) IRFs to EPU (GARCH).



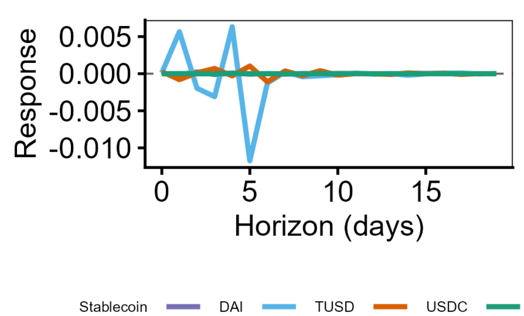
(e) IRFs to VIX (Cholesky).



(f) IRFs to VIX (GARCH).



(g) IRFs to BTC (Cholesky).



(h) IRFs to BTC (GARCH).

Figure 2: Impulse response functions to various shocks.

The observed heterogeneity in stablecoin responses has important implications for financial stability and the role of stablecoins as safe-haven assets.

The consistent insulation of USDT suggests it may function more reliably as a medium of exchange during periods of macroeconomic or market stress, reinforcing its perceived stability. In contrast, the heightened sensitivity of TUSD and USDC to various shocks, particularly in the short term, raises concerns about their vulnerability under tightening financial conditions or during episodes of heightened volatility. These dynamics underscore the need for careful monitoring of stablecoin behavior in systemic risk assessments, especially as their market roles expand.

4.2 Dynamic Connectedness Analysis

To supplement the analysis of the impulse responses of stablecoins to macro-financial factors, we assess how volatility spillovers between stablecoins and key macro-financial variables evolve over time using a TVP-VAR framework. Further, we compare these results to the connectedness analysis performed on the rolling-window VAR and end with the outcomes of the sensitivity checks to validate robustness against prior choices, window lengths, and forgetting factors.

The total connectedness index (TCI) exhibits clear temporal variation, with distinct spikes aligned to major stress events such as the COVID-19 outbreak, Federal Reserve tightening cycles, and the SVB banking crisis (Figure 3). These periods are characterized by heightened cross-asset volatility, confirming the utility of a dynamic approach.

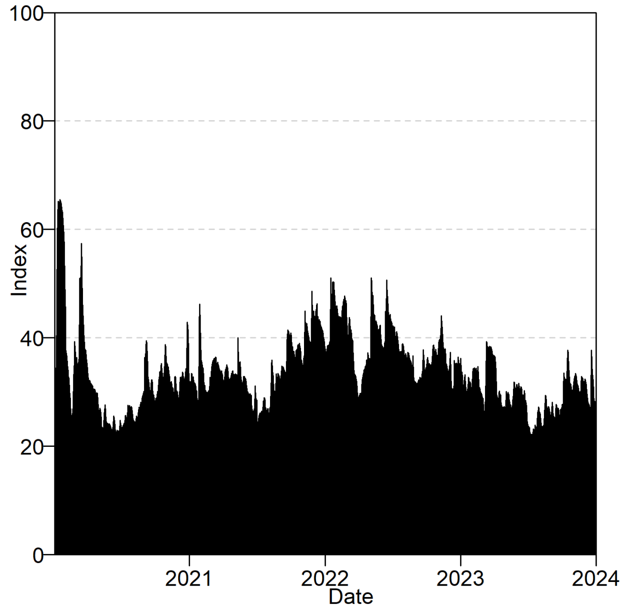


Figure 3: Total connectedness index (TVP-VAR).

Notably, connectedness surged in March 2020 as the COVID-19 pandemic triggered widespread market dislocation, demonstrating the integration of stablecoins into broader risk cycles. Additional spikes occur during periods of crypto market correction and monetary tightening, particularly in May 2021 and early 2022, when inflation fears and the Russian invasion of Ukraine heightened global uncertainty. Each instance coincides with sharp rises in the VIX and EPU indices, further amplifying cross-market contagion. The collapse of SVB and the temporary depegging of USDC in March 2023 provides a further example, as traditional banking risk directly spilled over into the stablecoin market, elevating system-wide connectedness. Overall, the TCI results provide robust evidence that stablecoins, despite their nominal price stability, become tightly linked to global risk networks during systemic episodes. Periods of calm see relatively low connectedness, but stress events rapidly propagate volatility to the stablecoin ecosystem, underscoring their susceptibility to shocks in broader macro-financial conditions.

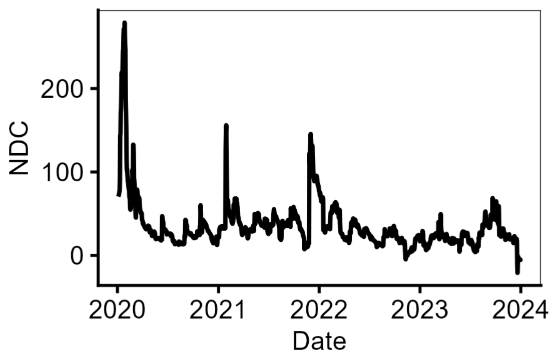
4.2.1 Net total and net pairwise directional connectedness (TVP-VAR)

In tandem, to understand the role that each variable in our system plays in volatility transmission over the sample period, we examine the time-varying net directional connectedness (NDC) and the net pairwise directional connectedness (NPDC). The NDC captures the net role of each variable as a transmitter or absorber of shocks, while the NPDC disentangles the bilateral volatility spillover patterns. Macro-financial variables, especially the VIX and Economic Policy Uncertainty (EPU) indices, consistently act as systemic volatility transmitters. The VIX exhibits pronounced peaks in early 2020, 2021, and mid-2022, confirming its forward-looking role in market stress. EPU spikes during monetary tightening and geopolitical upheavals, underscoring its systemic impact.

