Spillover Effects of Tether Depegs on Bitcoin Jumps and Crypto-asset Market cojumps

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Abstract

This study shows that, contrary to their intended purpose of stabilizing the crypto-asset ecosystem, stablecoins can become a significant source of market destabilization. While stablecoins like Tether (USDT) were designed to facilitate stable digital transactions and mitigate volatility in crypto portfolios, instances of depegging—where the stablecoin's value deviates from its target—have introduced new risks. Using high-frequency 5-minute price data across 70 non-stable crypto-assets, we show that stablecoin depegging events significantly increase the likelihood of abrupt price jumps in non-stable crypto-assets. Specifically, within the first 5 minutes following a depegging event, the probability of price jumps in the BTC/USD pair surges by 35 times compared to normal conditions, with the probability of cojumps rising by a factor of 39. Our results also reveal that these jumps tend to be of greater magnitude than those typically observed. These findings underscore the destabilizing role stablecoin depegging can play in the broader crypto market, challenging the assumption that stablecoins inherently contribute to market stability.

Keywords: Crypto-assets, Stablecoins, Depegs, Jumps

1. Introduction

In July 2014, the first stablecoin tokens pegged to the US Dollar, named BitUSD, were launched on the BitShares platform. Latter that year, Realcoin, subsequently rebranded as Tether, also introduced its stablecoin project on the Bitcoin blockchain with the objective of making government currencies more compatible with the new global crypto-asset market,

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which operates continuously. Through the issuance of tokens pegged to a reference asset like the US Dollar, stablecoins have introduced the possibility to transfer a stable value swiftly and often at a lower cost than the legacy system. Although the viability of stablecoins had been established since 2014, it was only between 2017 and 2018 that the volume of outstanding Tether experienced a substantial surge, escalating from approximately $10 million to an unprecedented $2.8 billion. Subsequently, its overall market capitalization has consistently expanded, attaining $95 billion in early January 2024. This growth trend has similarly extended to other stablecoins in the market, with USDC serving as a notable example, currently ranked among the top 10 crypto-assets by market capitalization. The driving force behind this dynamic in stablecoins does not exclusively rely on synchronizing fiat currency with the crypto-asset market, but also on digitizing government currencies to facilitate its integration with smart contracts and, consequently, the realm of Decentralized Finance (DeFi). However, instances such as the Terra Luna crash or the recent depegging of USDC precipitated by the insolvency of Silicon Valley Bank underscore the reality that stablecoins are not immune to deviations from their peg relative to the reference asset. These episodes of depegging could be interpreted as shocks to the broader crypto-asset market, with potential repercussions extending to both DeFi tokens actively leveraging the stablecoin within their protocols and non-DeFi crypto-assets traded on exchanges against said stablecoin. These depegging events can occur in both directions, not only negative, as seen in the case of Terra Luna, but also positive. A pertinent example is the case of stablecoins trading above their intended peg during the geopolitical upheavals in Ukraine, where heightened demand for stable assets resulted in values exceeding 1 USD. These instances underscore that, despite being designed for stability, stablecoins remain vulnerable to market fluctuations, with significant capital inflows leading to temporary deviations from their peg. This volatility has implications for risk across the entire crypto market.

Considering the substantial potential effects of depegging events on the crypto-asset market and the interconnected relationships between stablecoins and non-stable crypto-assets, we aim to deepen our understanding of these interactions by analyzing extreme events a standard metrics of risk recently used in Scaillet et al. (2020) in the context of crypto-asset market. Our research question is: What are the spillover effects of Tether depegging on

Bitcoin and the broader crypto-asset market?

Our initial step involves establishing criteria for identifying instances where a stablecoin deviates from its intended value (depegging) and subsequently detecting such occurrences. We employ the methodology outlined by Lee and Mykland (2008) and Boudt et al. (2011) to identify jump events in Bitcoin and Bollerslev et al. (2008) for cojumps. Upon completing the detection of both depegging events and jumps, we conduct an event study following the approach outlined by Dewachter et al. (2014). This event study aims to investigate the impact of USDT depegging events on the likelihood of observing jumps in the BTC/USD pair as well as cojumps in the crypto-market.

Based on our event study, we find that USDT depegging events significantly increase the probability of price jumps in the BTC/USD pair, compared to periods of stablecoin stability. The likelihood of these jumps is statistically distinct from regular periods, and this elevated probability persists for at least 4 hours following the depeg. Furthermore, USDT depegs not only increase the probability of jumps by up to 35 times but also tend to generate jumps of greater magnitude compared to our control sample, regardless of the direction of the depeg or the jump. In addition to BTC/USD-specific movements, we observe a notable rise in market-wide cojumps following a USDT depegging event, with the probability of such events being up to 39 times higher than in stable periods. This finding underscores the broad market impact of stablecoin disruptions, highlighting the interconnectedness of stablecoins and the wider crypto-asset market during periods of instability.

This study offers valuable insights for various stakeholders in the crypto-asset and decentralized finance (DeFi) sectors. By examining the impact of stablecoin depegging events on the likelihood of price jumps in non-stable crypto-assets, this research contributes to a deeper understanding of the interconnected dynamics between stablecoins and the broader crypto market. For investors and traders, the findings highlight the potential risks associated with stablecoin depegging, even for those who primarily hold non-stable crypto-assets. Understanding the increased likelihood of market volatility and price jumps surrounding depegging events can inform better risk management and investment strategies. DeFi participants, particularly those engaged in protocols reliant on stablecoins, can benefit from this study by gaining awareness of how stablecoin instability may impact the value of assets locked within these protocols. This knowledge is crucial for optimizing yield while mitigating the risks posed by market fluctuations. Moreover, the study's findings could inform regulatory frameworks aimed at enhancing the resilience of both stablecoins and the broader crypto-financial system. In sum, this research provides essential knowledge that can aid market participants, DeFi users, and regulators in navigating the complexities of the crypto-asset market, particularly in relation to the stability and reliability of stablecoins.

The academic literature on depegging events has traditionally focused on fiat currencies, with foundational studies dating back several decades. Key works such as Krugman (1979) and Obstfeld (1996) have explored the dynamics of currency crises and depegging in traditional monetary systems, providing a robust theoretical framework for understanding how pegged exchange rates can fail. More recently, this body of literature has been extended to the realm of crypto-assets, where stablecoins like USDT, pegged to the US dollar, have raised new questions about stability in highly volatile markets. Notable contributions to this emerging field include Grobys et al. (2021); Jarno and Kołodziejczyk (2021); Briola et al. (2023) and other studies that have begun to examine their volatility and how external shocks influence stablecoin depegging events in crypto-asset markets. While much of the existing research in the crypto-asset contexts has focused on average returns and volatility with respect to stablecoins, our study aims to fill a gap by analyzing extreme market movements which are particularly important when documenting risk (see Scaillet et al. (2020) in the context of crypto-assets). By focusing on these extreme values, rather than the more commonly studied average market dynamics, we provide new insights into the destabilizing effects of depegging events on both Bitcoin and the broader market.

The remainder of this paper is structured as follows. Section 2 reviews the relevant literature on depegging events in both traditional currencies and cryptocurrencies. Section 3 outlines the data used in this analysis. Section 4 presents the methodology, covering depeg detection, jump detection (for individual assets and market-wide cojumps), and the event study approach. Section 5 presents the results, including descriptive statistics, the event study findings, and an analysis of jump sizes. Section 6 discusses the implications of the findings, and Section 7 addresses the robustness of the results by examining alternative detection methods, depeg directions, and potential reverse causality. Finally, Section 8 offers concluding remarks.

2. Literature review

This literature review examines the role of stablecoins as safe havens, their volatility, and the impact of stablecoin depegging events, such as the Terra-Luna crash, on the broader crypto market. Stablecoins are designed to act as secure assets during market downturns. As a result, a significant portion of the literature focuses on their role as safe havens within the crypto-asset market (Baur and Hoang, 2021; Wang et al., 2020; Wasiuzzaman and Rahman, 2021). Baur and Hoang (2021) conduct their analysis using intraday data on the six largest stablecoins and Bitcoin. Their approach involve applying an econometric model to regress stablecoin returns against dummy variables representing extreme Bitcoin returns, along with normal bitcoin returns. The researchers argue that if the coefficients are zero, stablecoins can be considered weak safe havens, whereas negative coefficients would indicate strong safe haven properties, albeit without stability. The findings of their study suggest that stablecoins can indeed be viewed as safe havens within the crypto-asset market, with Tether displaying the most pronounced effect. Furthermore, the researchers show that investors tend to reallocate their resources towards stablecoins in response to extreme negative price fluctuations in Bitcoin. The study conducted by Wang et al. (2020), examines the diversification, hedging, and safe haven characteristics of stablecoins in relation to traditional crypto-assets. To assess these properties, the researchers employ a Dynamic Conditional Correlation-GARCH (DCC-GARCH) model and conduct robustness tests using time-varying copula models. The findings indicate that stablecoins exhibit effective diversification qualities during normal market conditions. Additionally, under specific circumstances, stablecoins can assume the role of a safe haven, although this role varies across different market conditions. The study also suggests that gold-pegged stablecoins display lower effectiveness as safe havens compared to USD-pegged stablecoins. Closely linked to studies tackling the safe-haven property that stablecoins can endorse, several papers have analysed the stability of stablecoins as well as the different mechanisms at play. Jarno and Kołodziejczyk (2021) as well as Jeger et al. (2020) tackles the question of stablecoin volatility by distinguishing them based on their design features. Both of them find divergence in stability depending on the mechanism ensuring the peg, with traditional asset-backed stablecoins outperforming all other forms. Those findings highlight the importance of the design choices and the impact on the volatility of the asset. Grobys et al. (2021) go one step further by also investigating the stochastic interdependencies between stablecoins and Bitcoin's volatilities. Their initial findings reveal the statistical instability of stablecoin volatilities. Furthermore, employing Granger causality analysis, the authors discern a noteworthy influence of past Bitcoin volatility on stablecoin volatility, ultimately affirming that the fluctuation of the most famous crypto-asset is a pivotal factor shaping the volatility of stablecoins. These papers emphasize the significant role and influence that stablecoins can have in the market, for instance, through their usage as safe haven.

Another aspect of their influence in the crypto-asset market is explored in studies by Ante et al. (2021); Kristoufek (2021); Wei (2018) and Griffin and Shams (2020), which investigate the effects of stablecoin issuance on the crypto-asset market. In their study, Ante et al. (2021) analyze the impact of 565 instances of stablecoin issuance, each amounting to \$1 million or more, across seven different stablecoins. The authors focus on the periods before and after the issuance of newly created tokens, conducting an event study to examine the effects on the returns of other crypto-assets. Abnormal returns were computed as the difference between observed and expected returns, with the expected return derived from the mean return during the estimation period. The results reveal a market downturn in the week prior to issuance, while positive abnormal returns were observed 24 hours before and after the issuance event. The authors argue that short-term investors in the crypto-asset market employ newly minted stablecoins to purchase more volatile crypto-assets, thereby explaining the abnormal positive returns observed in proximity to the issuance of stablecoins. Likewise, Wei (2018) investigates the impact of Tether issuances on Bitcoin prices using a VAR model. Contrary to Ante et al. (2021), Wei (2018) revealthe absence of impact of Tether issuance on Bitcoin prices even though it has a significant positive effect on the volume traded. They also indicate an increase in the volume of Tether traded following a period of negative returns in Bitcoin. Also focusing on Tether, Griffin and Shams (2020) takes advantage of blockchain data to highlight the impact of Tether on the Bitcoin price during the 2017 boom. Authors find that Tether purchases are timed after a market downturn which significantly increase the price of Bitcoin. Kristoufek (2021) investigates the position of stablecoins within the crypto-asset market by employing a generalized Vector Autoregression (VAR) model developed by Diebold and Yilmaz (2009, 2012) to analyze directional spillovers. The study uses daily observations of a range of stablecoins and three major crypto-assets (BTC, ETH, XRP). The findings indicate no evidence of artificial price boosting of other crypto-assets by stablecoins. In fact, it suggests an inverse relationship, where an increase in the price of crypto-assets triggers a subsequent increase in stablecoin issuance as a reactive measure. This result implies that the growing demand in the crypto-asset market translates into a demand for fiat-pegged stablecoins. For a systematic overview of the empirical literature on stablecoins, see Ante et al. (2023).

