Prague Economic Papers
2026, Volume 35, Issue 2
https://doi.org/10.18267/j.pep.909

PRAGUE UNIVERSITY OF ECONOMICS AND BUSINESS

How the Terra-LUNA Collapse Reshaped Tether's Role in Crypto Market Volatility

Ekin Tokat , Hakki Arda Tokat

Ekin Tokat, TOBB University of Economics and Technology, Söğütözü Cad. No: 43, 06560, Ankara, Turkey. E-mail: etokat@etu.edu.tr

Hakki Arda Tokat (*Corresponding author*), TOBB University of Economics and Technology, Söğütözü Cad. No: 43, 06560, Ankara, Turkey. E-mail: hatokat@etu.edu.tr

Abstract

This study examines the evolving role of Tether in cryptocurrency market volatility, particularly in the context of the Terra–LUNA collapse. Using a multivariate asymmetric BEKK-GARCH model, we analyze volatility transmission between Tether's trading volume and the return volatilities of Bitcoin and Ethereum. Unlike prior studies that rely on issuance based measures, we employ trading volume volatility as a proxy for real time stablecoin related liquidity dynamics. The results indicate that, in the pre-collapse period, Tether exhibited a stabilizing association with Bitcoin volatility, consistent with its role as a liquidity buffer. Following the Terra–LUNA collapse, this relationship weakens, while evidence of volatility interaction between Tether and Ethereum becomes more pronounced, although this interaction appears sensitive to the sample definition around the crash. Overall, the findings highlight the asset specific and time varying nature of stablecoin related volatility dynamics and underscore how major systemic events can reshape liquidity and volatility transmission within the cryptocurrency markets. The study provides useful insights for regulators and investors as crypto assets become more integrated into traditional financial systems.

Keywords: Tether, Bitcoin, Ethereum, Volatility spillover, Multivariate GARCH models.

JEL Classification: C32, G1, G12

1. Introduction

The cryptocurrency market has experienced rapid growth over the past decade, evolving from the introduction of Bitcoin as an early application of blockchain technology into a diverse ecosystem of digital assets and platforms, with aggregate market capitalization surpassing $4.2 trillion in the third quarter of 2025 (BIS, 2018; IMF, 2025). These developments have attracted considerable attention from investors, policymakers, and regulators seeking to understand both the potential and the risks related to decentralized finance. While cryptocurrencies exhibit high liquidity and substantial market valuations that create opportunities for investment and risk management (Dyhrberg, 2016; Bouri et al., 2017), international institutions emphasize that their extreme volatility remains a major concern for financial stability (BIS, 2018).

Recent political and regulatory developments, such as the announcement of a U.S. Strategic Bitcoin Reserve (The White House, 2025), signal growing governmental recognition of crypto assets. Meanwhile, major financial players are beginning to incorporate cryptocurrencies and stablecoins into traditional financial systems. For instance, JPMorgan recently approved the use of Bitcoin and Ethereum directly as loan collateral, signaling a shift toward crypto-backed lending (Nicolle, 2025). Similarly, Zelle, a major U.S. digital payment network, is preparing to allow users pay with stablecoins directly without going through banks or exchanges (PR Newswire, 2025). These developments emphasize the need to better understand the interactions between cryptocurrency volatility and liquidity mechanisms.

Existing research on cryptocurrency markets has primarily focused on the distinctive volatility characteristics of major crypto assets and their implications for diversification and risk management. Early studies highlight the unusually high and persistent volatility of cryptocurrencies relative to traditional financial assets, often modeling these dynamics within GARCH-type frameworks (e.g., Ardia et al., 2018; Baur and Dimpfl, 2018). More recent contributions extend the subject by examining volatility spillovers and interconnectedness across cryptocurrency markets, emphasizing that crypto assets are not isolated but linked through time-varying transmission mechanisms (e.g., Katsiampa, 2018; Katsiampa et al., 2019). Despite this growing literature on crypto volatility spillovers, the role of stablecoin trading volume in transmitting volatility across major cryptocurrencies remains underexplored, particularly during periods of systemic stress.

Stablecoins occupy a distinct economic position within the cryptocurrency ecosystem by combining functions that are traditionally separated across different instruments and institutions in traditional financial systems. In practice, they operate simultaneously as a medium of exchange facilitating transactions, a unit of account for trading pairs and decentralized finance (DeFi) activity, and a liquidity buffer that allows investors to adjust their exposure to volatile crypto assets without exiting the crypto market (Financial Stability Board, 2023).

The relative importance of these functions does not need to be uniform across assets and market segments due to differences in underlying platform architecture and usage patterns. Differences in market structure, such as the relative importance of spot versus derivatives trading, the degree of DeFi platform-based financial activity, and the role of stablecoins in collateralization and settlement, imply that stablecoins may be used primarily for liquidity management in some markets, while having more operational or transactional roles in others. Therefore, stablecoin activity may interact with volatility dynamics in asset-specific ways across cryptocurrency markets, even in the absence of new fundamental information.

Volatility dynamics between cryptocurrencies and stablecoins can be understood through a set of interrelated mechanisms linking information flow, liquidity conditions, and investor behavior. Building on the sequential information arrival hypothesis of Tauchen and Pitts (1983), trading volume and volatility are expected to co-move because both respond to the rate at which new information reaches the market. This mechanism is particularly relevant in cryptocurrency markets, where trading is characterized by fragmented liquidity, with the same asset traded simultaneously across multiple exchanges and venues that are only partially integrated. In such an environment, volatility reflects not only asset-specific fundamentals but also the speed with which information is transmitted across venues and incorporated into prices, as well as the intensity of trading associated with portfolio rebalancing (Tauchen and Pitts, 1983; Karpoff, 1987). Beyond information transmission, stablecoins play a central role by functioning as a common settlement and liquidity instrument across dispersed trading venues, particularly under conditions where capital mobility and rapid rebalancing are essential (Financial Stability Board, 2023). During periods of increased uncertainty, portfolio rebalancing into stablecoins can generate co-movement between stablecoin volume and cryptocurrency return volatility even in the absence of new fundamental information, operating through liquidity adjustment mechanisms rather than information-driven price discovery (Karpoff, 1987; Kyle, 1985). Moreover, by facilitating the rapid movement of capital across trading venues, stablecoins can transmit liquidity shocks across interconnected cryptocurrency markets. Sudden changes in stablecoin demand may therefore be reflected in volatility spillovers that differ across assets and prevailing market conditions.

Given the role of stablecoins in facilitating these cross market liquidity flows, their trading volume may provide a more immediate indicator of real-time market adjustments than issuance-based measures.Within this context, Tether (USDT) has emerged as the dominant stablecoin in terms of trading volume and market usage, serving as a primary liquidity bridge across exchanges (European Systemic Risk Board, 2025). While early studies examined Tether issuance and its potential relationship to cryptocurrency prices (Wei, 2018; Griffin and Shams, 2020), issuance based measures may fail to capture real-time liquidity conditions and short term investor responses. In contrast, trading volume reflects immediate market activity and portfolio rebalancing behavior, particularly during periods of stress, making it a more responsive proxy for stablecoin related liquidity dynamics.