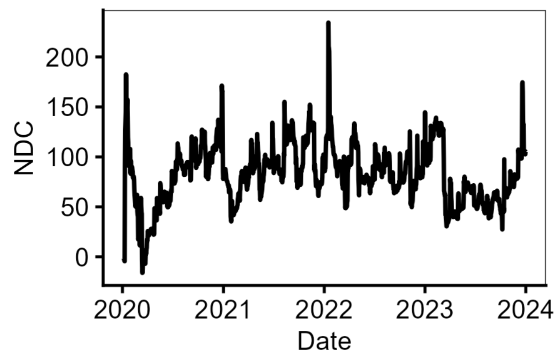
Stablecoins (USDT, USDC, DAI, and TUSD) consistently exhibit negative NDC values (Figures 4c to 4f), establishing them as net volatility absorbers, especially during stress episodes such as the COVID-19 crisis. TUSD shows higher variation and a modest upward trend, hinting at increasing integration. Bitcoin plays a regime-dependent role, switching between net receiver and mild transmitter status (Figure 4g). The Federal Funds Rate (FFR) acts as a volatility transmitter primarily during tightening cycles, with transitory effects concentrated near policy announcements (Figure 4h).

The NPDC analysis (Figure 5) reveals that VIX and EPU spillovers into stablecoins peak during major stress events, notably affecting USDC and DAI, while TUSD responses are more idiosyncratic. Volatility spillovers from FFR are detectable during rate-hike periods and prominently impact USDT and USDC. Bitcoin influences stablecoins variably, with stronger transmission to USDC and DAI, consistent with their prominent roles in crypto trading. Spillovers to USDT and TUSD are steadier and less volatile.

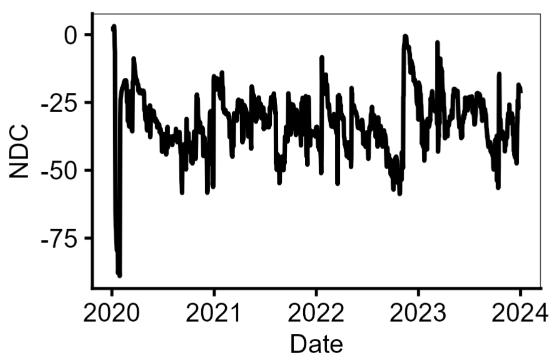
These findings reinforce a hierarchical structure of volatility spillovers: macro-financial variables dominate as volatility transmitters, while stablecoins primarily absorb shocks, rarely transmitting back. The transient and sporadic nature of stablecoin spillovers further indicates they presently lack independent systemic risk.



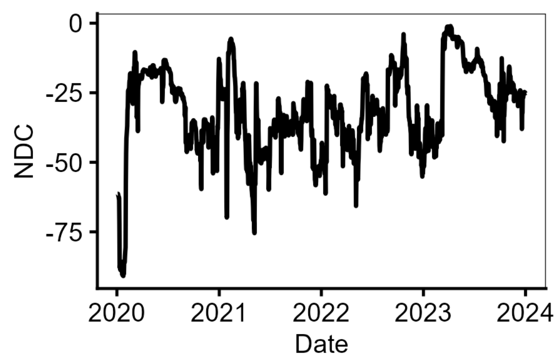
(a) VIX.



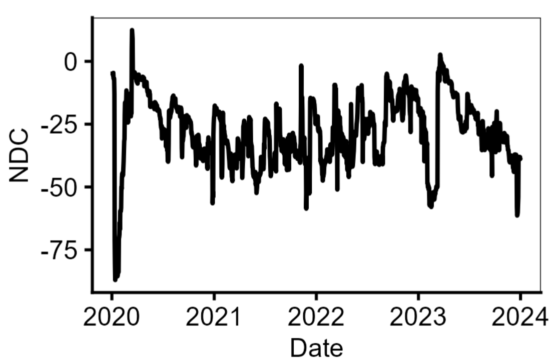
(b) EPU.



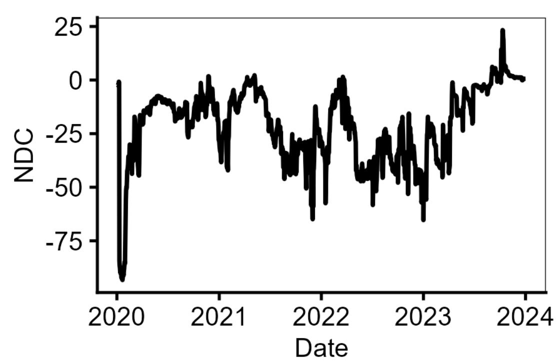
(c) USDT.