Although stable crypto-assets generally fulfill their purpose, events like the UST collapse or the USDC depegging event have demonstrated that they can also instigate broader market disruptions, turning a stable asset into a catalyst for market downturns. These events have drawn attention from researchers seeking to understand the dynamics and interplay within the ecosystem. In their work, Briola et al. (2023) provide a precise timeline of events that led to the Terra project's collapse, drawing on diverse sources. The authors use smoothed weighted correlations on hourly data to capture the dependency structures of crypto-assets, finding a high co-movement level up until May 11th, when the LUNA token was entirely excluded from the network. They then use public trades extracted from Kraken to uncover the role of Bitcoin in the initial stage of the collapse. The authors do not identify any herding behavior during the downturn, indicating that investors did not consider this collapse to be a structural shock. In contrast, De Blasis et al. (2023) analyze the market's response following this exogenous shock using a BEKK model on minute-by-minute data of Bitcoin and the six most liquid stablecoins. Their findings indicate a contagion effect across all crypto-assets studied. In contradiction to Briola et al. (2023)'s analysis, De Blasis et al. (2023) identify evidence of potential herding behaviors among traders who were willing to pay a premium for safer stablecoins. Finally, Lee et al. (2023) employs the methodology of Diebold and Yilmaz (2012) as well as the Shannon Transfer Entropy on hourly and 5-min prices to capture the spillover effects as well as the information flows before and after the Terra-Luna crash. Their results suggest that the crash that occurred in May 2022 had a significant impact on the connectedness of crypto-assets as well as on the investor confidence and the market sentiment.

The finance literature has long been concerned with extreme risks, particularly extreme losses, due to their profound impact on financial markets and investment strategies. Traditionally, this literature has focused on extreme events in standard asset classes, employing methods like extreme value theory and jump diffusion models to analyze rare but significant market movements (e.g., Longin (2000),Aït-Sahalia and Jacod (2009),Boudt et al. (2011)). With the advent of crypto-assets, researchers have extended their analyses to those assets, acknowledging the heightened volatility and the unique risk profiles of these digital assets. Studies such as Chaim and Laurini (2018) and Scaillet et al. (2020) have delved into extreme price movements in Bitcoin, revealing insights into the frequency, clustering, and market impact of jumps in this emerging asset class. While both of these studies focus on the behavior of Bitcoin, they employ different methodologies and data sources. Chaim and Laurini (2018) examine daily Bitcoin data and identify two distinct periods of elevated volatility within their dataset. They identify that jumps in mean returns are particularly valuable for capturing significant price fluctuations, primarily negative ones, linked to pivotal events in crypto-asset markets, such as security breaches and failed fork attempts. On the other hand, Scaillet et al. (2020) employs a comprehensive dataset from the MtGox exchange, including trader identification information. Their research reveals that jumps in crypto-asset prices tend to be frequent and clustered in time. Furthermore, their findings suggest that these jumps have a short-term positive impact on market activity and illiquidity and can trigger persistent changes in prices.

Following those two papers, other studies have tackled the subject of crypto-asset jumps. The paper by Dutta and Bouri (2022) examines the presence of outliers and time-varying jumps of four crypto-asset return series and the CCI30 index. The study shows that only Bitcoin returns are affected by outliers, while time-varying jumps occur in most studied assets. Even after accounting for outliers, Bitcoin continues to exhibit significant jumps. These findings highlight price instability in major crypto-assets and emphasize the need to consider large shocks and time-varying jumps when modeling volatility in crypto-asset markets. Numerous researches have also been interested in detecting cojumps in the crypto-asset market

(Bouri et al., 2020; Zhang et al., 2023; Ben Omrane et al., 2021; Xu et al., 2022; Gkillas et al., 2022; Bouri et al., 2022). Bouri et al. (2020) reveal evidence of cojumping behavior among crypto-assets, indicating that jumps in one crypto-asset are likely to induce jumps in others. Additionally, cojumping is associated with increased trading volume, emphasizing the role of trading volume in crypto-asset volatility, in line with earlier research.

More recently, researchers have been trying to link those jumps to specific events, be it macroeconomic news (Ben Omrane et al., 2021) or geopolitical risks (Bouri et al., 2022). For the former, Ben Omrane et al. (2021) find several key takeaways by using 5-min price data for Bitcoin and Ethereum while gathering macroeconomic news from the US, Germany and Japan. First, they find that Ethereum experiences intraday price jumps three times more frequently than Bitcoin with more responsiveness to macroeconomic news from Ethereum than Bitcoin in terms of jumps. Second, as one might expect, U.S. news releases have a more significant impact on price jumps in both crypto-assets when compared to German and Japanese news announcements. Interestingly, co-movements between Bitcoin and Ethereum are infrequent and are primarily associated with specific U.S. news releases. The latter study using geopolitical risks employs the methodology of Laurent et al. (2016) to detect daily jumps in several crypto-asset price series. Subsequently, they investigate cojumps between crypto-assets and a geopolitical risk index using logistic regressions. The findings indicate that the price behavior of all the studied crypto-assets exhibits jumpiness. However, it is notable that only Bitcoin displays a dependence on cojumps with the geopolitical risk index. This discovery underscores the argument put forth in prior research that Bitcoin serves as a hedge against geopolitical risk.

Building upon this body of work, we extend the literature on extreme market events by linking stablecoin depegging incidents with sudden, significant price movements in non-stable crypto-assets. While previous research has primarily examined extreme returns and volatility within individual crypto-assets, our study bridges this gap by exploring how instability in stablecoins can propagate extreme risks to the broader crypto-asset ecosystem. To the best of our knowledge, this study is the first to bridge the stablecoin literature with research on jumps in crypto-assets. In doing so, we provide novel evidence on the transmission of risk during extreme market events. By establishing this connection, we offer a novel perspective on the systemic implications of stablecoin depegging events, thus enhancing the understanding of extreme risks in crypto-asset markets.

3. Data

This study applies intra-day jump detection methods to non-stable crypto-assets and depeg detection procedures to stablecoin. To conduct the two methodologies, we gather data at a 5-minute granularity, encompassing prices, market capitalization, and 24-hour trading volumes for both Tether and non-stable crypto-assets from coinpaprika. Our sample period spans from January 1, 2022, to June 30, 2023 which allows us to capture most of the significant stablecoin depegs that have recently occurred. To ensure representation of a substantial portion of the market, we construct our sample based on the top 100 crypto-assets in terms of market capitalization as of July 1, 2023. Wrapped tokens, representing other assets, are excluded, along with crypto-assets that were first emitted after January 1, 2022, or exhibit recurrent missing observations. We end up with a total sample of 70 non-stable crypto-assets and 1 stablecoin (Tether) composed of 157,248 observations per asset.

4. Methodology

4.1. Depeg detection

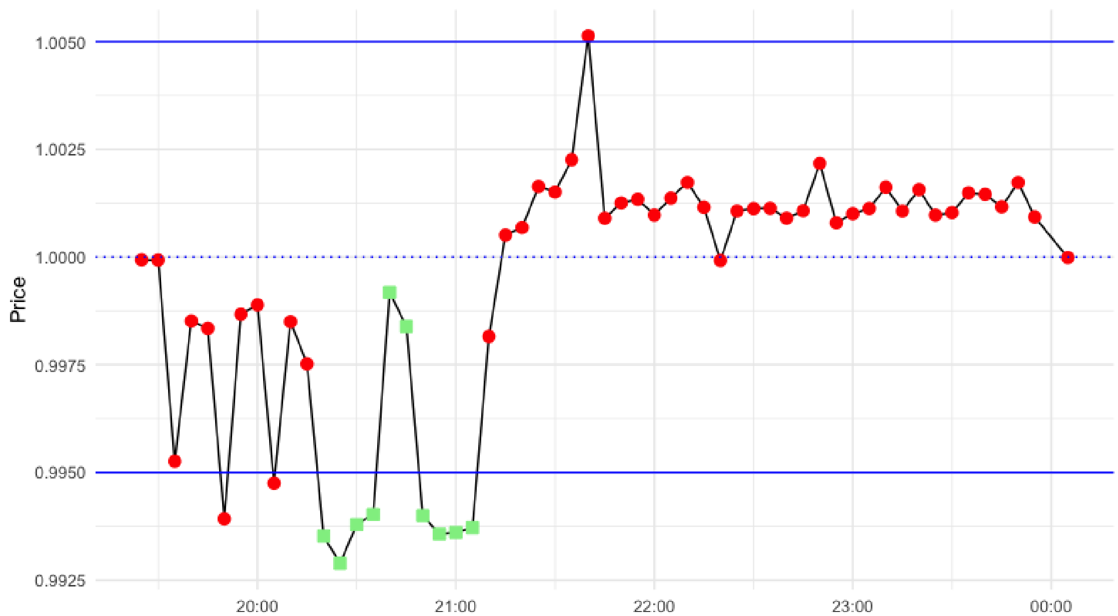
A stablecoin depeg occurs when its market value significantly diverges from its intended value. In the case of Tether (USDT), the intended value is set at 1 USD. Various factors can contribute to deviations from this intended value. One such factor is counterparty risk, which refers to the risk that the entity or entities responsible for maintaining the stablecoin's pegged value may experience financial distress or even default, potentially jeopardizing the stability of the stablecoin. Another crucial factor is collateral risk, which involves the value of the assets used as collateral to back the stablecoin. If these collateral assets depreciate significantly, it could threaten the stability and redeemability of the stablecoin. Regulatory risk also plays a role, arising from changes or uncertainties in the regulatory environment. As stablecoins may be subject to evolving regulatory frameworks, any changes in these regulations could impact their operation, legal status, and overall acceptance. Additionally, there is liquidity risk, which is the risk associated with the inability to meet the demand for stablecoin redemptions, akin to a "bank run" scenario. This risk occurs when the entity managing the stablecoin faces challenges in quickly converting its assets or reserves into cash to meet a sudden increase in withdrawal requests. Finally, algorithmic stability risk is related to the algorithmic mechanisms employed to maintain the value of algorithmic stablecoins. Algorithmic stablecoins rely on code-driven processes, and any vulnerabilities or unexpected behaviors in the algorithm can cause deviations from the intended pegged value.

Strictly speaking, any deviation from the 1$ value should be considered as a depeg. However, as observed in their historical performance, stablecoins frequently exhibit deviations from their target value which would result in an unrealistic selection of depegs (Duan and Urquhart, 2023). We recognize the difficulty in precisely identifying the exact timing of stablecoin depegging events, as the stringency of the depegging event definition can yield varying outcomes. Our approach is influenced by S&P Global (2023), where the authors employ multiple threshold levels to precisely assess the intensity of the depeg. Positive deviations occur when the stablecoin's market value exceeds its intended value, while negative deviations happen when its value falls below the intended level. Our threshold levels span from 0.975 to 1.025, with increments of half a percent. Overall, this is what we propose as a main algorithm to flag depegging events:

- A depegging event starts when the stablecoin price crosses the predefined threshold.
- A depegging event ends when the stablecoin's price reverts below or above the threshold, depending on the depeg direction.
- If a depegging event is detected within 20 minutes after the prior one, it is considered part of the initial detection.
- Instances of depegging detected for less than 2 consecutive observations are excluded.

