The Backbone of Stability: A Reserve-Based Analysis of Stablecoin Pegging Mechanisms

immediate

February 9, 2026

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Abstract

This paper examines the determinants of stablecoin peg stability, focusing on USDT and USDC. Contrary to the common emphasis on the U.S. Dollar Index, we find that DXY has limited influence on USDT's peg. Instead, stability is primarily driven by internal structural factors: reserve quality (higher Treasury bill shares reduce deviations), market competition (lower concentration shortens deviation duration), and scale dynamics. Results indicate that policies promoting transparent, high-quality reserves and competitive stablecoin markets are more effective for peg resilience than reacting to episodic dollar fluctuations.

Keywords: Stablecoins, Peg mechanism, Crypto, Dollar index, USDT

1 Introduction

According to latest BIS Bulletin Statistics (Aldasoro, Iñaki et al., 2025), most stablecoins are pegged to the US dollar, promising investors to redeem one dollar for each stablecoin on demand. Stablecoins can generally be categorized into four types based on their backing portfolios: (1) those supported by assets tied to fiat currencies, such as Tether (USDT) and USD Coin (USDC); (2) those collateralized by other cryptocurrencies, like Dai and Frax; (3) those backed by commodities, for instance, PAX Gold and Tether Gold; and (4) those maintained by algorithmic mechanisms using reserve assets, such as TerraUSD and sUSD. Major stablecoin issuers back their tokens primarily with fiat-denominated short-term assets such as Treasuries, repurchase agreements and bank deposits(Bank for International Settlements, 2025).

Stablecoins have experienced rapid growth in recent years, with the market capitalization growing from $125 billion in 2023 to around $255 billion nowadays. Citigroup's latest assessment suggests that by 2030, the stablecoin sector could expand to a market size of $1.6 trillion under a conservative estimate, potentially soaring to $3.7 trillion in a more optimistic outlook[2]. Separately, the Treasury Borrowing Advisory Committee projects that stablecoins might achieve a total market value of $2 trillion as early as 2028[3]. The market remains highly concentrated, with around 90% of market capitalization accounted for by just two

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[1] Data and code available at: https://github.com/WildChenzi/Massive-Manual-Collection-Stablecoin-Finance-Data
[2] Citigroup Report: Global Perspectives & Solutions - Banks and Public Sector Drive Blockchain Adoption Digital Dollars (April 2025).
[3] TBAC Presentation: Digital Money (April 30, 2025).

stablecoins which are USDT and USDC. The market is also overwhelmingly dominated by the US dollar as the reference asset. To date, almost 70% of active stablecoins by count, and almost 99% by market value, are denominated in dollars, see Figure1 (Bank for International Settlements, 2025; Kosse et al., 2023).

From the perspective of stablecoin usage, stablecoins have seen their aggregate market cap expand by 42% from January 2025 to October 2025, doubling the total crypto market's 21% growth over the same period. JPMorgan believes this trend—stablecoins outpacing the broader market—reinforces their ongoing divergence from the crypto ecosystem as their practical applications and institutional adoption continue to mature. According to a BCG white paper in 2024 that analyzed 5.6 billion unique stablecoin transactions, 88% of transactions were used for crypto trading, while the remaining 12% served other purposes and are gradually diversifying, see Figure 2.[4]

Stablecoins, despite their promise of value stability, often experience significant price volatility. Even fiat-backed stablecoins, which are the least volatile among stablecoins, rarely trade exactly at par with their reference currency in secondary markets. From the perspective of payment instruments, this contrasts sharply with traditional forms of money, such as bank deposits, used for daily transactions, raising doubts about stablecoins' reliability as a means of payment (Bank for International Settlements, 2025). Within the cryptocurrency ecosystem, stablecoins facilitate trading by streamlining the purchase and sale of other digital assets, according to a report filed with the US Securities and Exchange Commission, two exchanges, Binance and Poloniex, only accept stablecoins as a medium of exchange (Hui et al., 2025). However, multiple episodes of substantial peg deviations further underscore these reliability concerns (Ahmed and Aldasoro, 2025).