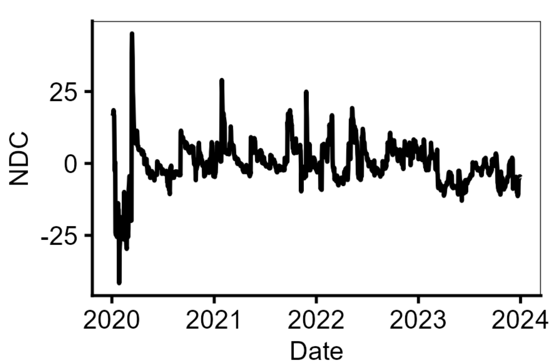
(d) USDC.



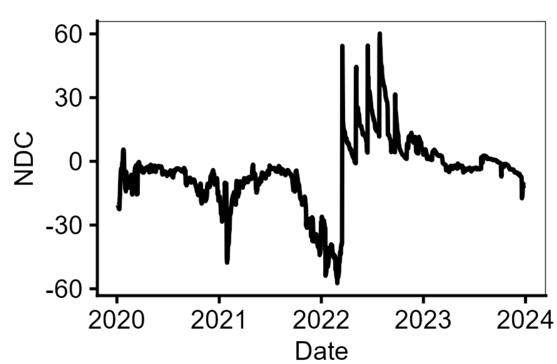
(e) DAI.



(f) TUSD.

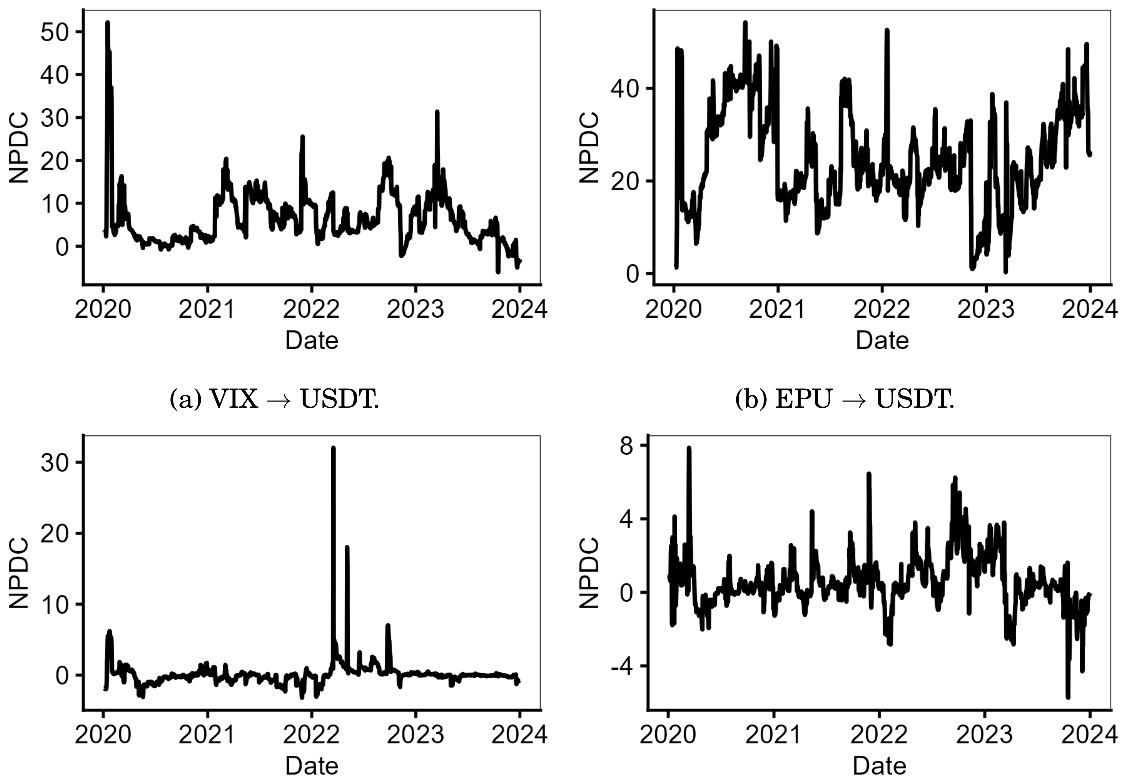


(g) Bitcoin.



(h) Differenced Federal Funds Rate.

Figure 4: Net Directional Connectedness (NDC) over time for key variables evaluated via TVP-VAR. VIX, EPU and d FFR are primary volatility transmitters. Stablecoins predominantly absorb volatility shocks. BTC acts as a regime-dependent intermediate transmitter/receiver.



(a) VIX → USDT.

(b) EPU → USDT.

(c) ΔFFR → USDT.

(d) BTC → USDT.

Figure 5: Net Pairwise Directional Connectedness (NPDC) between volatility transmitters (VIX, EPU, ΔFFR, BTC) and stablecoins (USDT). Positive values indicate net volatility spillovers from the transmitter to recipient. Scales differ to facilitate visual comparison due to heterogeneous spillover magnitudes.