As an illustration of the detection algorithm, Figure 1 displays the price of Tether on April 11, 2022, where a deviation from the intended peg is observed. Specifically, just before and after 8:00 PM, the USDT price briefly crossed below the lower threshold of $0.995 on two occasions. However, in both cases, the price quickly returned above the threshold, thereby violating the fourth rule of our algorithm, which requires that the deviation persist for at least two consecutive observations in order to be classified as a depegging event. The green squares in the figure indicate the instances where our algorithm successfully detects a depegging event, beginning at 8:20 PM and continuing until 9:05 PM. Since the price remained below the threshold for two consecutive observations starting at 8:20 PM, this situation is identified as a depeg. Although the price briefly rose above the threshold at approximately 8:40 PM, it subsequently fell below the threshold again. According to the third rule of our algorithm, if a depegging event is detected within 20 minutes of a prior event, it is considered a continuation of the initial event. Consequently, this scenario is treated as a single depegging event rather than two distinct occurrences.

Figure 1: Tether price with depeg detection



The algorithm is designed to filter out noise caused by minor deviations from the stablecoin's target price, ensuring the accurate identification of depegging events. To assess the impact of a particular degree of depegging, we create a new variable that merges both positive and negative depegs of equal magnitude. This procedure yields depegging events of varying strength, ranging from deviations of 0.5% to 2.5%, irrespective of the direction of the event. The employed threshold methodology facilitates not only the identification of the start of a depegging event but also the quantification of its persistence by counting the number of periods during which the market price breaches the established threshold.

Additionally, we can compute the frequency of depegs by straightforwardly enumerating the occurrences of depegs within a specified timeframe. To assess the robustness of our results derived from the methodology used to detect depegging events, we introduce an alternative depeg detection mechanism. Under this alternative approach, upon detecting a crossing of the predefined threshold, we retrospectively identify the exact moment when the price first deviated from its $1 level.

4.2. Jump detection

4.2.1. Individual jump

We adopt the assumption that the logarithm of the crypto-asset price, $p(t)$, conforms to a jump-diffusion process as in Andersen et al. (2007). The log-price process $p(t)$ evolves according to the following equation:

$$dp(t) = \mu(t)\, dt + \sigma(t)\, dW(t) + k(t)\, dq(t), \quad 0 \leq t \leq T \tag{1}$$

where dp(t) denotes the logarithmic price increment, μ(t) the drift,σ(t) the instantaneous volatility, W(t) a standard Brownian motion, q(t) a counting process, and k(t) the jump size. In the absence of jumps, the data generating process follows an Ito process. We consider T days with M equally spaced intra-day returns, where $M \equiv [1/\Delta]$ represents the number of intra-day observations within a day. Thus, $\Delta = 1/M$ denotes the time interval between consecutive observations.

To identify the intra-day arrival times of jumps, we follow the methodology developed in Lee and Mykland (2008). However, we discern the presence of periodicity in crypto-asset volatility at both the hourly and daily levels from Figure 2, which illustrates the hourly volatility of bitcoin log returns for each day of the week. To address this intra-day periodicity in volatility, we extend our analysis by incorporating the approach proposed by Boudt et al. (2011). Following this methodology, we derive a modified test statistic for jump detection given by

$$Jump_{t,i} = \frac{|r_{t,i}|}{\hat{S}_{t,i}\hat{f}_{t,i}}, \tag{2}$$

where $r_{t,i}$ is the ith intra-day return of day t while $s_{t,i}$ and $\hat{f}_{t,i}$ are respectively the stochastic and the periodic components of intra-day volatility. We estimate $\hat{f}_{t,i}$ by using the Truncated Maximum Likelihood (TML) estimator introduced by Marazzi and Yohai (2004). The computation of the estimator for $s_{t,i}$ is expressed as

$$\hat{S}_{t,i} = \sqrt{\frac{1}{M-1} BV_t}, \tag{3}$$

where the bipower variation, BV_t, introduced in Barndorff-Nielsen and Shephard (2004), is given by

$$BV_t = \frac{\pi}{2} \sum_{i=2}^{M} |r_{t,i}||r_{t,i-1}| \tag{4}$$

Finally, as discussed in Boudt et al. (2011), the jump detection method, which identifies a jump when $J_{t,i}$ exceeds the $1-\alpha/2$ quantile of the standard normal distribution, often results in numerous 'spurious jumps' or false positives. To mitigate this issue, Lee and Mykland (2008) incorporates principles from extreme value theory, which suggests that the maximum of n independent and identically distributed realizations of the absolute value of a standard normal variable follows a Gumbel distribution as $n \to \infty$. As a result, the null hypothesis of no jumps is rejected when

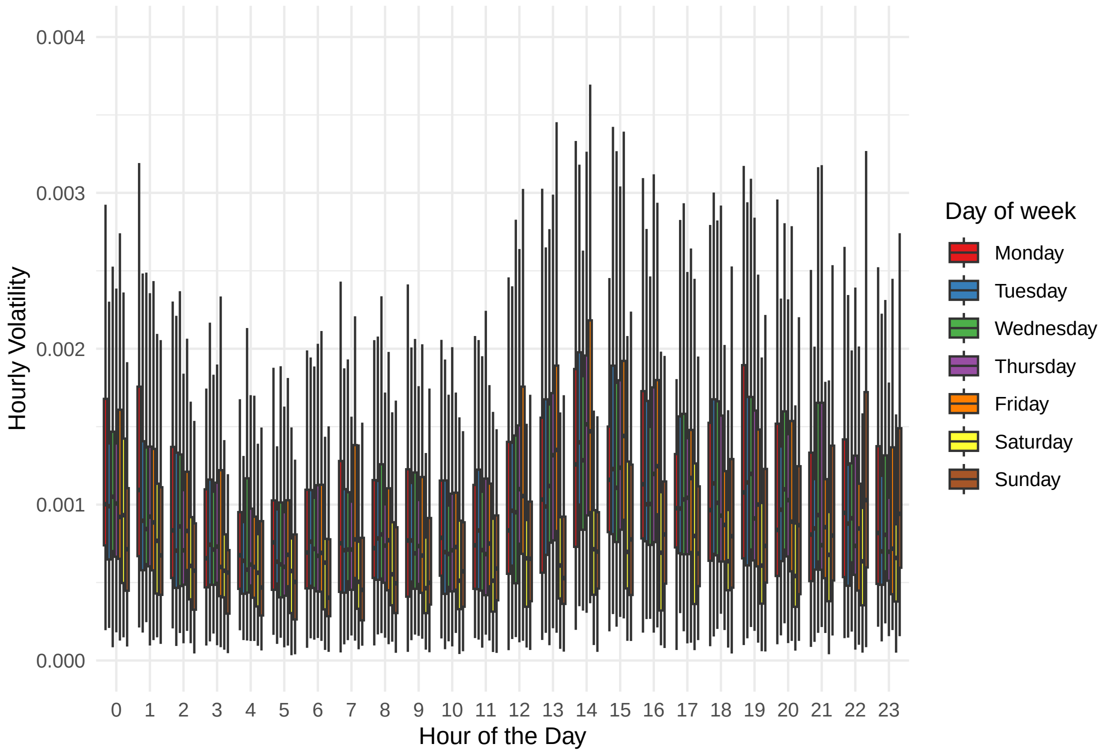
$$J_{t,i} > G^{-1}(1-\alpha) S_n + C_n \tag{5}$$

where $G^{-1}(1-\alpha)$ is the $1-\alpha$ quantile function of the standard Gumbel distribution, $C_n = \sqrt{2\log n} - \log(\pi) + \frac{\log(\log n)}{2\sqrt{2\log n}}$ and $S_n = \frac{1}{\sqrt{2\log n}}$, with n as the total count of observations.

4.2.2. Cojumps

We employ the methodology outlined by Bollerslev et al. (2008) to characterize cojumps, denoting simultaneous jumps across different assets. We opt for this methodological framework given the extensive array of crypto-assets under consideration and the granularity inherent in our dataset. Notably, as elucidated in their study, this methodology proves instrumental in encapsulating cojumps manifested within a broad spectrum of returns, as opposed to specifically isolating cojumps between individual asset pairs. In their paper, Bollerslev et al. (2008) define the mean cross-product (mcp) statistic as follows:

Figure 2: Bitcoin log returns' distribution of hourly volatility by day of the week



$$mcp_{t,j} = \frac{2}{n(n-1)} \sum_{i=1}^{n-1} \sum_{l=i+1}^{n} r_{i,t,j} r_{l,t,j}, \quad j = 1, 2, ...M. \tag{6}$$

This statistic is designed to gauge the degree of co-movement among assets by computing, for each intra-day interval, the normalized sum of individual 5-minute returns. This computation mirrors the principles of a U-statistic. As the mcp-statistic in Equation (6) does not inherently possess a zero mean even in the absence of cojumps, Bollerslev et al. (2008) propose to studentize the statistic as follows:

$$z_{mcp_{t,j}} = \frac{mcp_{t,j} - \overline{mcp_t}}{S_{mcp_t}}, \quad j = 1, 2, ..., M, \tag{7}$$

where

$$\overline{mcp_t} = \frac{1}{M} mcp_t = \frac{1}{M} \sum_{j=1}^{M} mcp_{t,j} \tag{8}$$

and

$$S_{mcp_t} = \sqrt{\frac{1}{M-1}\sum_{j=1}^{M}(mcp_{t,j} - \overline{mcp_t})^2} \tag{9}$$

Given the absence of a readily available asymptotic distribution for the z_{mcp}-statistic, Bollerslev et al. (2008) resort to a direct bootstrap procedure to derive its distribution under the null hypothesis of no jumps. To operationalize this statistic, we bootstrap its null distribution assuming the absence of jumps. Specifically, we simulate realizations of a 70 x 1 diffusion process with zero drift and a covariance matrix derived from the unconditional covariance matrix of our intra-day returns, upon which the mcp-statistic detailed in Equation (6) is computed. These realizations match the length of our dataset, consisting of 288 steps per day over a span of 546 days, and are generated iteratively 1,000 times, resulting in 157.25 million simulated observations under the null hypothesis of no jumps. Subsequently, we extract the 99.9% quantile, or critical value for a 0.001 level test for no cojumps, from the z_{mcp}-statistic computed on our simulated realizations, which amounts to 6.64.

4.3. Event Study

We follow the event-study analysis developed in Fatum and Hutchison (2003, 2006) and Dewachter et al. (2014) to investigate the impact of USDT depegging events on the probability of observing jumps in non-stable crypto-asset. We consider each depeg of the USDT stablecoin as an event with a timestamp of 5 minutes. As to analyse both the anticipation of a depegging event as well as the impact of such an event on the crypto-asset market, we fix pre-event and post-event windows. The length of those windows ranges between 5-min to 4 hours.