In this context, the primary objective of this study is to examine how volatility is transmitted between major cryptocurrency markets, represented by Bitcoin and Ethereum, and the dominant stablecoin Tether (USDT), with a particular focus on stablecoin related liquidity mechanisms. To capture these transmission mechanisms empirically, we employ an asymmetric multivariate BEKK-GARCH framework that distinguishes between symmetric volatility persistence and asymmetric shock responses. Specifically, the study investigates whether fluctuations in Tether trading volume are associated with volatility spillovers to and from Bitcoin and Ethereum, and whether these relationships exhibit asymmetric response. Importantly, these transmission mechanisms need not be uniform across crypto assets, as differences in market structure and usage may shape how stablecoin related liquidity interacts with volatility dynamics. In this respect, Bitcoin's role as a store of value and primary reference asset (Baur et al., 2018), contrasts with Ethereum's smart contract functionality that supports complex DeFi applications (Schär, 2021), suggesting that stablecoin interactions with these two assets may operate through distinct channels. These structural differences motivate our separate analysis of Tether's interaction with Bitcoin and Ethereum, representing distinct market structure within the crypto ecosystem. We further explore whether major systemic events reshape the structure of volatility transmission across crypto markets. A particularly important stress event in this regard is the collapse of the Terra–LUNA stablecoin system in May 2022. Prior to its failure, TerraUSD (UST) was among the most widely used algorithmic stablecoins and the Terra blockchain had become the second-largest network in the DeFi ecosystem. The total loss of approximately USD 50 billion in combined market capitalization within a single week triggered severe liquidity stress and widespread reassessment of stablecoin-related risks (Badev and Watsky, 2023). Recent evidence from Lee et al. (2023) shows that the Terra–LUNA collapse was marked by strong internal spillovers between UST and LUNA and a breakdown in sentiment-based information transmission. Following the crash, volatility linkages between LUNA and major cryptocurrencies such as Bitcoin and Ethereum weakened substantially, suggesting a disruption in cross-market transmission mechanisms (Lee et al., 2023). This event therefore provides a natural setting for examining whether and how the role of collateralized stablecoins such as Tether in volatility transmission changed following a major systemic shock.

This study contributes to the growing literature on cryptocurrency market dynamics by advancing the understanding of how stablecoin related liquidity interacts with volatility in major crypto markets. Rather than focusing on issuance-based measures of stablecoin activity, the analysis emphasizes trading volume volatility as a proxy for real-time liquidity dynamics and investor behavior. By examining volatility transmission patterns before and after the Terra–LUNA collapse, the study highlights how the role of stablecoins in crypto markets can shift following systemic shocks. This perspective is particularly relevant as stablecoins become increasingly integrated into traditional financial systems, raising new questions about their implications for market volatility and financial stability.

The remainder of the paper is organized as follows. Section 2 reviews the related literature. Section 3 describes the data and methodology. Section 4 presents the empirical results, and Section 5 concludes with a discussion of the main findings and their implications.

2. Literature Review

The literature on cryptocurrency markets has expanded rapidly, primarily focusing on the volatility characteristics of cryptocurrencies, volatility spillovers across crypto assets, and the role of stablecoins in shaping market dynamics. Early studies have investigated the volatility characteristics of cryptocurrencies, particularly Bitcoin. Dwyer (2015) highlighted Bitcoin's significantly higher average monthly return volatility compared to gold and major currencies. Following studies further improved this characterisation through the application of GARCH-family models. Katsiampa (2017) conducted a systematic comparison of GARCH specifications for Bitcoin, while Baur et al. (2018) and Troster et al. (2019) employed similar frameworks to establish the persistence and clustering properties of cryptocurrency volatility. Together, these studies confirmed that Bitcoin returns share key volatility characteristics with traditional financial assets, but at substantially higher levels. Extending the analysis beyond univariate volatility, Ardia et al. (2019) document multiple volatility regimes in Bitcoin, implying that return properties evolve over time in response to changing market conditions. Chaim and Laurini (2018) further contribute by identifying volatility jumps with direct relevance for risk measurement and extreme-value modeling.

The hedging and diversification properties of Bitcoin have also attracted considerable attention. Dyhrberg (2016) and Bouri et al. (2017) both found evidence that Bitcoin can function as a diversification instrument, although the strength of this property is sensitive to the time horizon and market regime under consideration. Meanwhile, a number of empirical investigations have moved beyond single-asset analysis to examine cross-market volatility transmission. Ciaian et al. (2018) showed both short- and long-run interdependencies between Bitcoin and major altcoins, while Gkillas and Katsiampa (2018) used extreme value theory to characterize tail dependence among leading cryptocurrencies. Extending this literature to the COVID-19 period, Özdemir (2022) applied DCC-GARCH and wavelet-based methods to show that volatility spillovers across crypto markets intensified during the pandemic. Taken together, these studies suggest that cryptocurrency markets are closely interconnected, with shocks propagating across assets and depending on prevailing market conditions.

Within this broader volatility literature, stablecoins have emerged as instruments of particular interest, and are intended to function simultaneously as a medium of exchange, a unit of account, and a temporary store of value within decentralised ecosystems. Adachi et al. (2022) provided a comprehensive overview of these functions, highlighting the role stablecoins play in reducing price volatility, facilitating settlement, and supporting risk management on decentralised finance (DeFi) platforms. Among all stablecoins, Tether (USDT) occupies a dominant position: having surpassed Bitcoin in daily trading volume in 2019, Tether currently commands approximately 57% of the stablecoin market (European Systemic Risk Board, 2025). Despite this market significance, the empirical literature on Tether's actual influence on cryptocurrency prices and dynamics remains challenged. Wei (2018) found no evidence that Tether issuance influences Bitcoin returns, suggesting that Tether serves a neutral liquidity intrument role. In contrast, Griffin and Shams (2020) argued that Tether issuance is supply-driven and strategically timed to support Bitcoin prices during downturns. Kristoufek (2022) later on, showed that Tether issuance is primarily driven by traders' liquidity demand, rather than by strategic price manipulation. Ante et al. (2021) examined a broader group of stablecoins and found statistically significant but quantitatively limited effects around stablecoin issuance events.

Despite these advances, the stablecoin literature remains heavily focused on issuance based measures, which capture longer term supply dynamics but may fail to reflect real time liquidity conditions and short term investor behavior. This limitation is particularly relevant during periods of market stress, when trading activity and volume adjustments may dominate issuance effects. De Blasis et al. (2023) highlighted that stablecoin behavior during crises is shaped by market turbulence and collateral dynamics, yet their analysis primarily concentrates on price deviations rather than volatility transmission mechanisms.

A related line of the literature examines the relationship between trading volume and volatility. Classical studies argue that trading volume reflects information flow and investor disagreement, both of which are associated with volatility dynamics (Tauchen and Pitts, 1983; Karpoff, 1987). While some evidence suggests that volume may predict volatility (Wang, 2002; Bonelli, 2016), findings in cryptocurrency markets are mixed. Balcilar et al. (2017) reported limited predictive power of Bitcoin volume for volatility, whereas Corbet et al. (2022) found stronger volume and volatility linkages during periods of increased uncertainty. Notably, most of these studies analyze volume and volatility within a single asset framework, largely ignoring cross market volatility transmission and asymmetry.

The Terra–LUNA collapse in May 2022 represents a critical turning point in the stablecoin literature. Badev and Watsky (2023) concluded that the collapse triggered severe liquidity stress and contagion within decentralized finance networks. Lee et al. (2023) showed that the episode was characterized by heightened internal spillovers between UST and LUNA, a breakdown of sentiment-driven information flows, and a subsequent weakening of volatility linkages between LUNA and major cryptocurrencies such as Bitcoin and Ethereum. These findings suggest that stablecoin-related shocks can alter not only the magnitude but also the structure of volatility transmission across crypto markets.