A growing body of literature explores the properties and dynamics of stablecoins. While a large share of Tether's reserves comprises short-term U.S. Treasury bills and other U.S. dollar cash equivalents, from a broad category perspective, the de-pegging of a stablecoin is primarily driven by three types of mismatch risks: credit, market, and liquidity (Hui et al., 2025). Azar et al. (2024) argue that the main financial vulnerabilities from SCs are funding risk and interconnectedness.

In the early days of stablecoins, Eichengreen (2019) highlights the vulnerability of stablecoin systems to speculative attacks when their pegs appear under-collateralized by fiat or cryptocurrencies. Rashad Ahmed, Iñaki Aldasoro and Chanelle Duley (2024) analyzes how stablecoins' peg stability is affected by the perceived quality and volatility of reserve assets, as well as reserve disclosure and transparency. However, as Azar et al. (2024) points out, in practice in recent years, stablecoin issuers may impose restrictions on redemptions. This leaves users wishing to liquidate their stablecoins with the option to trade them only in secondary markets, thereby weakening the influence of reserve assets on stablecoin prices. Naturally, some scholars have turned their attention to the relationship between stablecoins and the cryptocurrency market. Based on this perspective, research on the relationship between stablecoins and volatile cryptocurrencies presents mixed findings.

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[4]see https://media-publications.bcg.com/Stablecoins-five-killer-tests-to-gauge-their-potential.pdf

Griffin and Shams (2020) argue that Tether issuance influenced Bitcoin and other cryptocurrency prices during the 2017 surge, Wei (2018) finds no significant impact of Tether issuance on cryptocurrency markets. Additionally, Ante et al. (2021), Kristoufek (2022), and Lyons and Viswanath-Natraj (2023) observe that stablecoin issuance often increases during Bitcoin market downturns. In summary, while a direct causal effect remains debated, a plausible interconnection exists between stablecoins and crypto market volatility. This link may not be a simple one-way causation but rather a complex interplay. The relationship is likely symbiotic, with crypto volatility driving stablecoin demand, and stablecoin liquidity, in turn, influencing market volatility dynamics. Further insights into stablecoin market dynamics and functions are provided by Berentsen and Schär (2019), Bullmann et al. (2019), Dell'Erba (2020), ECB Crypto-Assets Task Force (2020), and Bianchi et al. (2020).

Setting aside the three major influencing factors of credit, market, and liquidity, the literature suggests that the stabilization mechanisms of stablecoins bear similarities to central bank interventions aimed at maintaining exchange rate stability, as explored in policy studies on fixed or flexible exchange rate regimes (such as Dominguez (2003, 2006), Neely (2005), Engel (2014)). Drawing inspiration from exchange rate modeling, Hui et al. (2025) describe the price dynamics of Tether (USDT) by CIR process. Inspired by exchange rate modeling, this paper posits that the volatility of stablecoins is influenced by the U.S. dollar through two primary channels: the value anchor effect and the market risk effect. First, as the pegged asset, the dollar's intrinsic strength directly affects the perceived credibility of the peg. Second, and perhaps more critically, fluctuations in the dollar's value significantly impact global liquidity and risk appetite, which in turn drive capital flows into or out of the entire cryptocurrency market. A strengthening dollar may trigger a broader crypto market downturn, increasing the demand for stablecoins as a safe haven within the crypto ecosystem. Conversely, a weakening dollar could fuel risk-on behavior, reducing the relative appeal of stablecoins. Therefore, this study incorporates the volatility of the U.S. Dollar Index (DXY) to empirically assess its compound impact on Tether's (USDT) price dynamics, reflecting both its role as a peg and as a barometer for global market risk.
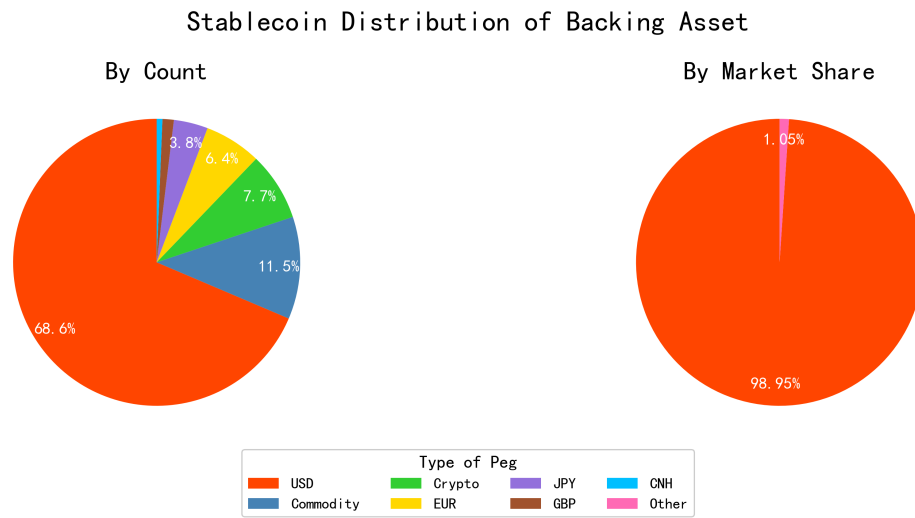
Stablecoin Distribution of Backing Asset