Our initial focus is on the following query: Does the occurrence of a USDT depegging event lead to any brief and abrupt market turbulence in the crypto-asset market? To address this, we assess the likelihood of observing a market jump under the condition of depegging events. That is,

$$p(\text{jump} \mid \text{event}) = \frac{\#\text{ of interventions followed by jumps}}{\text{total }\#\text{ of interventions}}$$

Furthermore, let $p(\text{jump}|\text{control})$ represent the probability of encountering a jump in the control sample. To calculate this probability, we form a sub-sample of intra-day return observations that omits days affected by a USDT depeg and, consequently, their corresponding intra-day periods. The probability of observing jumps is then determined by the ratio of the number of jump occurrences to the total number of observations in this control sample, expressed as:

$$p(\text{jump} \,|\, \text{control}) = \frac{\#\text{ of jumps in control sample}}{\#\text{ of observations in the control sample}}$$

We examine whether there exists a significant difference between the likelihood of observing jumps during regular non-event days and the likelihood of observing jumps given the depegging events. In both pre-event and post-event periods, we formulate the null and alternative hypotheses as:

$$H_0 : p(\text{jump} \,|\, \text{event}) = p(\text{jump} \,|\, \text{control})$$

$$H_1 : p(\text{jump} \,|\, \text{event}) \neq p(\text{jump} \,|\, \text{control})$$

Under the null hypothesis, the likelihood of observing a jump when a depegging event occurs is identical to the probability of observing a jump on regular non-event days. To put it differently, such hypothesis posits that the conditional and unconditional probabilities should be equal. This assumption implies that stablecoin depegging events do not influence the probability of jump occurrences. To test this null hypothesis, we employ a non-parametric sign test as done in Fatum and Hutchison (2003) and Dewachter et al. (2014). A rejection of the null hypothesis would suggest that USDT depegging events effectively induce jumps in the analyzed crypto-asset pair.

5. Results

5.1. Descriptive Statistics

Table 1 presents descriptive statistics concerning the price dynamics of three of the main stablecoins. The results show that both mean and median prices closely align with their intended target of \$1. Additionally, the table highlights occurrences wherein each stablecoin deviated from its designated target price, exhibiting both upward and downward depegging events, as indicated by their respective maximum and minimum values.

Table 1: Descriptive statistics on stablecoin prices.

	Ticker	Mean	Median	Std. Dev	Max	Min
Tether	USDT	1.00093	1.00087	0.00127	1.02500	0.96472
USD Coin	USDC	1.00059	1.00069	0.00352	1.03324	0.89002
Dai	DAI	1.00056	1.00067	0.00306	1.02567	0.89398

Notes: Descriptive statistics on stablecoin prices. We report the full stablecoin name as well as its ticker on financial markets. We include summary statistics on the stablecoin 5-min prices. The sample covers the period from 01-01-2022 to 30-06-2023.

Table 2 summarizes the frequency of depegging events across various threshold levels for each stablecoin. The table first distinguishes between downward and upward deviations, and then combines these deviations for each threshold level (0.5%, 1%, and 1.5%). For example, the second column shows that there were 41 instances in which the stablecoin USDT depegged below the threshold level of $0.995. At the lower thresholds, representing deviations of 0.5% or 1% from the $1 target price, stablecoins tend to exhibit more frequent upward depegs than downward depegs (Columns 2, 3, 5, and 6). A clear declining trend in the number of depegging events is observed as the threshold level increases. For instance, deviations of 1.5% from the target price occurred fewer than 5 times for each stablecoin in our sample, while deviations of 0.5% resulted in approximately 200 instances per stablecoin. We also observe that for USDT, as the threshold is increased to 1.5% deviations, the proportion of negative depegs rises from less than 20% to 75% of all depegs. This suggests that the largest depegs, in terms of deviation magnitude, tend to be negative for Tether.

Table 2: Number of depegs per threshold and stablecoin.

	0.5% Deviations			1% Deviations			1.5% Deviations		
Threshold level:	<0.995	>1.005	$\sum$	<0.990	>1.010	$\sum$	<0.985	>1.015	$\sum$
USDT	41	196	237	6	10	16	3	1	4
USDC	28	174	202	4	9	13	1	2	3
DAI	27	171	198	6	9	15	2	1	3

Notes: Frequency of depegging occurrences for individual stablecoins across various threshold levels. We report the count of stablecoin depegs for positive and negative deviations from their target price of $1. The specified threshold levels, denoted by 0.5%, 1%, and 1.5%, involve the aggregation of positive and negative depegging events of equal magnitude. The sample covers the period from 01-01-2022 to 30-06-2023.

We concentrate on the summary statistics pertaining to detected jumps [2] in three specific crypto-assets: Bitcoin, Ethereum, and Aave, as presented in Table 3. The table illustrates a nearly symmetrical distribution of positive and negative jumps for Bitcoin and Ethereum, whereas Aave is characterised by a higher percentage of negative jumps compared to positive ones. Additionally, there is a notable prevalence of jump-days for the two major crypto-assets, Bitcoin and Ethereum, with at least 85% of the observed days affected by jumps. Aave, in constrast, exhibits a notably lower percentage of jump-days, with 64% of days featuring at least one jump. Though, the overall probability of encountering a jump, irrespective of the day, remains low for all three crypto-assets, indicating that the likelihood of observing an intra-day jump is less than 1%. Regarding the magnitude of the jumps, positive jumps exhibit slightly higher levels than their negative counterparts for all three crypto-assets, albeit with a marginal difference for Bitcoin.

[2] Jumps are detected using the R package introduced by Boudt et al. (2022), which implements the methodology outlined in Boudt et al. (2011).

Table 3: Descriptive statistics on detected jumps.

Critical level: $\alpha = 0.01$	Bitcoin	Ethereum	Aave
Panel I. Sample			
# of observations	157,248	157,248	157,248
# of sample days	546	546	546
E(|Return|)	0.081	0.104	0.159
# of jumps	1233	1008	629
# of jump-days	481	469	353
E(# of jumps|jump-day)	2.563	2.149	1.782
E(|jump-size|)	0.640	0.817	1.165
Std(|jump-size|)	0.433	0.569	0.868
Panel II. Quantities			
# of (+) jumps	612	496	295
# of (-) jumps	621	512	334
% of (+) jumps	49.635	49.206	46.900
% of (-) jumps	50.365	50.794	53.100
E(|Jump-size| | (+) jump)	0.656	0.861	1.265
Std(|Jump-size| | (+) jump)	0.470	0.666	0.914
E(|Jump-size| | (-) jump)	0.623	0.775	1.077
Std(|Jump-size| | (-) jump)	0.392	0.454	0.816
Panel III. Unconditional probabilities			
P(jump-days)(%)	88.095	85.897	64.652
P(jumps)(%)	0.787	0.643	0.401
P((+) jumps)(%)	0.391	0.317	0.188
P((-) jumps)(%)	0.396	0.327	0.213

Notes: Descriptive statistics on the detected BTC/USD, ETH-USD and AAVE-USD jumps. Panel I gives general information on the sample and the detected jumps. E(|Return|) is the average of absolute returns. E(# of jumps|jump-day) is the average number of jumps per jump-day. E(|jump-size|) and Std(|jump-size|) are respectively the average and standard deviation of the jump-size. Panel II splits the detected jumps into positive and negative jumps. E(|Jump-size| | (+) jump) and E(|Jump-size| | (-) jump) are the average size of positive and negative jumps while Std(|Jump-size| | (+) jump) and Std(|Jump-size| | (-) jump) are the standard deviations of positive and negative jump sizes. Panel III summarizes unconditional probabilities.

Tables 4 and 5 present the frequency of positive and negative jumps, as well as large jumps, following positive or negative depegs of USDT. Our analysis shows that, following positive depegs, the number of positive and negative jumps within 5 minutes is relatively balanced. However, when extending the time window to one hour, positive depegs exhibit a clear tendency to induce negative jumps in Bitcoin. This pattern becomes less pronounced when focusing specifically on large jumps (Table 5), as opposed to regular jumps.[3]

In the case of negative depegs, we observe a tendency to trigger positive jumps in Bitcoin more frequently than negative ones, regardless of whether we consider regular or large jumps. Several hypotheses may explain these observations. First, the occurrence of positive jumps following negative depegs could reflect a market shift towards riskier assets, with capital flowing from Tether into Bitcoin, thereby exerting downward pressure on Tether's price and positively impacting Bitcoin returns. Second, negative depegs leading to negative jumps may signal broader market fears, triggering a general sell-off across crypto-assets, irrespective of their risk profile. Third, positive depegs followed by positive jumps could suggest an influx of capital into the crypto-asset market initially moving through Tether, and then reinvested into Bitcoin within the subsequent minutes or hour.

Table 4: Jumps After Positive and Negative Depegs (5-minute and 1-hour)

	5-minute		1-hour	
	Positive Jumps	Negative Jumps	Positive Jumps	Negative Jumps
Positive Depeg	20	26	27	68
Negative Depeg	9	7	18	7

A more complex phenomenon emerges with the substantial number of instances where USDT trades at a premium relative to the US dollar are followed by negative jumps in Bitcoin prices. This pattern contrasts with the typical flight-to-safety scenario, where a negative jump in Bitcoin would precede a positive depeg in Tether. In our observations, the positive depeg occurs before or during the negative jump in Bitcoin, suggesting a different underlying mechanism. One potential explanation lies in the market dynamics and arbitrage opportunities that arise when USDT trades at a premium.

When USDT is valued above its $1 peg, the purchasing power of USDT increases, causing

[3]Large jumps are defined in section 5.3. Jumps are identified with a significance level of $\alpha = 0.01$ in Eq. 5, while large jumps are detected using $\alpha = 0.0001$.

the BTC/USDT trading pair to adjust downward in USDT terms to maintain equilibrium with the BTC/USD pair. This creates an arbitrage opportunity: traders can buy Bitcoin with USDT at the lower BTC/USDT price and sell it for USD at the higher BTC/USD price. This process increases the supply of Bitcoin in the BTC/USD market as more traders sell BTC for USD, exerting downward pressure on the BTC/USD price and potentially triggering negative jumps in Bitcoin. Additionally, the premium on USDT may signal that investors are moving into USDT in anticipation of market volatility or as a risk-averse strategy, leading to increased selling of Bitcoin. This collective selling amplifies the downward pressure on Bitcoin prices following positive depegging events. Thus, the arbitrage activities and investor behavior not only push Bitcoin prices downward but also contribute to realigning the BTC/USDT and BTC/USD markets, helping USDT move back toward its equilibrium peg. Assessing this conjecture empirically would go beyond this research as it would required to analyze order book data, especially considering that depegging events may not occur simultaneously across all platforms.

Table 5: Large Jumps After Positive and Negative Depegs (5-minute and 1-hour)

	5-minute		1-hour	
	Positive Jumps	Negative Jumps	Positive Jumps	Negative Jumps
Positive Depeg	16	12	25	30
Negative Depeg	4	4	12	5

5.2. Event study

Using statistical inference, we investigate the impact of USDT depegging events on the probability of observing jumps in the BTC/USD pair, considering both pre- and post-depeg periods. In Table 6, we detail the number of jumps observed within a given window, along with conditional and unconditional jump probabilities before detecting a depeg in the USDT/USD pair. The null hypothesis of no effect is rejected for all pre-event windows, except for the 3-hour, 3.5-hour, and 4-hour windows.

Moving to Table 7, we provide the number of observed jumps and conditional and unconditional jump probabilities after detecting a depeg in the USDT/USD pair. In this scenario, we reject the null hypothesis without exception, indicating that the probabilities of observing jumps in the BTC/USD pair are significantly higher than the unconditional probabilities across all window lengths. When comparing the pre and post-event tables, we observe that the number of matches and conditional probabilities are notably higher in the post-event table than in the pre-event counterpart. It is also striking from our tables that the probability of observing a jump increases as the matching windows expand for both pre and post-event windows. This outcome is logically expected, as extending the time window before or after an event increases the number of observations, thereby mechanically raising the likelihood that one of these observations contains a jump.