The volatility and spillover literature has demonstrated that cryptocurrency markets are interconnected and that shocks propagate across assets. The stablecoin literature has established Tether's significance as a liquidity instrument, while pointing to the limitations of issuance based proxies for capturing real time market dynamics. The volume and volatility literature has identified trading activity as an informative signal of market sentiment and liquidity conditions, however the analysis is largely based on to single asset settings. The present study addresses these limitations by shifting the analytical focus from Tether issuance to Tether trading volume as a more immediate proxy for liquidity conditions and investor behaviour. By modeling asymmetric volatility transmission between Tether activity and the return volatilities of Bitcoin and Ethereum, and by explicitly distinguishing between pre- and post-Terra–LUNA periods, the analysis provides new insights into the evolving, asset specific role of stablecoins in cryptocurrency market volatility.

3. Data and Methodology

This study employs daily data for Bitcoin, Ethereum, and Tether (USDT), reflecting their central but distinct roles within the cryptocurrency market structure. Bitcoin and Ethereum represent two distinct but complementary segments of the crypto ecosystem. Bitcoin operates as the primary reference asset, characterized by deep liquidity, extensive exchange coverage, and highly developed derivatives markets that play a key role in price discovery and risk transfer (Baur et al., 2018; Corbet et al., 2019). Trading activity in Bitcoin derivatives markets is particularly important during periods of increased uncertainty, making Bitcoin volatility informative for broader market conditions.

Ethereum has a different position within the market structure. In addition to being a major traded asset, it serves as the foundational platform for decentralized finance (DeFi) applications, including lending, automated market making, and collateralized trading (Schär, 2021; Financial Stability Board, 2023). This dual role implies a more complex market environment in which volatility reflects both speculative trading and DeFi related liquidity demand. Therefore, the coexistence of centralized exchange trading and DeFi activity differentiates Ethereum's market microstructure and motivates an asset specific analysis of volatility transmission.

The stablecoin selected for analysis is Tether (USDT), which plays a dominant role in cryptocurrency market liquidity. USDT accounts for the largest share of stablecoin trading volume and functions as the primary quote and settlement currency across major centralized exchanges, particularly in spot and derivatives markets (European Systemic Risk Board, 2025). Its extensive use as an intermediary asset in trading pairs links Tether activity closely to short term liquidity conditions and portfolio rebalancing decisions. While other stablecoins, such as USD Coin (USDC), are widely used within decentralized finance applications and institutional payment networks, their activity is more closely associated with decentralized trading, lending, and protocol specific liquidity dynamics (Behrens, 2021). In contrast, USDT is predominantly used in exchange based trading to facilitate rapid transitions between risky crypto assets and stable holdings, making it particularly informative for studying market wide liquidity dynamics.

Our dataset consists of daily observations of Tether volume and the prices of Bitcoin and Ethereum from February 2018 to February 2025. Bitcoin and Ethereum Composite Spot Price data, sourced from Refitiniv, and Tether volume, sourced from CoinDesk are used for the analysis. All data is supplied by Refinitiv, a London Stock Exchange Group (LSEG) business.

Table 1 presents the descriptive statistics of the price return series of the two cryptocurrencies, as well as the changes in Tether trading volume. The average return is positive for both Bitcoin and Ethereum. Ethereum's volatility (5.63%), as measured by the standard deviation of returns, is higher than that of Bitcoin (4.38%). Tether transactions, on the other hand, present the highest average change in volume (0.71%) and volatility (28.23%). All of the series are leptokurtic, with Bitcoin having the largest excess kurtosis and characterized by positive skewness. The Jarque-Bera test results reject the null hypothesis of normal distribution and confirm the non-normality of the underlying series, as is common in high-frequency financial data. Based on the Q-statistic as evidence of autocorrelation, serial correlation is detected in the Ethereum and Tether series.

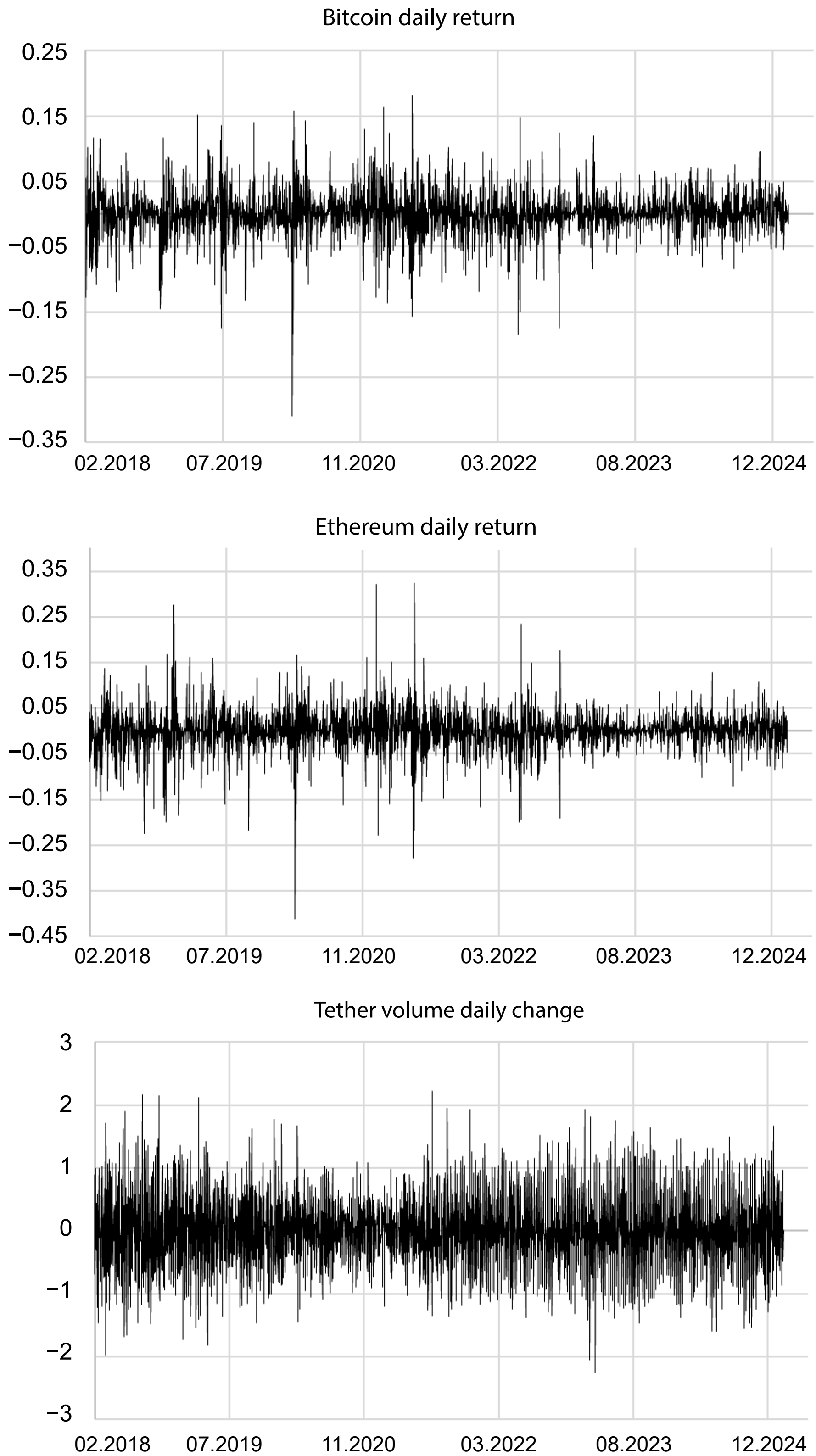
Table 1. Descriptive statistics

	Bitcoin	**Ethereum**	**Tether**
Mean	0.0019	0.0012	0.0071
Std. Dev.	0.0438	0.0563	0.2823
Skewness	0.05318	0.1486	0.4701
Kurtosis	6.36658	6.1391	5.8017
Jarque-Bera	454.74	398.53	350.08
Probability	0.0000	0.0000	0.0000
Q(12)			
Probability	0.174	0.029	0.000

Source: authors' calculations

Figure 2 provides a plot of the daily returns of Bitcoin, Ethereum, and the daily change in Tether volume. The volatility pattern shows the property of volatility clustering for all series, which is a common phenomenon for financial time series; volatility changes over time, and there is a tendency for large changes to cluster together, resulting in the persistence of changes in amplitudes.