4.2.2 Frequency domain connectedness

To capture horizon-specific connectedness patterns, we apply a frequency decomposition to the TVP-VAR connectedness measures, distinguishing short-term (1-2 days), medium-term (2-10 days), and long-term (10+ days) spillovers. Figures 6 and 7 illustrate the frequency-resolved total connectedness index (TCI) and net pairwise directional connectedness (NPDC).

The short-term band dominates volatility transmission during systemic shocks, notably the COVID-19 onset in March 2020, the 2021 GameStop and Crypto market events, and the March 2023 SVB failure with USDC depegging. These periods exhibit sharp short-term NPDC spikes from VIX and EPU to stablecoins, with rapid decay in longer-term bands. Similarly, intense short-term spillovers from Federal Funds Rate and Bitcoin to USDC and DAI correspond with liquidity shocks and investor repositioning post-SVB collapse.

From mid-2021 onward, long-term connectedness becomes the primary component, indicating persistent integration between stablecoins and macro-financial volatility regimes. Notably, NPDC from ΔFFR and VIX to stablecoins increases during prolonged monetary tightening and inflationary pressures, highlighting the influence of enduring macroeconomic conditions. Bitcoins spillovers to USDC and DAI also gain persistence post-2021, reflecting deeper crypto-stablecoin market integration. Medium-term spillovers, while less dominant, remain consequential during adjustment phases following shock events, signaling gradual market rebalancing.

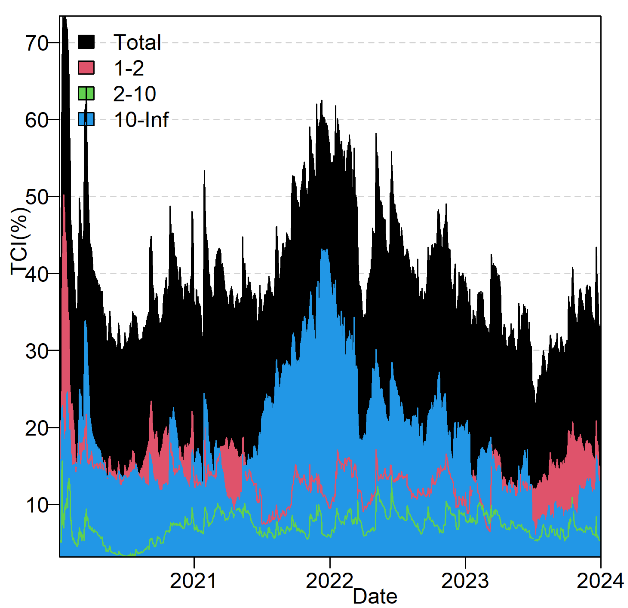
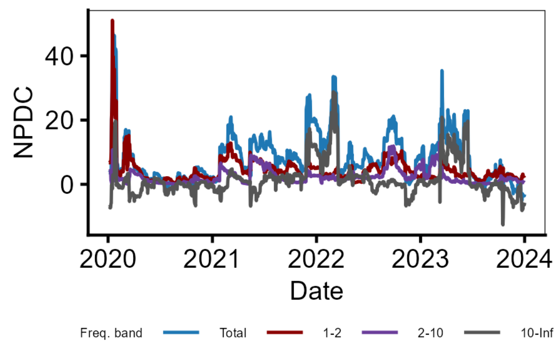
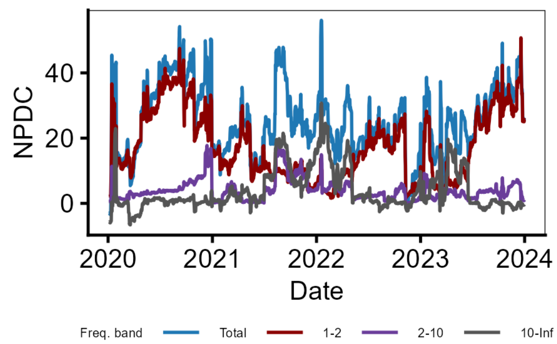


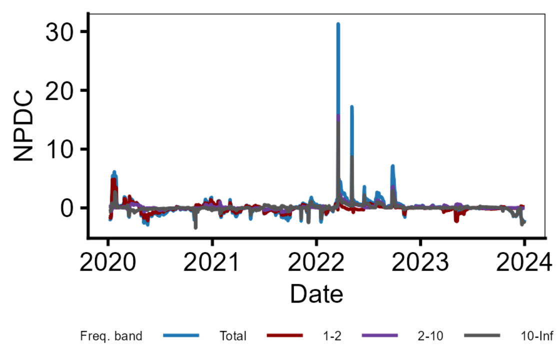
Figure 6: Frequency-Decomposed TCI via TVP-VAR. Short-term connectedness (pink) spikes during systemic crises dominate, while long-term connectedness (blue) gains prominence mid-2021 onward, indicating persistent integration.