Table 6: USDT Depeg and BTC/USD jumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	13	19	20	21	25	27	30	31	32
P(jump|event)(%)	5.48***	8.02***	8.44***	8.86***	10.55***	11.39***	12.66***	13.08***	13.50***
P(jump|control)(%)	0.73	1.46	2.18	2.91	3.64	4.37	5.09	5.82	6.55
Probability ratio	7.51	5.49	3.87	3.04	2.90	2.61	2.49	2.25	2.06
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	33	36	40	51	60	69	73	76	77
P(jump|event)(%)	13.92***	15.19***	16.88***	21.52***	25.32***	29.11***	30.80	32.07	32.49
P(jump|control)(%)	7.28	8.01	8.73	13.10	17.47	21.84	26.20	30.57	34.94
Probability ratio	1.91	1.90	1.93	1.64	1.45	1.33	1.18	1.05	0.93

Notes: BTC/USD jump dynamics before USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps before the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 7: USDT Depeg and BTC/USD jumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	62	76	81	86	88	91	100	105	109
P(jump|event)(%)	26.16***	32.07***	34.18***	36.29***	37.13***	38.40***	42.19***	44.30***	45.99***
P(jump|control)(%)	0.73	1.46	2.18	2.91	3.64	4.37	5.10	5.82	6.55
Probability ratio	35.94	22.03	15.65	12.46	10.2	8.79	8.28	7.61	7.02
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	110	116	120	129	134	137	138	143	146
P(jump|event)(%)	46.41***	48.95***	50.63***	54.43***	56.54***	57.81***	58.23***	60.34***	61.60***
P(jump|control)(%)	7.28	8.01	8.73	13.10	17.47	21.84	26.20	30.57	34.94
Probability ratio	6.38	6.11	5.8	4.15	3.24	2.65	2.22	1.97	1.76

Notes: BTC/USD jump dynamics after USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps after the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

We subsequently conduct an analysis focusing on the impact of USDT depegging events on market cojumps, broadening the scope from a specific trading pair to encompass market-wide cojumps. The findings for the periods preceding and following these events are presented in Tables 8 and 9, respectively. As illustrated in Table 8, the null hypothesis of no effect is rejected for pre-event windows up to 1.5 hours prior to the depegging event, with a 99% confidence level. Furthermore, Table 9 reveals significant results across all post-event windows, suggesting that USDT depegging events positively influence the probability of observing market cojumps.

Table 8: USDT Depeg and cojumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	10	14	15	16	18	19	22	24	24
P(cojump|event)(%)	4.22***	5.91***	6.33***	6.75***	7.59***	8.02***	9.28***	10.13***	10.13***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.85	3.33	3.80	4.28
Probability ratio	8.88	6.22	4.44	3.55	3.2	2.81	2.79	2.66	2.37
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	24	25	28	32	36	42	43	46	48
P(cojump|event)(%)	10.13***	10.55***	11.81***	13.50**	15.19*	17.72	18.14	19.41	20.25
P(cojump|control)(%)	4.75	5.23	5.70	8.55	11.41	14.26	17.11	19.96	22.81
Probability ratio	2.13	2.02	2.07	1.58	1.33	1.24	1.06	0.97	0.89

Notes: cojumps dynamics before USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps before the USDT depegged. P(cojumps|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojumps|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojumps|event) to P(cojumps|control). The sample covers the periods from 01-01-2022 to 30-06-2023. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

Table 9: USDT Depeg and cojumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	44	51	56	61	63	64	68	71	74
P(cojump|event)(%)	18.57***	21.52***	23.63***	25.74***	26.58***	27.00***	28.69***	29.96***	31.22***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.85	3.33	3.80	4.28
Probability ratio	39.07	22.64	16.57	13.54	11.19	9.47	8.63	7.88	7.30
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	74	78	80	89	91	97	99	104	107
P(cojump|event)(%)	31.22***	32.91***	33.76***	37.55***	38.40***	40.93***	41.77***	43.88***	45.15***
P(cojump|control)(%)	4.75	5.23	5.70	8.55	11.41	14.26	17.11	19.96	22.81
Probability ratio	6.57	6.30	5.92	4.39	3.37	2.87	2.44	2.20	1.98

Notes: cojumps dynamics after USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps after the USDT depegged. P(cojumps|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojumps|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojumps|event) to P(cojumps|control). The sample covers the periods from 01-01-2022 to 30-06-2023. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

5.3. Jump size

In this section, we analyze the magnitude of Bitcoin price jumps following a USDT depeg in comparison to our control sample. By examining descriptive statistics across various time windows after the event, we can identify potential differences between periods with and without depegs. Specifically, we isolate and retrieve jumps occurring within a specified time window after a depegging event and compute key statistics on the returns associated with these jumps. The same statistical analysis is applied to jumps in the control sample. Table 10 presents the statistics for positive Bitcoin jumps following a depegging event, while Table 11 provides the data for negative jumps. Concerning the former, the mean jump size across all time windows is larger than the mean jump returns observed in the control sample. The median, which is less sensitive to outliers, reflects a similar trend as the mean. However, the largest maximum return associated with a jump is found in the control sample. The null hypothesis of identical distributions, as assessed by the Wilcoxon test, is rejected for all time windows at the 1% significance level. This result reinforces the conclusion that returns associated with jumps following a depegging event are not distributed in the same way as those in the control sample. Together with the descriptive statistics, this suggests that jumps occurring after a USDT depeg tend to be larger than those observed in the control group.

Table 10: Descriptive statistics on positive BTC jump sizes post-event.

	Mean	Median	Std. Dev	Min	Max	Wilcoxon Test
5-Min	0.798	0.674	0.424	0.222	2.1351	8658***
30-Min	0.782	0.640	0.410	0.222	2.1351	10034***
1-Hour	0.890	0.696	0.537	0.222	2.9402	13968***
Control	0.578	0.493	0.406	0.051	3.1836	

Notes: Descriptive statistics for positive Bitcoin jump sizes within specified time windows following a USDT depeg event. All values, except for the Wilcoxon test statistic, are expressed as percentages. The table includes the Wilcoxon test statistic along with its corresponding significance level. '5-Min', '30-Min', and '1-Hour' refer to the duration of the observation windows post-depeg, while 'Control' represents a comparison sample of jump sizes outside of depeg events. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

We conduct the same descriptive analysis of negative Bitcoin jumps following a depegging event, as presented in Table 11. Consistent with our previous findings, regardless of the time window, the mean and median returns associated with depegging events are larger in absolute terms compared to those in the control sample. Additionally, the largest negative Bitcoin jump occurred after a Tether depegging, as shown in the column 'Min'. Furthermore, we reject the null hypothesis of the Wilcoxon test for all time windows at the 1% significance level. As with Table 10, the combination of the descriptive statistics and the rejection of the Wilcoxon test null hypothesis suggests that the absolute magnitude of negative Bitcoin jumps is greater than that of the control sample.

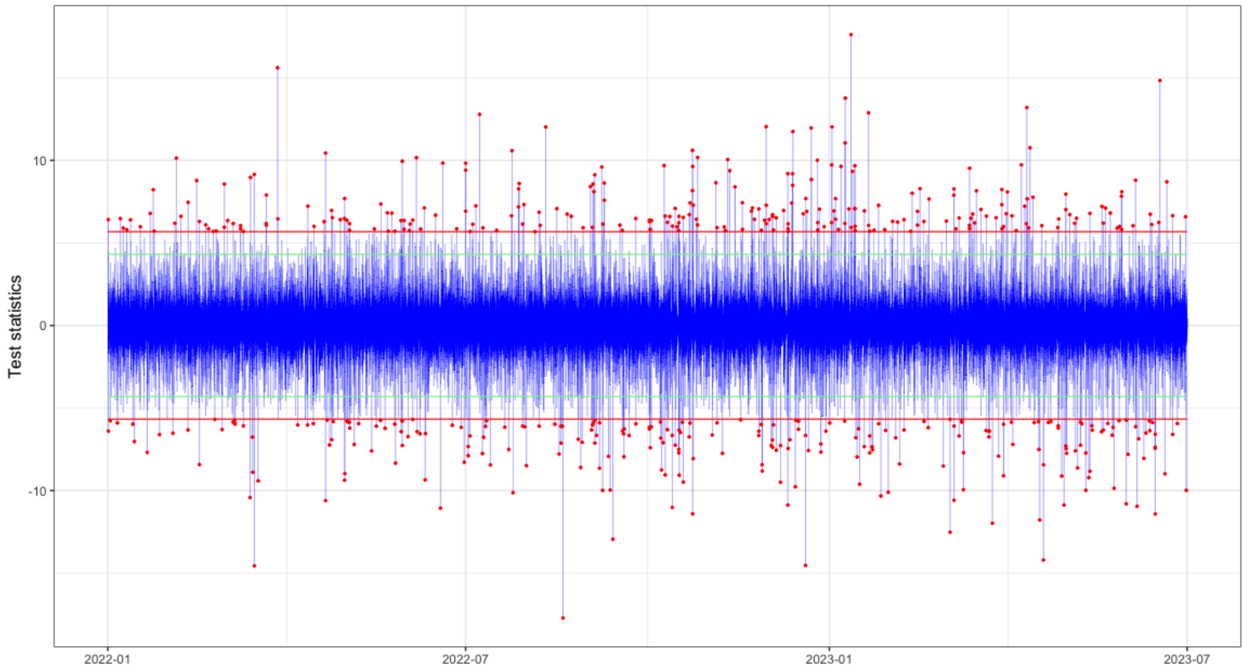
Table 11: Descriptive statistics on negative BTC jump sizes post-event.

	Mean	Median	Std. Dev	Min	Max	Wilcoxon Test
5-Min	-1.237	-1.099	0.703	-3.092	-0.289	2228***
30-Min	-1.047	-0.899	0.606	-3.092	-0.289	4650***
1-Hour	-0.936	-0.742	0.575	-3.092	-0.272	7782***
Control	-0.534	-0.475	0.306	-1.879	-0.078	

Notes: Descriptive statistics for negative Bitcoin jump sizes within specified time windows following a USDT depeg event. All values, except for the Wilcoxon test statistic, are expressed as percentages. The table includes the Wilcoxon test statistic along with its corresponding significance level. '5-Min', '30-Min', and '1-Hour' refer to the duration of the observation windows post-depeg, while 'Control' represents a comparison sample of jump sizes outside of depeg events. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

An alternative approach to analyzing the magnitude of jumps following a USDT shock, compared to our control sample, involves focusing exclusively on very large jumps. To achieve this, we increase the critical threshold used to classify returns as jumps. While we previously applied an α value of 0.01 in Equation 5 to compute the critical value, we now employ an α level of 0.0001 to identify only the largest jumps. The distinction between these critical values is illustrated in Figure 3, where the red lines correspond to the $\alpha = 0.0001$ level and the green lines to the $\alpha = 0.01$ level. As this lower α level results in higher critical values in absolute terms, only observations where the null hypothesis can be rejected with extremely high confidence are identified, thus capturing only the most significant jumps in our dataset. Given that stablecoin depegging events are considered extreme occurrences that can disrupt the crypto-asset market, this analysis aims to compare the likelihood of observing large jumps following such events with that in the control sample.

Figure 3: Test statistics and critical values of Bitcoin over time



Notes: The figure illustrates the test statistics from the jump detection method proposed by Boudt et al. (2011) applied to Bitcoin returns. The red lines indicate the critical threshold for rejecting the null hypothesis of no jump at a significance level of $\alpha = 0.0001$, while the green lines denote the critical values for $\alpha = 0.01$. Red dots mark the observations where the null hypothesis of no jump is rejected, corresponding to instances where the test statistic exceeds the critical value at $\alpha = 0.0001$.

Table 12 presents descriptive statistics for the previously identified jumps as well as the large jumps computed using the more stringent threshold with $\alpha = 0.0001$. As shown in column 2, the number of jumps identified with this new critical value is reduced by more than half compared to those identified with $\alpha = 0.01$. Naturally, as the number of identified jumps decreases, the proportion of jumps—calculated as the number of jumps relative to the total number of observations in the sample—also declines. Additionally, the mean and median of the absolute value of returns classified as jumps indicate that large jumps, as identified by the $\alpha = 0.0001$ threshold, have a higher average and median compared to those identified with $\alpha = 0.01$. This confirms that smaller jumps previously detected are excluded with the application of the higher critical threshold.