Figure 1: Daily returns in Bitcoin, Ethereum, and daily change in Tether volume.



Source: authors' calculations

As the visual analysis of the cryptocurrency series suggests the heteroscedastic behavior of volatility, we proceed to the volatility modeling within a GARCH framework. First, we estimated the following mean equation for each series and then tested the existence of autoregressive conditional heteroscedasticity (ARCH), following Engle (1982). Based on the significant ARCH effects detected, we continue with the bivariate GARCH model.

Modelling conditional volatility using multivariate GARCH (MGARCH) models helps us to analyze the possible spillover effects among the markets. The VECH and BEKK models are two of the most widely used specifications of the MGARCH model in the literature. Eq.(1) presents the VECH model proposed in Bollerslev et al. (1988):

$$VECH(H_t) = C + AVECH(\epsilon_{t-1}\epsilon'_{t-1}) + BVECH(H_{t-1}) \quad (1)$$

where H_t is the N × N conditional variance-covariance matrix, A and B are square matrices of order (N(N+1)/2 × 1). The VECH operator stacks the lower portion of an (N × N) square matrix as an (N(N+1)/2 × 1) vector, therefore in a bivariate case, $VECH(H_t)$ refers to the column stacked (3 × 1) vector transformed from the matrix H_t where the matrices are (3 × 3) and there are 27 parameters to be estimated.

In the BEKK model (Engle and Kroner, 1995) on the other hand, a new parametrization of the conditional variance matrix H_t leads to the guaranteed positive definiteness of conditional covariance matrix and reduced number of parameters. This parameterization allows us to determine volatility interaction effects by overcoming the complexity associated with VECH parameterization. Moreover, an asymmetric extension of BEKK introduced by Kroner and Ng (1998) would capture the asymmetric impact of news on volatility:

$$H_{t+1} = C'C + A'\epsilon_t\epsilon'_tA + B'\,H_tH'_tB + D'U_tU'_tD \quad (2)$$

where A, B, C and D are 2 × 2 parameter matrices and C is a lower triangular matrix in a bivariate case. The constant term is expressed as the product of two triangular matrices to guarantee the positive definiteness of H_{t+1}. The elements of matrix A capture the effects of past shocks on conditional volatility. Matrix B controls the effect of past volatility on the current levels of conditional variances. Matrix A and B's off-diagonal elements represent the cross-market impacts which make possible to analyze the shock transmission and volatility spillover between the markets. The parameters of D matrix represent the potential asymmetric responses. In case of an asymmetric response, the return will be lower than expected, and it will be considered bad news. Therefore, conditional variance can be modeled within a bivariate GARCH asymmetric BEKK model as:

$$h_{11,t+1} = a_{11}^2\varepsilon_{1,t}^2 + 2a_{11}a_{21}\varepsilon_{1,t}\varepsilon_{2,t} + a_{21}^2\varepsilon_{2,t}^2 + b_{11}^2h_{11,t} + 2b_{11}b_{21}h_{12,t} + b_{21}^2h_{22,t} + d_{11}^2u_{1,t}^2 + 2d_{11}d_{21}u_{1,t}u_{2,t} + d_{21}^2u_{2,t}^2 \quad (3)$$

$$h_{22,t+1} = a_{12}^2\varepsilon_{1,t}^2 + 2a_{12}a_{22}\varepsilon_{1,t}\varepsilon_{2,t} + a_{22}^2\varepsilon_{2,t}^2 + b_{12}^2h_{11,t} + 2b_{12}b_{22}h_{12,t} + b_{22}^2h_{22,t} + d_{12}^2u_{1,t}^2 + 2d_{12}d_{22}u_{1,t}u_{2,t} + d_{22}^2u_{2,t}^2 \quad (4)$$

Equations (3) and (4) represent the evolution of conditional variance over time and the transmission of shocks and volatility across the markets. As explained earlier, for example, the coefficient $b2_{21}$ in equation (3) represents the volatility spillover effect from Tether to the Bitcoin market. The coefficient $d2_{12}$ in equation (4) will capture the asymmetric volatility response of Tether market to the negative innovations in Bitcoin market.

The model parameters are estimated through the following likelihood function:

$$L(\theta) = -Tln(2\pi) - \frac{1}{2}\sum_{t=1}^{T}(ln|H_t| + \varepsilon_t' H_t^{-1}\varepsilon_t) \quad (5)$$

where θ is the vector of parameters and T is the number of observations. The nonlinear log-likelihood function requires to use numerical maximization techniques for the model estimation. Since the coefficients in equations (3) and (4) are nonlinear functions of the parameters estimated in equation (2), significance tests need to be performed following the calculation of expected value and error terms of these nonlinear functions. While the expected value of a nonlinear function (e.g. $2a_{12}a_{22}$) can be calculated as a function of the estimated parameters, this is not the same method for the calculation of the error terms. The error terms of the coefficients were calculated using the first-order Taylor expansion and the t-statistics were reported in the relevant tables. For obtaining the final estimate of the variance–covariance matrix with corresponding standard error, initial conditions for the BHHH (Berndt, Hall, Hall, and Hausman) algorithm are determined through the several initial iterations using a simplex algorithm (see Engle and Kroner, 1995).

3. Empirical Results

Two bivariate GARCH models with BEKK parameterization were estimated to evaluate the volatility transmission mechanisms between Tether and the two leading cryptocurrencies, Bitcoin and Ethereum. According to the estimation results (Table 2), both cryptocurrencies' return volatility is significantly dependent on their own previous shocks and previous volatility. The coefficient estimates of $a_{11}2$ and $b_{11}2$ were statistically significant at the 1% level, and the size of the impact of past volatility is higher than that of past shocks ($b_{11}2 > a_{11}2$). In the cross-market analysis, there is no significant volatility interaction between the cryptocurrency pairs. However, cross-market effect appears to be significant in terms of shock transmission from Tether to Ethereum market with the cross-product coefficient estimated at 0.00128 and significant at the 1% level.