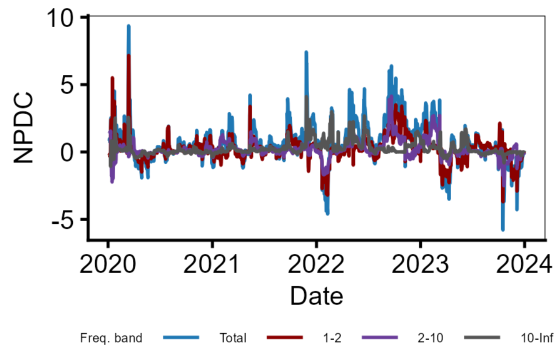
(a) VIX → USDT.



(b) EPU → USDT.



(c) ΔFFR → USDT.



(d) BTC → USDT.

Figure 7: Frequency-resolved NPDC from transmitters (VIX, EPU, ΔFFR, BTC) to USDT. Short-term spillovers dominate during crises with longer-term integration prevalent post-2021. Vertical scales differ across subfigures for clarity.

4.3 Sensitivity Analysis

We assess the robustness of our connectedness results by comparing the TVP-VAR with alternative specifications. Figure 8 compares the TCI from the TVP-VAR with rolling-window VARs (200- and 300-day windows). The rolling-window models generate smoother, generally lower TCI values and tend to lag in capturing spillover surges during stress episodes such as the COVID-19 outbreak, 2022 monetary tightening, and SVB banking crisis. This confirms the superior responsiveness of the TVP-VAR for tracking abrupt systemic changes in real time.

Figure 9 evaluates sensitivity to prior choices in the Bayesian TVP-VAR framework. Estimates under Bayesian and Minnesota priors closely track each other until early 2023. Post-March 2023, looser priors (uninformative and Minnesota) produce higher connectedness levels, reflecting greater parameter drift amid structural change. This

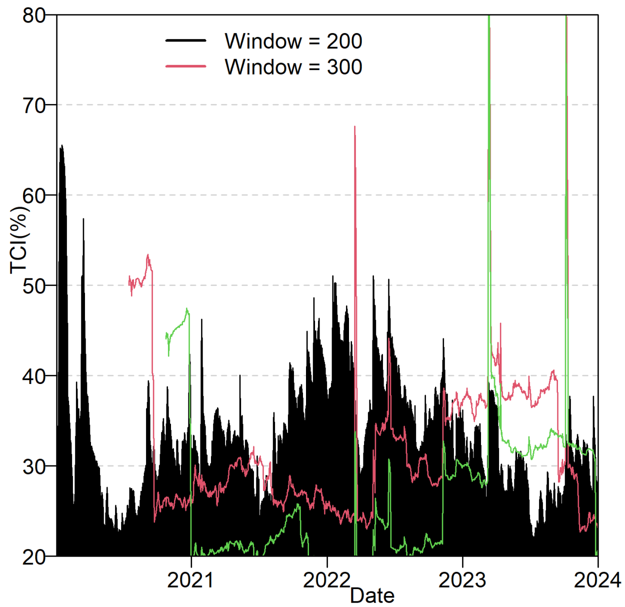


Figure 8: Dynamic Total Connectedness Index from TVP-VAR compared with rolling-window VARs (windows of 200 days in red and 300 days in green). Rolling-window models smooth spillover variations and lag stress event peaks.

highlights how the degree of shrinkage shapes the model's responsiveness, with the Bayesian prior tempering transitory volatility spikes.

Lag order sensitivity tests reported in Figure 10 indicate that the timing and magnitude of connectedness peaks remain stable across lag lengths from 5 to 10. Slight increases in TCI magnitude with higher lags reflect richer temporal dynamics rather than fundamental pattern changes, confirming robustness to lag choice.

Finally, sensitivity to the forgetting factors (κ_1, κ_2) in the TVP-VAR updating scheme was tested through forecast error metrics across a grid of values. The results indicate minimal impact on connectedness estimates from small adjustments, further confirming parameter stability. Collectively, these sensitivity checks affirm that the key findings on systemic spillover dynamics are robust to alternative estimation methods, prior choices, lag specifications, and parameter updating schemes.

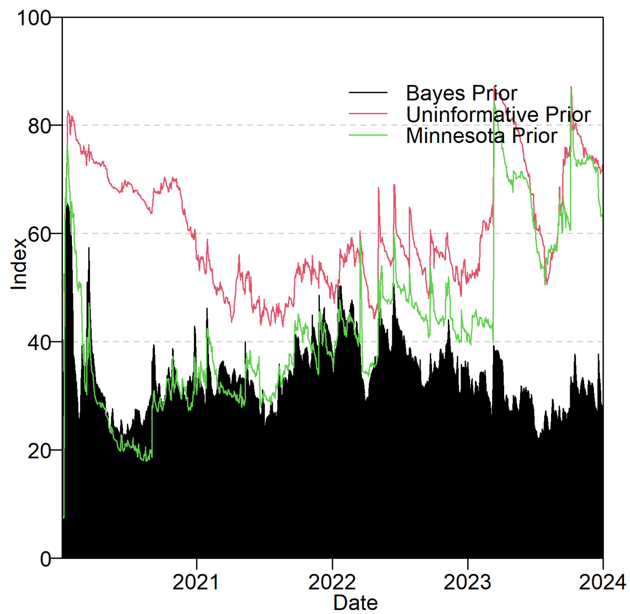


Figure 9: TCI under alternative prior specifications in the TVP-VAR. The Bayesian prior moderates transitory fluctuations compared to looser priors during structural change periods.