Table 12: Summary Statistics for Jumps and Large Jumps

	No of jumps	Mean Return	Median Return	Pct of jumps in sample
Jumps	1233	0.64	0.55	0.79
Large Jumps	504	0.78	0.67	0.32

Notes: Descriptive statistics for jumps and large jumps in the complete sample. Jumps are identified with an α level of 0.01, while large jumps are identified with an α level of 0.0001. 'No of jumps' refers to the number of observations where a jump or large jump is detected, and 'Pct of jumps in sample' represents the proportion of observations classified as jumps within the entire sample. 'Mean return' and 'Median return' refer to the average and median of the absolute value of returns classified as jumps.

With the filtering of our dataset to retain only large jumps, we will now compare the occurrence of these extreme returns between the depeg and control samples in Table 13. The control sample consists of all days without any detected depegs, while the depeg sample includes all observations within a 4-hour window following a depegging event. The control sample contains 115,948 observations, whereas the depeg sample comprises 11,376 observations. Despite the control sample being nearly ten times larger, the number of large jumps observed is only 3.79 times greater than in the depeg sample. Large jumps in the control sample account for 65% of the total of large jumps, while those in the depeg sample constitute 17%. In other words, 17% of the large jumps in our full sample occur following the detection of a depeg, a significant proportion that highlights the triggering effect stablecoin depegs can have on the market. The remaining 17% of large jumps occur on days where a depeg was detected but outside the 4-hour window. As previously noted, although the control sample is ten times larger, it contains only three times more large jumps than the depeg sample. This discrepancy between the sample size and the number of large jumps suggests that large jumps occur more frequently within the 4-hour window following a USDT depeg than on days without a depegging event. This becomes particularly evident when examining the last two columns, which display the proportion of large jumps relative to the number of observations and the odds ratio. Both metrics reveal that the likelihood of observing a large jump in the depeg sample is 2.7 times greater than in the control sample. This finding reinforces the earlier conclusion, revealing that USDT depegging events are associated with a significantly higher frequency of large jumps in Bitcoin compared to non-depeg periods. Our results suggest that not only do depegs lead to a higher overall incidence of jumps, but the jumps that occur during these events are also more frequently large in magnitude compared to what might be observed during periods of market stability.

Table 13: Summary Statistics for Large Jumps in Control and Depeg Samples

	No of obs	Pct of all obs	No of large jumps	Pct of all large jumps	Prop of large jumps	Odds ratio
Control Sample	115948	73.99	330	65.48	0.28	2.7
Depeg Sample	11376	7.26	87	17.26	0.76	

Notes: Descriptive statistics for large jumps in both the control and depeg samples. The control sample includes all days without a depegging event, while the depeg sample consists of all observations within a 4-hour window following a depeg. "No of obs" gives the number of observations in each sample, "Pct of all obs" reflects the percentage of the total dataset comprised by each sample, "No of large jumps" represents the number of large jumps identified in each sample, "Pct of tot large jumps" indicates the percentage of large jumps in each sample relative to the total number of large jumps in the complete sample, "Prop of large jumps" indicates the proportion of large jumps relative to the number of observations in each sample expressed in percentages and 'Odds ratio' refers to the odds of observing a large jump in the depeg sample in comparison to the control sample.

6. Discussion

In the analysis of pre-event periods, we propose the hypothesis that anticipation of a USDT shock may be present if the conditional probability of observing a jump in the BTC/USD pair before a depegging event significantly deviates from the unconditional probability of a jump occurring in the control sample. We posit that if investors foresee a probable depegging of a stablecoin in the coming hours, this anticipation could lead to an increased likelihood of price jumps in Bitcoin and cojumps in the market. Indeed, if traders expect that a USDT depegging will negatively affect the crypto-asset market, they may preemptively exit their positions to mitigate potential losses, thereby triggering market movements ahead of the event. Tables 6 and 8 underscore this effect, showing an increased probability of jumps in BTC and market cojumps prior to Tether depegging events. However, as outlined in Section 7, when adjustments are made to the algorithm used for detecting depegging events, the findings related to investors' anticipation in Table 6 no longer hold. This is confirmed by the results in Table 14, which show no significant effects in the BTC/USD pair prior to a Tether depegging event. These conclusions can also be applied to the cojumps analysis. The initial results in Table 8 indicate some level of market anticipation. However, the robustness checks presented in Table 16 challenge this interpretation, showing no significant effect of USDT depegging events on the probability of cojumps occurring prior to the event.

In contrast, the conditional and unconditional probabilities presented in Table 7 regarding post depeg jumps show significant differences even four hours after the depegging event. The rejection of the null hypothesis, imposing similar conditional and unconditional probabilities, suggests that USDT depeggings have a positive impact on the probability of observing jumps in the BTC/USD pair. Specifically, the likelihood of observing a price jump in BTC/USD at the onset of the depeg or within the initial five minutes exceeds 25%, while the unconditional probability in the control sample is below 1%. Despite the gradual reduction in the gap between conditional and unconditional probabilities as the window length increases, the effect persists for up to four hours after the start of the depeg. This result implies that the BTC/USD pair experiences a higher frequency of price jumps during at least the four hours following a USDT depeg, compared to days without depegging events. Results show that the probability of observing a jump in the BTC/USD pair five minutes after a stablecoin depegging event is 35 times higher than in our control sample, and it remains 3 times higher even two hours after the depeg begins. Unlike the pre-event analysis, the findings presented in Table 7 are corroborated by the robustness checks in Section 7. Similarly for market cojumps, Table 9 rejects the null hypothesis across all considered windows. This finding, supported by the robustness checks in Table 17, underscores the destabilizing effect that stablecoins can have on the crypto-asset market during depegging phases. As shown by the probability ratios in Table 9, the likelihood of observing cojumps in the market increases by a factor of 2 to 39 after USDT loses its peg, compared to our control sample.

In Tables 10 and 11, we present statistics on the magnitude of Bitcoin jumps following a depegging of the stablecoin Tether. As discussed in section 5.3, the results suggest that the returns associated with both positive and negative Bitcoin jumps do not follow the same distribution as those in our control sample, as indicated by the Wilcoxon test. Furthermore, the descriptive statistics across all time windows post-depeg show higher mean and median absolute values compared to the control group. These findings lead us to believe that jumps occurring after depegging events tend to be larger in absolute terms, underscoring the destabilizing effects that arise when stablecoins fail to fulfill their primary function of price stability. Additionally, as shown in section 7.2, the direction of the depeg, whether positive or negative, does not alter these conclusions. Table 13 further indicates that large jumps occur more frequently during depegging events compared to periods of stable Tether prices. This finding strengthens the conclusion that the loss of Tether's peg exerts disruptive effects on Bitcoin and the broader market, as evidenced by the increased frequency of large jumps in these non-stable assets.

Building on the results presented above, it is essential to consider the broader implications of these findings. Tether, and stablecoins more broadly, are intended to serve as stable assets within an otherwise highly volatile market. Under normal conditions, they fulfill this role effectively, providing stability and utility to the market. However, during extreme events such as depegging, this stability can be compromised, leading to the opposite effect. Rather than anchoring the market, USDT's loss of its peg has the potential to destabilize the crypto-asset market, as evidenced by the significant increase in cojumps and price fluctuations following depegging events. This dual role of USDT—offering stability in typical market conditions while contributing to instability during crises—highlights the complex and sometimes paradoxical nature of stablecoins in the broader financial ecosystem.

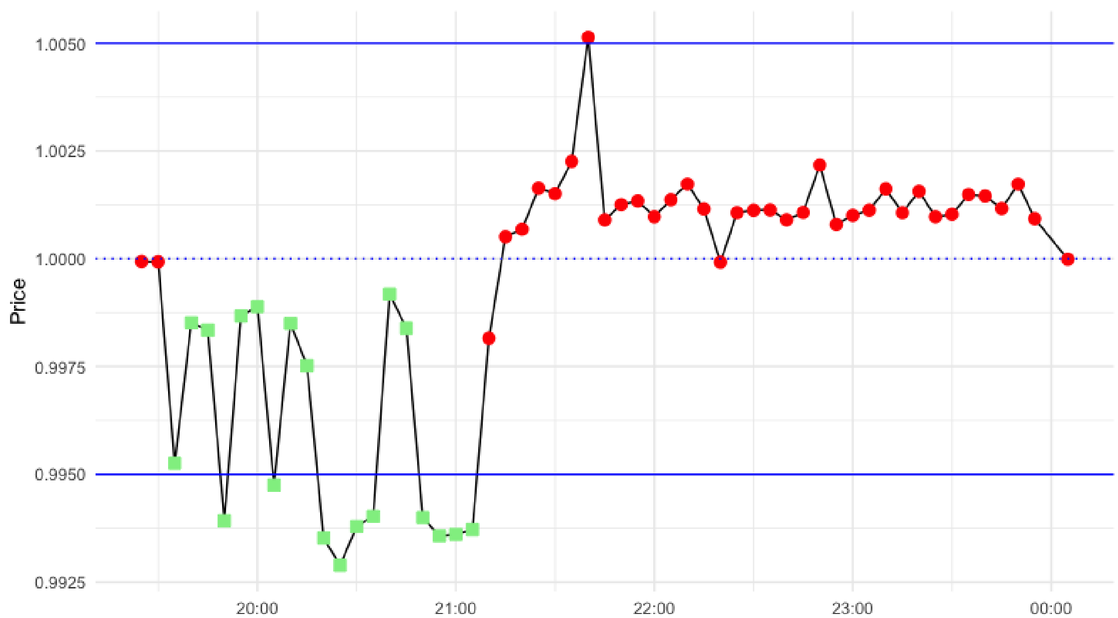
7. Robustness

7.1. Depeg detection method

In our analysis, pinpointing the exact moment of a depegging event using 5-minute interval data presents a significant challenge. Simply defining a depegging event as any instance where the price deviates from $1 would result in an excessive number of detected events, many of which may not be meaningful. To address this, we established specific conditions, as outlined in Section 4.1, to ensure that only significant depegging events are detected. However, the current algorithm we employ might identify the precise moment of depegging slightly later than it actually occurs as the price must cross a predefined threshold to be recognized as a depegging event. If the price hovers near this threshold without crossing it for an extended period, we might not detect the event as a depegging until it has already passed the critical point. This delay in detection can have substantial implications for our event study, as it may result in classifying a price jump as occurring before the depeg when, in reality, it happened after the depeg. The misalignment occurs solely because our algorithm detected the depegging event too late.

To address this issue, we retrospectively identify the exact moment when the price first deviated from its $1 peg once we detect the crossing of the threshold. This retrospective adjustment involves marking the start of the depeg as soon as the price deviates from $1, even if the initial deviation is minimal. As indicated by the green squares in our example in Figure 4, the alternative detection algorithm identifies the onset of the depegging event at 7:35 PM. In contrast, the original algorithm, shown in Figure 1, detects the initiation of the event at 8:20 PM. By adopting this alternative approach to depeg detection, we aim to test the robustness of our event study, particularly concerning the pre-event windows. These pre-event windows, in our current results, suggest that investors may anticipate depegging events. By refining our detection method, we ensure that our findings on investor anticipation are not artifacts of delayed depeg detection but rather reflect true market behavior in response to early signs of depegging.