Table 2. Bivariate GARCH Models

	Bitcoin - Tether		**Ethereum - Tether**	
Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$\varepsilon^2_{1,t}$	0.0706*** (5.08282)	0.19018 (0.49297)	0.06244*** (6.68325)	0.005825 (0.25900)
$\varepsilon_{1,t}\varepsilon_{2,t}$	−8.68E−04 (−1.04761)	0.00465 (0.17140)	0.00128** (1.99046)	0.000848 (0.22369)
$\varepsilon^2_{2,t}$	2.671E−06 (0.55046)	0.000028 (0.08479)	6.563E−06 (1.02081)	0.00003 (0.12560)
$h_{11,t}$	0.8453*** (35.40460)	0.058007 (0.40609)	0.91252*** (75.41677)	0.00061 (0.27138)
$h_{12,t}$	−0.00021 (−0.05460)	−0.34475 (−0.82175)	0.000268 (0.48944)	0.04878 (0.54271)
$h_{22,t}$	1.309E−08 (0.02730)	0.512261*** (6.74072)	1.975E−08 (0.24458)	0.9743*** (112.31993)
$u^2_{1,t}$	0.04507*** (2.69635)	1.81822 (0.99281)	0.02546** (2.31861)	0.03673 (1.5769)
$u_{1,t}u_{2,t}$	0.00009 (0.10665)	1.24521* (1.96981)	0.00023 (0.41876)	0.26407*** (2.64033)
$u^2_{2,t}$	4.526E−08 (0.05337)	0.21319*** (4.94959)	5.458E−07 (0.21154)	0.047458*** (3.2204)

Note: h_{11} denotes the conditional variance for the Bitcoin and Ethereum markets and h_{22} denotes the conditional variance for Tether volume change. e_1 is the shock on conditional variances for Bitcoin and Ethereum, and e_2 is the shock on the Tether market. The cross-subscripts denote the cross-market effects. While u_{11} represents the asymmetric effects of news on Bitcoin and Ethereum market, u_{22} represents the same effect for the Tether market. For each estimated parameter coefficient, the corresponding *t*-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Source: authors' calculations

This implies that Ethereum volatility is sensitive to the interaction of shocks between its own market and that of Tether. The analysis of asymmetric effects shows that all cryptocurrency markets under study exhibit statistically significant asymmetric responses to negative own-market shocks, reflected in the positive and significant coefficients. Moreover, the flow of information between cryptocurrency markets and Tether appears to be asymmetric. In particular, Tether volume volatility shows a significant response to negative shocks in both Bitcoin and Ethereum markets. The asymmetric impact is more pronounced from Bitcoin market to Tether, however, the corresponding coefficient is significant at the 10% level. These findings highlight the sensitivity of Tether trading activity to adverse conditions in both cryptocurrency markets.

3.1 Subperiod Analysis: Pre- and Post-Terra–LUNA Crash

To account for potential changes in market behavior, the sample is divided into two subperiods around the collapse of the Terra-LUNA stablecoin system in May 2022. This event caused major turmoil in the cryptocurrency ecosystem, resulting in liquidity stress, widespread contagion, and a reassessment of stablecoin risks. As noted by Lee et al. (2023), the Terra-LUNA crash significantly changed the volatility spillover dynamics and transformed the investor sentiment across digital asset markets. Building on their findings, we reestimate the model for the pre- and post-crash periods. Tables 3 and 4 present the estimation results. In terms of heteroscedastic volatility behavior, both Bitcoin and Ethereum exhibit strong and statistically significant GARCH coefficients across periods, confirming persistent volatility. However, the cross-market volatility transmission patterns change significantly between the two subperiods.

In the pre-crash period, the Bitcoin–Tether system displays a bidirectional volatility relationship that is consistent with Tether acting as a liquidity buffer. The negative and significant cross-GARCH coefficient from Tether to Bitcoin ($h_{12} = -0.0028$, significant at the 1% level) indicates that higher past Tether volume volatility is associated with lower subsequent Bitcoin volatility, suggesting that Tether activity helped adjust liquidity pressures during this period. Conversely, the positive and significant coefficient from Bitcoin to Tether ($h_{21} = 0.3084$, significant at the 5% level) indicates that elevated Bitcoin market uncertainty was associated with higher volatility in Tether trading volume, consistent with increased reliance on Tether as a liquidity instrument. The asymmetric cross-market effects between Bitcoin and Tether are bidirectional and statistically significant. The negative and significant coefficients on both sides indicate that negative shocks are associated with a moderation in conditional volatility, consistent with liquidity rebalancing or short-term market adjustment dynamics rather than persistent volatility amplification..

Table 3: Pre-crash Bivariate GARCH Models

	Bitcoin - Tether		Ethereum - Tether	
Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$\varepsilon_{1,t}^2$	0.15361*** (16.66460)	0.244498*** (016.37481)	0.0630248*** (4.92041)	0.0055203 (0.17260)
$\varepsilon_{1,t}\varepsilon_{2,t}$	−0.0025528 (−1.48143)	−0.03092 (−0.82151)	0.004113** (2.94722)	−0.005253 (−0.35093)
$\varepsilon_{2,t}^2$	1.061E−05 (0.73729)	0.000978 (0.41075)	6.711E−05 (1.60847)	0.0012498 (0.56091)
$h_{11,t}$	0.43123060 *** (119.37046)	0.072802 (1.13219)	0.805308*** (21.900)	0.0042018 (0.21738)
$h_{12,t}$	−0.0028361*** (−2.67508)	0.308337** (2.25560)	0.002699* (1.67485)	0.1276498 (0.43446)
$h_{22,t}$	4.663E−06 (1.33179)	0.326472*** (20.23845)	2.263E−06 (0.83034)	0.9694*** (88.667)
$u_{1,t}^2$	0.028711*** (19.08483)	0.341714 (1.58942)	0.061880*** (2.60143)	0.515136 (1.38087)
$u_{1,t}u_{2,t}$	−4.97E−05** (−2.05247)	−0.646573*** (−3.83295)	0.002529 (1.52818)	0.321513** (2.36416)
$u_{2,t}^2$	2.149E−08 (1.02478)	0.305852*** (8.91006)	2.585E−05 (0.80205)	0.050166*** (2.68485)

Note: h_{11} denotes the conditional variance for the Bitcoin and Ethereum markets and h_{22} denotes the conditional variance for Tether volume change. e_1 is the shock on conditional variances for Bitcoin and Ethereum, and e_2 is the shock on the Tether market. The cross-subscripts denote the cross-market effects. While u_{11} represents the asymmetric effects of news on Bitcoin and Ethereum market, u_{22} represents the same effect for the Tether market. For each estimated parameter coefficient, the corresponding t-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Source: authors' calculations

In contrast, the interaction between Ethereum and Tether volatility remains relatively weak in the pre-crash period. Although the shock spillover coefficient from Tether to Ethereum is positive and significant, the cross-GARCH coefficients are not statistically significant. This pattern may be attributable to the relatively prevailing role of USDC in DeFi protocol integration, which may limit Tether's function in Ethereum markets primarily to cross-exchange speculative activity. This pattern may be attributable to the emergence of USD Coin (USDC) as the preferred stablecoin for DeFi protocol integration (IMF, 2025), which may limit Tether's role in Ethereum markets largely to cross-exchange trading rather than protocol level use.

The post-crash results point to a change in volatility transmission patterns. In particular, the bidirectional volatility relationship between Bitcoin and Tether disappears, as neither the cross-GARCH coefficients nor the asymmetric cross-market effects remain significant. This suggests that the liquidity reallocation behavior observed in the pre-crash period weakened after the Terra–LUNA collapse, potentially reflecting a reassessment of stablecoins' role as short-term volatility buffers following the Terra-LUNA collapse. In contrast, the interaction between Ethereum and Tether strengthens in the post-crash period. The cross-GARCH coefficient from Tether to Ethereum (h_{12} = 0.0201, at 1% significance level) is now positive and highly significant, representing a reversal of the pre-crash pattern. This shift may be attributable to the failure of a DeFi platform based algorithmic stablecoin, which appears to weaken confidence in stablecoin usage linked to particular platforms. As a result, market participants may have relied more heavily on highly liquid and exchange-dominant instruments such as Tether when adjusting exposure in Ethereum markets. This finding is also in line with Lee et. al.'s (2023) findings that volatility linkages between LUNA and major cryptocurrencies such as Bitcoin and Ethereum weakened significantly following the crash, pointing to a broader disruption and restructuring of cross-market transmission mechanisms.