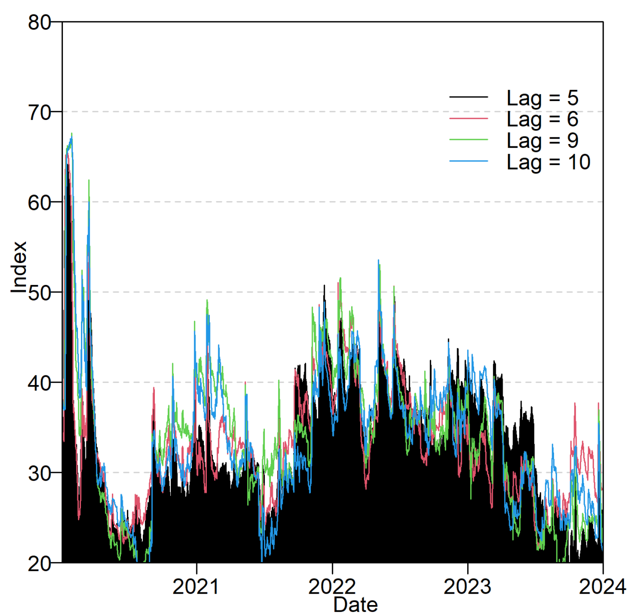


Figure 10: Lag sensitivity analysis of the Total Connectedness Index (TCI) using TVP-VAR with lag lengths 5, 6, 9, and 10. Connectedness peaks persist with minor magnitude variation.

5 Conclusion

This paper examined how major stablecoins respond to macro-financial shocks and their integration within the broader volatility spillover network linking traditional finance, macroeconomic indicators, and crypto markets. Using structural VAR and time-varying connectedness measures, we revealed a dynamic and heterogeneous role for stablecoins within the evolving monetary-financial ecosystem.

Impulse response analysis showed that TUSD and USDC are highly sensitive to U.S. monetary policy and market volatility, while USDT remained largely inert and DAI exhibited brief, muted reactions. These differences reflect design features such as collateral composition, market depth, and reserve transparency, underscoring that stablecoins cannot be treated as a uniform asset class. Tightening monetary conditions triggered short-term peg deviations for some coins, echoing liquidity stresses observed in demand deposits and exchange rate regimes under tightening cycles. This linkage illustrates how stablecoins may transmit the effects of monetary and funding conditions into the digital asset space, effectively extending the reach of conventional policy shocks into new payment and settlement channels.

Connectedness analysis added a systemic lens: stablecoins mostly absorbed volatility, while macro-financial indicators like the VIX, EPU, and ΔFFR consistently transmitted it. Bitcoin's role was episodic, with volatility links to USDC and DAI during stress events such as COVID-19, the 2021 crypto crash, 2022 rate hikes, and the 2023 SVB crisis. These results suggest that while stablecoins can dampen shocks in tranquil markets, they become entangled with the broader financial cycle during stress, potentially amplifying liquidity mismatches when confidence erodes or redemptions surge.

Frequency-domain analysis revealed that short-term spillovers dominate in crises, while long-term integration has strengthened since mid-2021, suggesting that stablecoins are increasingly embedded in macro-financial transmission mechanisms. This growing comovement implies that stablecoins now interact more directly with the monetary and credit cycle, making them relevant to both macroprudential surveillance and liquidity regulation.

In sum, stablecoins act as volatility sinks in calm periods but become conduits of systemic stress when liquidity tightens. TUSD and USDC show notable short-term vulnerabilities, raising concerns about their resilience amid policy normalization and shifts in money-market conditions. These dynamics mirror the behavior of non-bank financial intermediaries whose balance-sheet structures expose them to runs when funding costs spike or collateral values decline.

From a policy standpoint, the implications are clear: while stablecoins are not yet independent sources of systemic risk, their growing integration with the banking and payments system means that prudential treatment, liquidity coverage, and disclosure standards must evolve in parallel with their market footprint. Differentiated regulation, sensitive to reserve composition, redemption structure, and operational interlinkages, can help mitigate procyclicality and prevent amplification of financial instability through digital settlement channels. In this context, stablecoins represent a new frontier of monetary-policy transmission and liquidity management, warranting continuous data-driven monitoring and alignment with emerging global standards (e.g., FSB, BCBS, and OSFI guidance). Indeed, this is of material importance as more traditional financial institutions move towards the issuance and exploration of their own stablecoins.