Figure 4: Tether price with alternative depeg detection



Tables 14 and 16 present the findings of our event study on pre-event windows, using a more conservative methodology for detecting the onset of depegging events. In contrast to the results shown in Tables 6 and 8, we do not observe any significant differences in probabilities that would suggest an effect of depegging events on the market prior to their occurrence. In fact, in stark contrast to our initial results, the probability of detecting a jump 3.5 to 4 hours before the depeg is significantly lower on days with depegging events, both for cojumps and the BTC/USD pair, compared to days without depegging events. As shown in Tables 15 and 17, our results regarding the probabilities of detecting a jump after a depegging event continue to hold. Beyond the statistical significance, the magnitude of the conditional probabilities and the probability ratios are largely consistent with our initial findings.

Table 14: USDT Depeg and BTC/USD jumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	2	2	5	5	6	7	11	12	12
P(jump|event)(%)	0.88	0.88	2.20	2.20	2.64	3.08	4.85	5.29	5.29
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	1.21	0.60	1.01	0.76	0.73	0.71	0.95	0.91	0.81
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	13	16	19	29	39	47	51	54	57
P(jump|event)(%)	5.73	7.05	8.37	12.78	17.18	20.70	22.47	23.79**	25.11***
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	0.79	0.88	0.96	0.97	0.98	0.95	0.86	0.78	0.72

Notes: BTC/USD jump dynamics before USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps before the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 15: USDT Depeg and BTC/USD jumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	58	72	78	81	85	91	93	98	101
P(jump|event)(%)	25.55***	31.72***	34.36***	35.68***	37.44***	40.09***	40.97***	43.17***	44.49***
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	35.05	21.76	15.71	12.24	10.27	9.17	8.03	7.40	6.78
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	106	109	115	125	131	138	140	144	147
P(jump|event)(%)	46.70***	48.02***	50.66***	55.07***	57.71***	60.79***	61.67***	63.44***	64.76***
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	6.41	5.99	5.79	4.20	3.30	2.78	2.35	2.07	1.85

Notes: BTC/USD jump dynamics after USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps after the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 16: USDT Depeg and cojumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	2	2	4	5	5	6	9	9	9
P(cojump|event)(%)	0.88	0.88	1.76	2.20	2.20	2.64	3.96	3.96	3.96
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	1.85	0.93	1.23	1.16	0.93	0.93	1.19	1.04	0.93
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	10	11	13	16	21	26	29	31	34
P(cojump|event)(%)	4.41	4.85	5.73	7.05	9.25	11.45	12.78*	13.66**	14.98***
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	0.93	0.93	1.00	0.82	0.81	0.80	0.75	0.68	0.66

Notes: Cojumps dynamics before USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps before the USDT depegged. P(cojumps|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojumps|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojumps|event) to P(cojumps|control). The sample covers the periods from 01-01-2022 to 30-06-2023. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

Table 17: USDT Depeg and cojumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	37	47	53	58	61	67	69	72	75
P(cojump|event)(%)	16.30***	20.70***	23.35***	25.55***	26.87***	29.52***	30.40***	31.72***	33.04***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	34.25	21.76	16.36	13.42	11.29	10.34	9.13	8.33	7.71
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	81	82	86	91	95	106	109	113	116
P(cojump|event)(%)	35.68***	36.12***	37.89***	40.09***	41.85***	46.70***	48.02***	49.78***	51.10***
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	7.50	6.90	6.63	4.68	3.66	3.27	2.80	2.49	2.24

Notes: Cojumps dynamics after USDT depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps after the USDT depegged. P(cojumps|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojumps|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojumps|event) to P(cojumps|control). The sample covers the periods from 01-01-2022 to 30-06-2023. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

The key takeaway from this robustness test relates to the analysis of pre-event windows. In our initial analysis, we observed evidence suggesting some level of market anticipation. However, when we apply the revised detection method, these findings are entirely refuted. Specifically, we find no effect of USDT depegging events on the probability of observing jumps in the BTC/USD pair or cojumps in the broader market prior to the depegging. In contrast, the results for post-event windows are upheld by the robustness test, as we continue to observe statistically significant differences in the probability of jumps following a depegging event compared to the control sample, which contains no Tether depegs.

7.2. Depeg direction

As shown in Table 2, Tether tends to depeg more frequently on the upside than on the downside, with 196 upward depegs compared to 41 downward depegs. In this section, we aim to ensure that our results are not predominantly driven by upward depegs, as we previously aggregated both upward and downward depegs in our analysis. To address this, we conduct an event study focusing solely on downward depegs at the 0.5% threshold. For all the following results, we use the detection methodology outlined in Section 7.1 to precisely identify the moment of the depegs. Consistent with our earlier robustness test, the pre-event results, shown in Tables 18 and 20, reveal no significant effects. The post-event results, displayed in Tables 19 and 21, reveal statistically significant findings for both the BTC/USD pair and market cojumps. Not only do these results remain significant when focusing exclusively on downward depegs, but the magnitude of the conditional probabilities and probability ratios are substantially higher compared to the combined analysis of both upward and downward depegs.

Table 18: USDT downward depeg and BTC/USD jumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	0	0	1	1	2	2	4	4	4
P(jump|event)(%)	0.00	0.00	2.50	2.50	5.00	5.00	10.00	10.00	10.00
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	0	0	1.14	0.86	1.37	1.14	1.96	1.71	1.52
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	4	4	5	8	11	12	13	13	14
P(jump|event)(%)	10.00	10.00	12.50	20.00	27.50*	30.00	32.50	32.50	35.00
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	1.37	1.25	1.43	1.52	1.57	1.37	1.24	1.06	1

Notes: BTC/USD jump dynamics before USDT downward depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps before the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 19: USDT downward depeg and BTC/USD jumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	16	20	22	22	22	23	23	25	25
P(jump|event)(%)	40.00***	50.00***	55.00***	55.00***	55.00***	57.50***	57.50***	62.50***	62.50***
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	54.87	34.3	25.15	18.86	15.09	13.15	11.27	10.72	9.53
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	25	25	26	27	29	30	30	32	32
P(jump|event)(%)	62.50***	62.50***	65.00***	67.50***	72.50***	75.00***	75.00***	80.00***	80.00***
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	8.57	7.79	7.43	5.14	4.14	3.43	2.86	2.61	2.29

Notes: BTC/USD jump dynamics after USDT downward depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps after the USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 20: USDT downward depeg and cojumps in pre-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	1	1	1	2	2	2	3	3	3
P(cojump|event)(%)	2.50	2.50	2.50	5.00	5.00	5.00	7.50	7.50	7.50
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	5.25	2.63	1.75	2.63	2.10	1.75	2.25	1.97	1.75
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	4	4	5	5	6	6	6	7	8
P(cojump|event)(%)	10.00	10.00	12.50*	12.50	15.00	15.00	15.00	17.50	20.00
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	2.10	1.91	2.19	1.46	1.31	1.05	0.88	0.88	0.88

Notes: Cojumps dynamics before USDT downward depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps before the USDT depegged. P(cojump|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojump|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojump|event) to P(cojump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 21: USDT downward depeg and cojumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	9	12	13	15	15	15	15	16	16
P(cojump|event)(%)	22.50***	30.00***	32.50***	37.50***	37.50***	37.50***	37.50***	40.00***	40.00***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	47.28	31.52	22.77	19.70	15.76	13.13	11.26	10.51	9.34
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	17	17	17	19	20	22	23	25	25
P(cojump|event)(%)	42.50***	42.50***	42.50***	47.50***	50.00***	55.00***	57.50***	62.50***	62.50***
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	8.93	8.12	7.44	5.55	4.38	3.85	3.36	3.13	2.74

Notes: Cojumps dynamics after USDT downward depegs with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps after the USDT depegged. P(cojump|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojump|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojump|event) to P(cojump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Building on the distinction between positive and negative depegging events of Tether, we now turn our attention to the magnitude of Bitcoin jump returns in relation to the direction of the depeg. As previously discussed in section 5.3, Bitcoin jump returns following a depeg of Tether exhibit a distribution distinct from that of non-depeg periods, with a tendency toward higher magnitudes. In both Table 22 and Table 23, we observe that the distribution of both positive and negative Bitcoin jump returns differs from the control sample, regardless of the depeg direction. Specifically, Table 22 shows that negative depegs produced larger jumps on average, with a maximum return of 2.9%, compared to a maximum return of 1.9% for positive depegs. A similar pattern is observed for negative Bitcoin jumps, as presented in Table 23, where both the mean and median indicate stronger jumps following negative depegs. Nevertheless, it is noteworthy that the largest negative Bitcoin return in absolute terms occurred after a positive depeg of Tether, as indicated in the 'Min' column of Table 23.

Table 22: Descriptive statistics on positive BTC jump sizes post-event.

	Mean	Median	Std. Dev	Min	Max	Wilcoxon Test
1-Hour (-)	1.056	0.873	0.682	0.214	2.940	5912***
1-Hour (+)	0.774	0.635	0.409	0.273	1.955	9489***
Control	0.578	0.493	0.406	0.051	3.184	

Notes: Descriptive statistics for positive Bitcoin jump sizes within 1-hour following a USDT depeg event. All values, except for the Wilcoxon test statistic, are expressed as percentages. The table includes the Wilcoxon test statistic along with its corresponding significance level. '1-Hour (-)' and '1-Hour (+)' refer to the observation windows following negative and positive depegs, respectively, while 'Control' represents a comparison sample of jump sizes outside of depeg events. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

Table 23: Descriptive statistics on negative BTC jump sizes post-event.

	Mean	Median	Std. Dev	Min	Max	Wilcoxon Test
1-Hour (-)	-1.041	-0.931	0.673	-2.563	-0.507	651***
1-Hour (+)	-1.028	-0.829	0.587	-3.092	-0.333	4430***
Control	-0.534	-0.475	0.306	-1.879	-0.078	

Notes: Descriptive statistics for negative Bitcoin jump sizes within 1-hour following a USDT depeg event. All values, except for the Wilcoxon test statistic, are expressed as percentages. The table includes the Wilcoxon test statistic along with its corresponding significance level. '1-Hour (-)' and '1-Hour (+)' refer to the observation windows following negative and positive depegs, respectively, while 'Control' represents a comparison sample of jump sizes outside of depeg events. ***,**,* respectively indicate significance at the 1%, 5% and 10% level.

To further analyze the likelihood of large jumps occurring based on the direction of the depeg, we replicate the analysis from Section 5.3, which compared all depegs to the control sample. This time, we apply it to the positive and negative depeg samples, as shown in

Table 24. As observed earlier, positive depegs are more frequent, resulting in a larger sample size. Consequently, the number of large jumps is also higher in the positive depeg sample, with 70 large jumps, compared to 21 large jumps following negative depegs. To account for the difference in sample sizes, we focus on the proportion of large jumps and the odds ratio. Both measures indicate that large jumps tend to occur more frequently after negative depegs than positive ones. This finding aligns with earlier conclusions, reinforcing the notion that negative depegs are more likely to trigger larger jumps compared to positive depegs and, of course, to periods without any depegging events.

Table 24: Summary Statistics for Large Jumps in Positive and Negative depeg Samples.

	No of obs	Pct of all obs	No of large jumps	Pct of all large jumps	Prop of large jumps	Odds ratio
Negative Depeg Sample	1,920	1.23	21.00	4.17	1.09	1.41
Positive Depeg Sample	8,976	5.73	70.00	13.89	0.78	

Notes: Descriptive statistics for large jumps in both the positive and negative depeg samples. The positive depeg sample includes all observations within a 4-hour window following a positive depeg, while the negative depeg sample consists of all observations within a 4-hour window following a negative depeg. "No of obs" gives the number of observations in each sample, "Pct of all obs" reflects the percentage of the total dataset comprised by each sample, "No of large jumps" represents the number of large jumps identified in each sample, "Pct of tot large jumps" indicates the percentage of large jumps in each sample relative to the total number of large jumps in the complete sample, "Prop of large jumps" indicates the proportion of large jumps relative to the number of observations in each sample expressed in percentages and 'Odds ratio' refers to the odds of observing a large jump in the negative depeg sample in comparison to the positive depeg sample.