These findings indicate that the Terra-LUNA collapse marked a structural break in volatility transmission mechanisms, with the Bitcoin-Tether stabilizing relationship weakening while the Ethereum-Tether linkage strengthened as activity concentrated in the most liquid instruments.

Table 4: Post-crash Bivariate GARCH Models

	Bitcoin - Tether		Ethereum - Tether	
Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$\varepsilon_{1,t}^2$	0.12263*** (3.35095)	0.19729000 (0.24580)	0.0398328* (1.76608)	0.15560034 (0.30415)
$\varepsilon_{1,t}\varepsilon_{2,t}$	−0.0027814* (−1.82620)	−0.0076968 (−0.20059)	−0.0010017 (−0.76175)	0.0058826 (0.18792)
$\varepsilon_{2,t}^2$	1.577E−05 (0.97254)	0.00007507 (0.10912)	6.297E−06 (0.41394)	0.00005560 (0.09959)
$h_{11,t}$	0.68767 *** (10.12070)	0.01818590 (0.08973)	0.656737*** (8.33174)	0.61739055 (0.85833)
$h_{12,t}$	−0.006001 (−0.70101)	0.19511786 (0.17939)	0.020147*** (3.57088)	1.288310* (1.72472)
$h_{22,t}$	1.309E−05 (0.34530)	0.523358*** (5.42614)	0.00015452* (1.70257)	0.672080*** (4.13805)
$u_{1,t}^2$	0.054040* (1.81544)	6.062918 (1.02035)	0.258824*** (3.29816)	3.521705 (1.17257)
$u_{1,t}u_{2,t}$	0.00075973 (0.61244)	1.929722* (1.65750)	0.0038004 (148593)	0.754743 (1.63687)
$u_{2,t}^2$	2.670E−06 (0.33127)	0.153549** (2.46132)	1.395E−05 (0.73319)	0.040437 (1.48489)

Note: h_{11} denotes the conditional variance for the Bitcoin and Ethereum markets and h_{22} denotes the conditional variance for Tether volume change. e_1 is the shock on conditional variances for Bitcoin and Ethereum, and e_2 is the shock on the Tether market. The cross-subscripts denote the cross-market effects. While u_{11} represents the asymmetric effects of news on Bitcoin and Ethereum market, u_{22} represents the same effect for the Tether market. For each estimated parameter coefficient, the corresponding *t*-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Source: authors' calculations

3.2 The Robustness Check

To verify that our main findings are not driven by extreme observations during the Terra-LUNA crash itself, we re-estimate the asymmetric BEKK-GARCH model excluding a symmetric ±14 trading day window around the cut-off date. This extended exclusion window reduces the potential influence of the most volatile period on the estimated parameters.

The results, reported in Appendix A (Tables A1 and A2), remain qualitatively consistent with the baseline findings. In the pre-crash period, the Bitcoin-Tether bidirectional volatility relationship persists, with the cross-GARCH coefficient from Tether to Bitcoin remaining negative and highly significant, while the reverse transmission from Bitcoin to Tether remains positive and significant. The asymmetric effects are also robust, with the bidirectional asymmetric transmission between Bitcoin and Tether confirmed. For Ethereum, the pre-crash shock spillover from Tether also remains present, indicating that the qualitative pre-crash dynamics are largely unaffected by the exclusion of the narrow event window surrounding the Terra-LUNA crash. In the post-crash period, the erosion of volatility linkages between Bitcoin and Tether is again confirmed, with cross-market effects losing statistical significance. The strengthened interaction between Ethereum and Tether observed in the baseline model, however, becomes less pronounced in the robustness specification. This suggests that the measured post-crash increase in Ethereum and Tether volatility transmission is sensitive to the definition of the crash event window. However, the underlying pattern of structural change, characterized by weakening Bitcoin and Tether linkages and shifting volatility dynamics for Ethereum, remains evident. Overall, these findings support the conclusion that the Terra-LUNA collapse coincided with a structural shift in the volatility relationships governing Tether's interaction with major cryptocurrencies.

Second, we verify that the specification of the conditional mean equations does not drive our findings. Throughout the analysis, we allow for lagged own and cross-market returns in the conditional mean equations. Estimation results show that the cross-market mean coefficients are generally small and statistically insignificant across all sample periods, indicating that interdependence between cryptocurrencies and Tether does not operate through return predictability or lead–lag effects. Instead, the results suggest that the documented interactions are driven primarily by volatility spillovers captured in the variance equations. This confirms that our focus on second-moment dynamics reflects the dominant transmission mechanism, and that the observed structural changes relate to volatility relationships rather than first-moment linkages. The corresponding estimates from the conditional mean equations are reported in Appendix B.

4. Conclusion

This study investigates the volatility and shock transmission mechanisms between major cryptocurrency markets, Bitcoin and Ethereum, and Tether, the leading stablecoin, using an asymmetric multivariate BEKK-GARCH framework. By focusing on Tether's trading volume rather than issuance, the study investigates liquidity driven dynamics and evaluates whether Tether serves as a stabilizing instrument or amplifies volatility in crypto markets.

Our baseline results confirm that both Bitcoin and Ethereum show strong own-market volatility persistence. Importantly, we detect statistically significant cross-market volatility spillovers from Tether to Ethereum, as well as evidence of asymmetric responses, particularly from Bitcoin to Tether, suggesting that Tether trading activity responds more to adverse market shocks.

To account for potential regime shifts, we extend our analysis by dividing the sample into pre- and post-crash subperiods after the failure of the Terra LUNA stablecoin system in May 2022. This event serves as a structural breakpoint because it creates major disruptions to stablecoin trust and crypto market liquidity. Subsample results highlight important asymmetries and structural changes. In the pre-crash period, significant shock spillovers are observed from Tether to Ethereum, indicating that Tether acted as a channel for liquidity shocks. In contrast, Tether appears to have a stabilizing effect on Bitcoin, as indicated by a significant negative volatility transmission from Tether to Bitcoin. At the same time, Bitcoin's own volatility exhibits significant spillover to Tether, suggesting a bidirectional volatility relationship between the two assets. The analysis also shows that there is a bidirectional asymmetric shock transmission between Bitcoin and Tether, implying Tether responded to negative shocks in Bitcoin returns.

In contrast, the post-crash period reveals lower market volatility and reduced shock transmission between Bitcoin and Tether. Evidence of volatility interaction between Ethereum and Tether becomes more pronounced in the baseline specification, suggesting a divergence in Tether's interaction with the two markets following the crypto market crash. At the same time, this relationship appears rather sensitive to the definition of the crash period, as indicated by the robustness analysis. Asymmetric responses diminished significantly across all pairs, indicating a moderation in market reactions to negative shocks after the Terra-LUNA collapse. These findings suggest that Tether's role in the volatility dynamics of crypto markets is both asset-specific and time-varying. Before the crash, Tether appeared to absorb shocks and reflect speculative responses, particularly in its interaction with Bitcoin. After the crash, its role became more neutral, potentially due to shifting investor perceptions and changes in liquidity behavior.

Our main conclusions remain qualitatively robust to alternative specifications and sample definitions. Overall, the findings provide important insights for regulators and market participants regarding the evolving role of stablecoins. As stablecoins become increasingly integrated into both crypto and traditional financial systems, understanding volatility linkages and liquidity driven transmission mechanisms is essential for assessing systemic risk and designing appropriate regulatory frameworks.