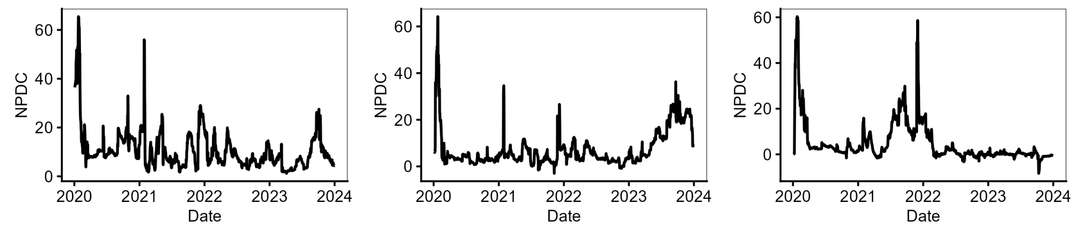
Future research should explore contagion dynamics using failed or depegged coins like TerraUSD and employ higher-frequency data to capture intraday responses to policy announcements and funding shocks. As stablecoins deepen their ties to traditional finance and the banking system, their oversight will become an essential component of modern liquidity risk and monetary-policy frameworks.

Appendix

6 Results with respect to USDC, DAI and TUSD

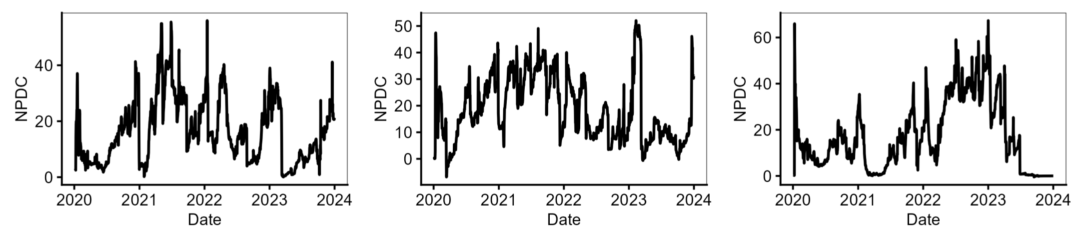
6.1 NPDC volatility transmitters

Figure 11 to 14 show the frequency-resolved Total Connectedness Index and Net Directional Connectedness for the VIX, EPU, FFR and BTC for the stablecoins USDC, DAI and TUSD.



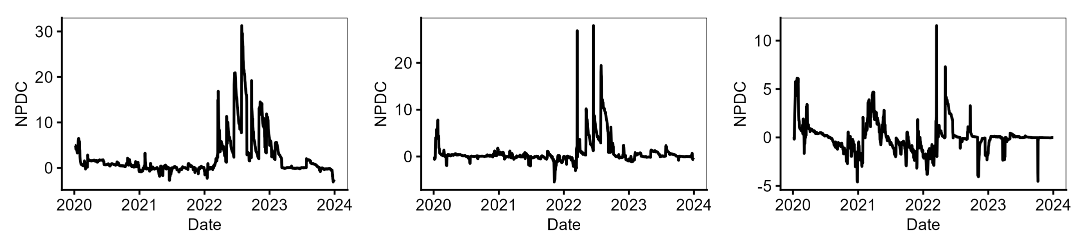
(a) VIX → USDC (b) VIX → DAI (c) VIX → TUSD

Figure 11: Net Pairwise Directional Connectedness (NPDC) between volatility transmitters (VIX) and stablecoins (USDC, DAI, TUSD). Positive values indicate net volatility spillovers from the transmitter to recipient. Scales differ to facilitate visual comparison due to heterogeneous spillover magnitudes.



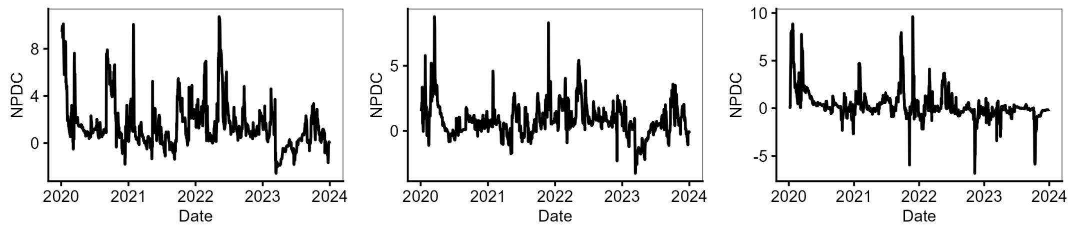
(a) EPU → USDC (b) EPU → DAI (c) EPU → TUSD

Figure 12: Net Pairwise Directional Connectedness (NPDC) between volatility transmitters (EPU) and stablecoins (USDC, DAI, TUSD). Positive values indicate net volatility spillovers from the transmitter to recipient. Scales differ to facilitate visual comparison due to heterogeneous spillover magnitudes.



(a) ΔFFR → USDC (b) ΔFFR → DAI (c) ΔFFR → TUSD

Figure 13: Net Pairwise Directional Connectedness (NPDC) between volatility transmitters (ΔFFR) and stablecoins (USDC, DAI, TUSD). Positive values indicate net volatility spillovers from the transmitter to recipient. Scales differ to facilitate visual comparison due to heterogeneous spillover magnitudes.