This section has been crucial in confirming the robustness of our findings when focusing on a specific type of depegging event. It also reveals that the impact of downward depegs on the likelihood of post-event jumps is more pronounced compared to upward depegs. Furthermore, we show that, regardless of the depeg direction, the magnitude of returns associated with jumps is significantly higher following a USDT shock than in the control sample. Specifically, jumps after negative depegs tend to be larger, on average, than those following positive depegs. Overall, our key results remain robust not only to the method of depeg detection but also to the direction of both the depeg and the jump.

7.3. Reverse causality

In this section, we aim to analyze the robustness of our results by focusing solely on depegging events that occur during periods of low volatility. As highlighted by Grobys et al. (2021), past Bitcoin volatility plays a crucial role in influencing the volatility of stablecoins. If this relationship holds, there is a concern that stablecoin depegging events may primarily result from volatility spillovers from Bitcoin, suggesting an inverse relationship to what we are currently examining. Specifically, it is possible that heightened Bitcoin volatility induces excessive volatility in stablecoins, leading to their depegging, which in turn amplifies market volatility and triggers jumps in both Bitcoin and the broader market. To ensure that our findings are not solely driven by this reverse causality, we divide the depegging events into high and low volatility regimes. We hypothesize that during periods of low Bitcoin volatility, depegging events occur independently of Bitcoin's past volatility, thereby mitigating the reverse causality issue previously discussed. Consequently, if we observe statistically significant differences between the conditional probability of a Bitcoin jump following a depegging event during low volatility periods and the probability of a jump in the absence of depegs, we can more clearly isolate the effect of depegging events on price jumps, independent of Bitcoin volatility's influence on stablecoins.

To achieve this, we compute Bitcoin's historical volatility using standard deviations over 2-hour and daily windows. We then use the median of these 2-hour and daily volatility measures to classify depegging events as occurring in either a high or low volatility regime. The high (low) volatility regime refers to depegging events where the volatility preceding the event exceeds (falls below) the median. For each depegging event, we compute the standard deviation of Bitcoin returns over both 2-hour and one-day windows prior to the depeg and compare these values to the median to classify the event. This dual approach—using both daily and 2-hour volatility—ensures that we capture the overall daily trend in volatility as well as any short-term spikes in volatility that may occur in the lead-up to the depegging event. Table 25 summarizes the distribution of depegging events across high and low volatility regimes based on the chosen window. In both windows, we observe that depegging events tend to occur more frequently during periods of high Bitcoin volatility. Nonetheless, there are also instances of depegging events occurring in low volatility regimes across both windows.

Table 25: Count of High and Low Volatility Regime Depegs

	High Volatility	Low Volatility
1-Day Window	141	86
2-Hour Window	169	58

Notes: High (low) volatility refers to depegging events that occur during periods when volatility prior to the depeg is above (below) the median historical volatility. The 1-Day Window and 2-Hour Window refer to the time frames used to compute historical volatility and the volatility period examined prior to a depegging event.

We replicate our event study using the alternative depeg detection methodology developed in Section 7.1, focusing exclusively on depegging events that occur during periods identified as low volatility regimes. Tables 26 and 27 present the results of this analysis, examining the impact of low volatility depegs on the conditional probability of observing jumps in the BTC/USD trading pair. The former table uses daily volatility measures, while the latter is based on 2-hour volatility. In both tables, we observe a significant difference between the conditional and unconditional probabilities of a Bitcoin jump, indicating that even depegging events occurring during low volatility periods—whether over the previous 24 hours or 2 hours—have a significant impact on the likelihood of extreme returns in Bitcoin, independent of volatility spikes.

Table 26: USDT low volatility depeg (1d) and BTC/USD jumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	31	38	40	41	43	46	47	48	49
P(jump|event)(%)	36.05***	44.19***	46.51***	47.67***	50.00***	53.49***	54.65***	55.81***	56.98***
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	49.45	30.31	21.27	16.35	13.72	12.23	10.71	9.57	8.68
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	51	53	58	64	66	69	70	71	73
P(jump|event)(%)	59.30***	61.63***	67.44***	74.42***	76.74***	80.23***	81.40***	82.56***	84.88***
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	8.14	7.69	7.71	5.67	4.39	3.67	3.10	2.70	2.43

Notes: BTC/USD jump dynamics after USDT depegs of low volatility regime computed on daily windows with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps after USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 27: USDT low volatility depeg (2h) and BTC/USD jumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	21	26	28	30	30	33	33	33	33
P(jump|event)(%)	36.21***	44.83***	48.28***	51.72***	51.72***	56.90***	56.90***	56.90***	56.90***
P(jump|control)(%)	0.73	1.46	2.19	2.92	3.64	4.37	5.10	5.83	6.56
Probability ratio	49.67	30.75	22.08	17.74	14.19	13.01	11.15	9.76	8.67
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	34	35	37	40	42	43	43	43	45
P(jump|event)(%)	58.62***	60.34***	63.79***	68.97***	72.41***	74.14***	74.14***	74.14***	77.59***
P(jump|control)(%)	7.29	8.02	8.75	13.12	17.49	21.87	26.24	30.62	34.99
Probability ratio	8.04	7.53	7.29	5.26	4.14	3.39	2.83	2.42	2.22

Notes: BTC/USD jump dynamics after USDT depegs of low volatility regime computed on 2hour windows with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by BTC/USD jumps after USDT depegged. P(jump|event)(%) is the probability of observing jumps conditional on the USDT depeg, and P(jump|control)(%) is the probability of observing jumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(jump|event) to P(jump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

We now shift our focus to the analysis of cojumps, rather than the BTC/USD pair. As in the previous analysis, Table 28 uses daily volatility measures, while Table 29 is based on 2-hour volatility. Focusing exclusively on depegging events that occur during low volatility regimes, we again detect a statistically significant difference between the depeg sample and the control sample. Both tables indicate that USDT depegs have a significant effect on the probability of observing cojumps in the market, with the likelihood of detecting a cojump within 5 minutes of a depegging event being 40 times higher than in the control sample.

Table 28: USDT low volatility depeg (1d) and cojumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	17	22	24	26	27	28	29	30	31
P(cojump|event)(%)	19.77***	25.58***	27.91***	30.23***	31.40***	32.56***	33.72***	34.88***	36.05***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	41.54	26.88	19.55	15.88	13.20	11.40	10.12	9.16	8.42
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	34	34	35	39	40	45	46	47	49
P(cojump|event)(%)	39.53***	39.53***	40.70***	45.35***	46.51***	52.33***	53.49***	54.65***	56.98***
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	8.31	7.55	7.13	5.29	4.07	3.67	3.12	2.73	2.49

Notes: Cojump dynamics after USDT depegs of low volatility regime computed on daily windows with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps after USDT depegged. P(cojump|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojump|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojump|event) to P(cojump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

Table 29: USDT low volatility depeg (2h) and cojumps in post-event windows.

Matching window (w):	5-min	10-min	15-min	20-min	25-min	30-min	35-min	40-min	45-min
# of matches	12	14	15	16	16	18	18	18	18
P(cojump|event)(%)	20.69***	24.14***	25.86***	27.59***	27.59***	31.03***	31.03***	31.03***	31.03***
P(cojump|control)(%)	0.48	0.95	1.43	1.90	2.38	2.86	3.33	3.81	4.28
Probability ratio	43.48	25.36	18.12	14.49	11.59	10.87	9.32	8.15	7.25
Matching window (w):	50-min	55-min	1-hour	1.5-hour	2-hour	2.5-hour	3-hour	3.5-hour	4-hour
# of matches	21	21	23	24	26	29	30	31	32
P(cojump|event)(%)	36.21***	36.21***	39.66***	41.38***	44.83***	50.00***	51.72***	53.45***	55.17***
P(cojump|control)(%)	4.76	5.23	5.71	8.57	11.42	14.28	17.13	19.99	22.84
Probability ratio	7.61	6.92	6.94	4.83	3.93	3.50	3.02	2.67	2.42

Notes: Cojump dynamics after USDT depegs of low volatility regime computed on 2hour windows with depeg threshold set at 0.5%. '# of matches' refers to the number of USDT depegs followed by cojumps after USDT depegged. P(cojump|event)(%) is the probability of observing cojumps conditional on the USDT depeg, and P(cojump|control)(%) is the probability of observing cojumps in the control sample without any depeg. The row labeled "Probability ratio" represents the ratio of P(cojump|event) to P(cojump|control). The sample covers the periods from 01-01-2022 to 30-06-2023. *** indicates significance at the 1% level.

The purpose of this section was to address potential reverse causality concerns, as discussed previously. Given the results obtained from our event study on depegging events during periods of low Bitcoin volatility, we are even more confident in our earlier findings that indicate a significant impact of USDT depegs on Bitcoin and the broader crypto-asset market. The consistency of the results in this section with those presented in earlier analyses strengthens our confidence that our findings are robust and not influenced by reverse causality.

8. Conclusion

In this paper, we have examined the spillover effects of Tether depegs on the broader non-stable crypto-asset market. Our central contribution is the identification of a significant increase in the probability of jumps in non-stable crypto-assets following depeg events, which suggests that depegging not only destabilizes the stablecoin market but also creates tail events in the wider crypto-asset ecosystem. Through a robust event study and jump detection methodology, we find that the probability of observing a jump in the BTC/USD pair within the first five minutes following a depegging event is 35 times higher than during periods without such events. This heightened probability is also observed when looking at cojumps and persists for several hours after the initial depeg, underscoring the lasting destabilizing effect that stablecoin failures can have on the broader market. The impact is not limited to increased jump frequency, our analysis also reveals that jumps occurring after depegging events are larger in magnitude than those observed during stable periods, with both positive and negative returns exhibiting significant deviations from control samples. Furthermore, we observe that negative depegging events tend to trigger larger jumps and more frequent market disruptions than positive depegs. This asymmetry in market behavior is a critical insight for understanding how downward pressure on stablecoin pegs can exacerbate volatility across the crypto-asset ecosystem. Additionally, our robustness checks confirm that these effects persist regardless of Bitcoin's pre-existing volatility, indicating that the spillover from depegging events is not simply a reflection of broader market conditions but an inherent feature of the stablecoin's failure to maintain its peg.

Our findings have several important implications. For market participants, the heightened volatility and risk associated with depegging events suggest the need for caution and adaptive risk management strategies, particularly in portfolios containing non-stable crypto-assets. For regulators, the systemic risks highlighted by our analysis indicate the potential for wider market contagion stemming from stablecoin instability, suggesting a need for clearer regulatory frameworks to mitigate these risks.

Looking ahead, our research opens new avenues for understanding the complex dynamics between stablecoins and the broader crypto-asset market. Future work could extend this analysis to other stablecoins and explore the long-term impacts of repeated depegging events. To extend this research and address the remaining questions, a detailed analysis of order book data from various exchanges would be beneficial. This approach would enable a deeper exploration of the underlying mechanisms that occur during depegging events, particularly in cases where positive depegging leads to negative jumps in the market. Moreover, as the crypto-asset market continues to evolve, more granular studies on the interactions between various stablecoin mechanisms and their market effects will be essential in crafting policies that ensure market stability and protect investors.

In sum, this paper provides critical insights into the destabilizing effects of USDT depegging events, contributing to the growing literature on the role of stablecoins in modern financial systems. By highlighting the potential for significant price jumps in non-stable crypto-assets, we underscore the importance of designing resilient stablecoins and preparing markets for the risks associated with their failure.

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