While the study focuses on Bitcoin, Ethereum, and Tether, which play key roles in the cryptocurrency ecosystem, it does not capture the full range of crypto assets or stablecoin structures currently in use. Consequently, the findings should be interpreted as characterizing volatility transmission within the most liquid and systemically relevant segments of the market, rather than the entire crypto universe. In addition, the use of daily data implies that short lived intraday liquidity adjustments and rapid trading responses, particularly during episodes of heightened market stress, are not explicitly captured.

These considerations also point to potential directions for future research. Extending the analysis to a broader set of stablecoins, including alternatives such as USDC or algorithmic stablecoins, could help clarify how different stablecoin designs shape volatility transmission and liquidity dynamics. Future studies may also benefit from incorporating higher-frequency data to capture intraday liquidity dynamics and order flow during stress episodes. Finally, examining the interaction between stablecoin-related liquidity and traditional financial markets would be particularly relevant as stablecoins become increasingly embedded in payment systems, lending arrangements, and cross-border financial infrastructure.

References

Adachi, M., Bento Pereira Da Silva, P., Born, A., Cappuccio, M., Czák-Ludwig, S., Gschossmann, I., Pellicani, A., Philipps, S.M., Plooij, M., Rossteuscher, I., Zeoli, P. (2022). *Stablecoins' role in crypto and beyond: Functions, risks and policy*. ECB Macroprudential Bulletin 18. European Central Bank

Ante, L., Fiedler, I., Strehle, E. (2021). The influence of stablecoin issuance on cryptocurrency markets. *Finance Research Letters*, 41, 101867.

Ardia, D., Bluteau, K., Rüede, M. (2019). Regime changes in Bitcoin GARCH volatility dynamics. *Finance Research Letters*, 29, 266–271.

Badev, A., Watsky, C. (2023). *Interconnected DeFi: Ripple Effects from the Terra Collapse*, Finance and Economics Discussion Series 2023-044. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/FEDS.2023.044

Balcilar, M., Bouri, E., Gupta, R., Roubaud, D. (2017). Can volume predict Bitcoin returns and volatility? A quantiles-based approach. *Economic Modelling*, 64, 74–81.

Bank for International Settlements. (2018). *Annual Economic Report 2018: Cryptocurrencies – looking beyond the hype*. June 2018

Baur, D.G., Dimpfl, T., (2018). Asymmetric volatility in cryptocurrencies. *Economic Letters*,. 173, 148–151, https://doi.org/10.1016/j.econlet.2018.10.008.

Baur, D. G., Dimpfl, T., Kuck, K. (2018). Bitcoin, gold and the US dollar–A replication and extension. *Finance Research Letters*, 25, 103–110.

Behrens, A. (2021). *USD Coin and AMMs: The Role of USDC in DeFi Trading*. (Retrieved 2025-02-04) Available at https://www.circle.com/blog/usd-coin-and-amms-the-role-of-usdc-in-defi-trading?

Bollerslev, T., Engle, R., Wooldridge, J. (1988). A Capital Asset Pricing Model with Time-Varying Covariances. *Journal of Political Economy*, 96(1), 116–131.

Bonelli, M. (2016). Stock Market Volatility Dynamics: A Volume Filtered-GARCH Model. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2743170

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I. (2017). On the hedge and safe haven properties of Bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192–198.

Chaim, P., Laurini, M. P. (2018). Volatility and return jumps in bitcoin. *Economics Letters*, 173, 158–163.

Ciaian, P., Rajcaniova, M., Kancs, D. (2018). Virtual relationships: Short- and long-run evidence from Bitcoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money*, 52, 173–195.

Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L. (2019). Cryptocurrencies as a Financial Asset: A Systematic Analysis. *International Review of Financial Analysis*, 62, 182-199, https://doi.org/10.1016/j.irfa.2018.09.003

Corbet, S., Hou, Y., Hu, Y., Larkin, C., Lucey, B., Oxley, L. (2022). Cryptocurrency liquidity and volatility interrelationships during the COVID-19 pandemic. *Finance Research Letters*, 45, 102137.

De Blasis, R., Galati, L., Webb, A., Webb, R. I. (2023). Intelligent design: stablecoins (in)stability and collateral during market turbulence. *Financial Innovation*, 9(85), 1-23, https://doi.org/10.1186/s40854-023-00492-4

Dwyer, G. P. (2015). The economics of Bitcoin and similar private digital currencies. *Journal of Financial Stability*, 17, 81–91.

Dyhrberg, A. H. (2016). Hedging capabilities of bitcoin. Is it the virtual gold?. *Finance Research Letters*, 16, 139-144, https://doi.org/10.1016/j.frl.2015.10.025

Engle R F. (1982). Autoregressive Conditional Heteroscedasticity with Estimates of the Variance of United Kingdom Inflation. *Econometrica*, 50(4), 987–1007.

Engle, R. F., Kroner, K. F. (1995). Multivariate Simultaneous Generalized Arch.. *Econometric Theory,* 11(1), 122–150.

European Systemic Risk Board. (2025). *Crypto-assets and decentralised finance*. October 2025

Financial Stability Board. (2023). *The Financial Stability Risks of Decentralised Finance*. February 2023

Gkillas, K., Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, 164, 109–111.

Griffin, J. M., Shams, A. (2020). Is Bitcoin really untethered? *The Journal of Finance*, 75(4), 1913–1964.

IMF (2025). *Crypto Assets Monitor*, October 2025

Karpoff, J. M. (1987). The relation between price changes and trading volume: A survey. *Journal of Financial and Quantitative Analysis*, 22(1), 109–126, https://doi.org/10.2307/2330874.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3–6, https://doi.org/10.1016/j.econlet.2017.06.023

Katsiampa, P. (2018). Volatility co-movement between bitcoin and ether. *Finance Reserach Letters*, 30, 221-227, https://doi.org/10.1016/j.frl.2018.10.005

Katsiampa, P., Corbet, S., Lucey, B. (2019). Volatility spillover effects in leading cryptocurrencies: A BEKK–MGARCH analysis. *Finance Research Letters*, 29, 68–74. https://doi.org/10.1016/j.frl.2019.03.009

Kristoufek L. (2022). On the role of stablecoins in cryptoasset pricing dynamics. *Financial Innovations*, 8(1), 1-26, https://doi.org/10.1186/s40854-022-00343-8

Kroner, K. F., Ng, V. K. (1998). Modeling Asymmetric Comovements of Asset Returns. *Review of Financial Studies*, 11, 817-844, https://doi.org/10.1093/rfs/11.4.817

Kyle, A. S. (1985). Continuous Auctions and Insider Trading. *Econometrica*, 53(6), 1315-1335, https://doi.org/10.2307/1913210

Lee, S., Lee, J., Lee, Y. (2023). Dissecting the Terra-LUNA crash: Evidence from the spillover effect in cryptocurrencies and information flow. *Finance Research Letters*, 53, 103590.