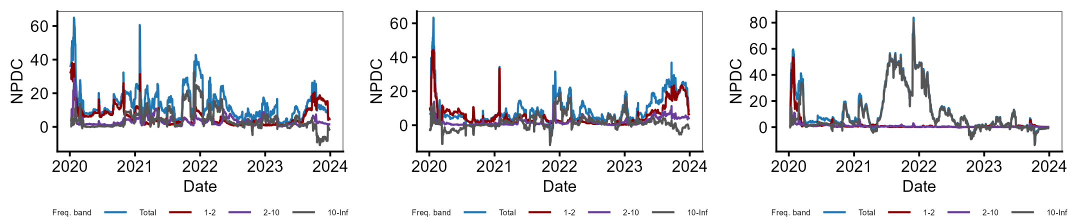


(a) BTC → USDC (b) BTC → DAI (c) BTC → TUSD

Figure 14: Net Pairwise Directional Connectedness (NPDC) between volatility transmitters (BTC) and stablecoins (USDC, DAI, TUSD). Positive values indicate net volatility spillovers from the transmitter to recipient. Scales differ to facilitate visual comparison due to heterogeneous spillover magnitudes.

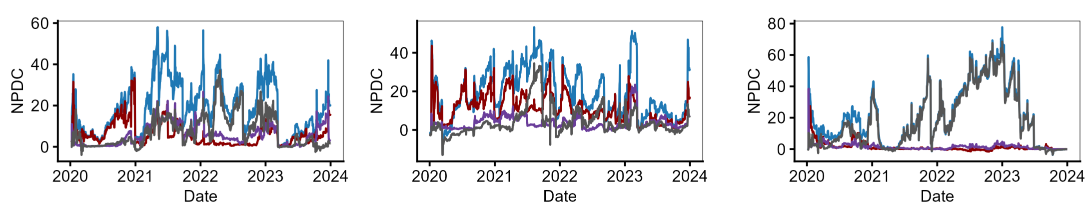
6.2 Frequency resolved NPDC for USDC, DAI and TUSD

Figures 15 to Figures 18 show the frequency-resolved Total Connectedness Index and Net Pairwise Directional Connectedness for the VIX, EPU, FFR and BTC for the stablecoins USDC, DAI and TUSD.



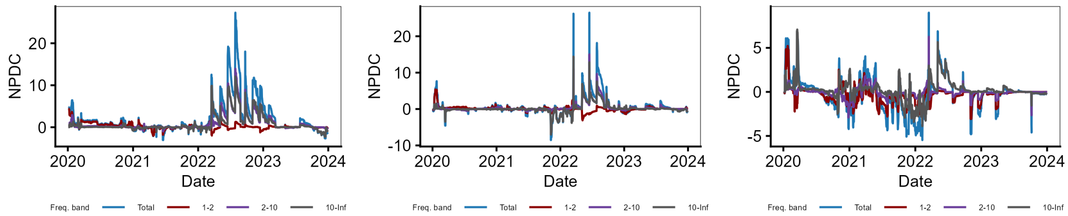
(a) VIX → USDC (b) VIX → DAI (c) VIX → TUSD

Figure 15: Frequency-resolved Net Pairwise Directional Connectedness (NPDC) from transmitters (VIX) to stablecoins (USDC, DAI, TUSD). Short-term spillovers dominate during crises with longer-term integration prevalent post-2021. Vertical scales differ across subfigures for clarity.



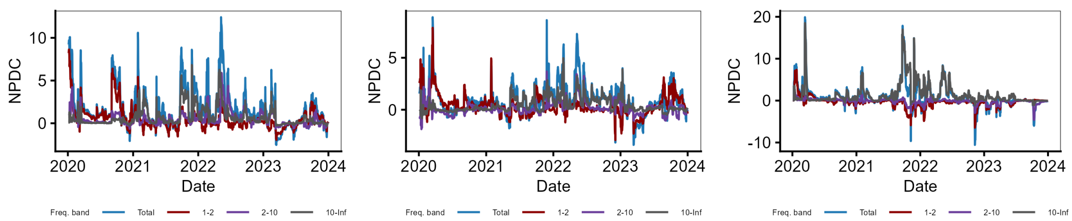
(a) EPU → USDC (b) EPU → DAI] (c) EPU → TUSD

Figure 16: Frequency-resolved Net Pairwise Directional Connectedness (NPDC) from transmitters (EPU) to stablecoins (USDC, DAI, TUSD). Short-term spillovers dominate during crises with longer-term integration prevalent post-2021. Vertical scales differ across subfigures for clarity.



(a) ΔFFR → USDC (b) ΔFFR → DAI (c) ΔFFR → TUSD

Figure 17: Frequency-resolved Net Pairwise Directional Connectedness (NPDC) from transmitters (ΔFFR) to stablecoins (USDC, DAI, TUSD). Short-term spillovers dominate during crises with longer-term integration prevalent post-2021. Vertical scales differ across subfigures for clarity.



(a) BTC → USDC (b) BTC → DAI (c) BTC → TUSD

Figure 18: Frequency-resolved Net Pairwise Directional Connectedness (NPDC) from transmitters (BTC) to stablecoins (USDC, DAI, TUSD). Short-term spillovers dominate during crises with longer-term integration prevalent post-2021. Vertical scales differ across subfigures for clarity.

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