Nicolle, E. (2025). *JPMorgan to allow Bitcoin, Ether as collateral in crypto push*. (Retrieved 2025-10-24) Available at: https://www.bloomberg.com/news/articles/2025-10-24/jpmorgan-to-allow-bitcoin-ether-as-collateral-in-crypto-push

Özdemir, A. (2022). Cue the volatility spillover in the cryptocurrency markets during the COVID-19 pandemic: evidence from DCC-GARCH and wavelet analysis. *Finanical Innovation*, 8(12), 1-38, https://doi.org/10.1186/s40854-021-00319-0

PR Newswire. (2025). *Zelle goes international: Early Warning expands $1T payments network with stablecoin initiative.* (Retrieved 2025-10-24) Available at: https://www.prnewswire.com/news-releases/zelle-goes-international-early-warning-expands-1t-payments-network-with-stablecoin-initiative-302593440.html

Schär, F. (2021). "Decentralized Finance: On Blockchain- and Smart Contract-Based Financial Markets," *Review, Federal Reserve Bank of St. Louis*, vol. 103(2), 153-174, April. https://doi.org/10.20955/r.103.153-74

Tauchen, G. E., Pitts, M. (1983). The price variability-volume relationship on speculative markets. *Econometrica*, 51(2), 485–505, https://doi.org/10.2307/1912002

The White House. (2025). *President Donald J. Trump establishes the Strategic Bitcoin Reserve and U.S. Digital Asset Stockpile.* (Retrieved 2025-03-20) Available at: https://www.whitehouse.gov/fact-sheets/2025/03/fact-sheet-president-donald-j-trump-establishes-the-strategic-bitcoin-reserve-and-u-s-digital-asset-stockpile/

Troster, V., Tiwari, A. K., Shahbaz, M., Macedo, D. N. (2019). Bitcoin returns and risk: A general GARCH and GAS analysis. Finance Research Letters, 30, 187–193, https://doi.org/10.1016/j.frl.2018.09.014

Wang, J. (2002). Trading volume and asset prices. *Annals of Economics and Finance, Society for AEF*, 3(2), 299-359.

Wei, W. C. (2018). The impact of Tether grants on Bitcoin. *Economics Letters*, 171, 19–22.

Appendix A

Table A1: Pre-crash Bivariate GARCH Models

	Bitcoin - Tether		Ethereum - Tether	
Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$\varepsilon^2_{1,t}$	0.136545*** (11.07465)	0.0798607*** (24.85485)	0.0623815*** (4.16259)	0.0061189 (0.18699)
$\varepsilon_{1,t}\varepsilon_{2,t}$	−0.0012537 (−0.83628)	−0.0126970 (−0.69920)	0.0040980*** (2.79355)	−0.0057254 (−0.38285)
$\varepsilon^2_{2,t}$	2.87E−06 (0.41957)	0.00050467 (0.34925)	6.730E−05 (1.57005)	0.00132395 (0.62243)
$h_{11,t}$	0.3737365 *** (32.17751)	0.20594641** (2.18679)	0.800047*** (21.35285)	0.00461593 (0.21571)
$h_{12,t}$	−0.003517*** (−28.00110)	0.5397763*** (4.38416)	0.0027541* (1.65624)	0.13380633 (0.43169)
$h_{22,t}$	8.277E−06*** (15.15867)	0.3536824*** (107.85465)	2.370E−06 (0.82093)	0.969691*** (89.97373)
$u^2_{1,t}$	0.070026*** (82.44480)	0.00070136** (2.43841)	0.0649496*** (2.62335)	0.50458588 (1.35451)
$u_{1,t}u_{2,t}$	0.0006449*** (7.14865)	−0.078533*** (−4.85712)	0.00262726 (1.27561)	0.3167862** (2.32258)
$u^2_{2,t}$	1.485E−06*** (3.58561)	0.2198387*** (134.13402)	2.657E−05 (0.67128)	0.049720*** (2.84708)

Note: h_{11} denotes the conditional variance for the Bitcoin and Ethereum markets and h_{22} denotes the conditional variance for Tether volume change. e_1 is the shock on conditional variances for Bitcoin and Ethereum, and e_2 is the shock on the Tether market. The cross-subscripts denote the cross-market effects. While u_{11} represents the asymmetric effects of news on Bitcoin and Ethereum market, u_{22} represents the same effect for the Tether market. For each estimated parameter coefficient, the corresponding *t*-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Table A2: Post-crash Bivariate GARCH Models

	Bitcoin - Tether		Ethereum - Tether	
Independent Variable	$h_{11,t+1}$	$h_{22,t+1}$	$h_{11,t+1}$	$h_{22,t+1}$
$\varepsilon_{1,t}^2$	0.10972799*** (17.36030)	0.11634253 (0.13040)	0.05792080 (1.62604)	0.03784765 (0.13010)
$\varepsilon_{1,t}\varepsilon_{2,t}$	−4.56E−04 (−0.53611)	0.00444939 (0.13037)	−0.0013738 (−0.83474)	0.00076363 (0.04415)
$\varepsilon_{2,t}^2$	4.743E−07 (0.26653)	0.00004254 (0.06891)	8.147E−06 (0.46829)	0.00000385 (0.02264)
$h_{11,t}$	0.34448795*** (28.88788)	0.08305034 (0.21444)	0.4911092*** (3.41711)	0.31843868 (0.39306)
$h_{12,t}$	0.0016099 (1.58069)	−0.2476905 (−0.42793)	−0.0237719 (−1.19229)	0.82510784 (0.77174)
$h_{22,t}$	1.881E−06 (0.79157)	0.1846789*** (5.77907)	0.00028767 (0.51948)	0.534485*** (4.67049)
$u_{1,t}^2$	0.2177758*** (24.85709)	1.89244327 (1.52592)	0.2714255*** (2.67707)	3.75837931 (0.98161)
$u_{1,t}u_{2,t}$	−0.004128*** (−50.00257)	0.1345165*** (2.83201)	0.00115081 (0.37641)	0.98615365 (1.34043)
$u_{2,t}^2$	1.956E−05*** (90.49659)	0.0023903*** (19.56041)	1.220E−06 (0.18631)	0.06468872 (1.38456)

Note: h_{11} denotes the conditional variance for the Bitcoin and Ethereum markets and h_{22} denotes the conditional variance for Tether volume change. e1 is the shock on conditional variances for Bitcoin and Ethereum, and e_2 is the shock on the Tether market. The cross-subscripts denote the cross-market effects. While u_{11} represents the asymmetric effects of news on Bitcoin and Ethereum market, u_{22} represents the same effect for the Tether market. For each estimated parameter coefficient, the corresponding *t*-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Source: authors' calculations

Appendix B

Table B1: Conditional Mean Equation Estimates for Bitcoin-Tether System

	Pre-Crash		Post-Crash	
Independent Variable	**Bitcoin**	**Tether**	**Bitcoin**	**Tether**
$Bitcoin_{t-1}$	−0.006986 (−0.28338)	0.210676 (0.63258)	−0.016806 (−0.60612)	0.052384 (0.06783)
$Tether_{t-1}$	0.000431 (0.25582)	−0.212588*** (−7.89512)	0.000527 (0.47194)	−0.073614** (−2.09547)
constant	0.001764** (1.980309)	−0.005482 (−0.39825)	0.001110* (1.65978)	0.000817 (0.04460)

Note: Bitcoin denotes the price return of Bitcoin, while Tether denotes the change in Tether volume. For each estimated parameter coefficient, the corresponding t-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.

Table B2: Conditional Mean Equation Estimates for Ethereum-Tether System

	Pre-Crash		Post-Crash	
Independent Variable	**Ethereum**	**Tether**	**Ethereum**	**Tether**
$Ethereum_{t-1}$	−0.046856 (−1.51181)	0.029096 (0.10792)	0.050868 (1.36955)	−0.049198 (−0.09749)
$Tether_{t-1}$	0.000392 (0.17902)	−0.218928*** (−8.21465)	−0.000473 (−0.29953)	−0.08729*** (−2.83509)
constant	0.001502 (1.19408)	−0.002069 (−0.14149)	0.000949 (0.96558)	−0.012305 (−0.61816)

Note: Ethereum denotes the price return of Ethereum, while Tether denotes the change in Tether volume. For each estimated parameter coefficient, the corresponding t-values are given in parentheses, while *, **, and *** represent significance level at 10%, 5% and 1%, respectively.