By Count

By Market Share

Type of Peg
- USD
- Commodity
- Crypto
- EUR
- JPY
- GBP
- CNH
- Other

Figure 1: Stablecoin Distribution of Backing Asset
Sources: BIS (2025); CoinDesk Data; CoinGecko; Kosse et al (2023).

Most popular stablecoin use cases (% of total global transactions)

- Crypto Trading: $23.0 tn, 88%
- On/Off Ramping: $1.0 tn, 4%
- Tokenized RWA Settlement: $0.8 tn, 3%
- Payments, P2P: $0.5 tn, 2%
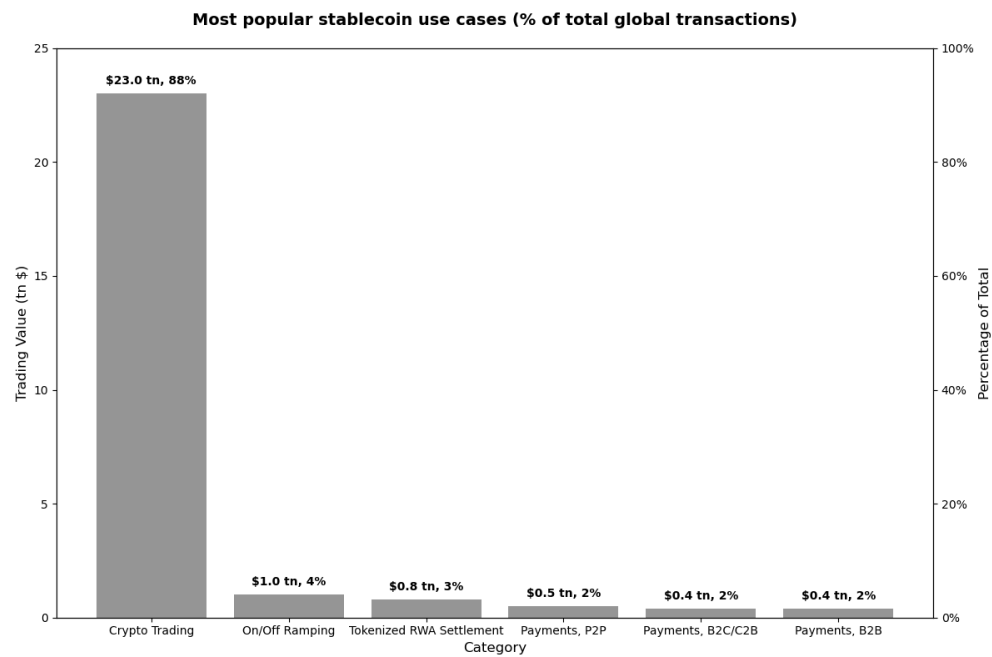- Payments, B2C/C2B: $0.4 tn, 2%
- Payments, B2B: $0.4 tn, 2%

Figure 2: Most Popular Stablecoin Use Cases
Sources: J.P. Morgan, Boston Consulting Group, Visa Onchain Analytics Dashboard

2 The Relationship Between Stablecoin Volatility and the U.S. Dollar Index

Essentially, most mainstream stablecoins are digital analogs of the traditional currency board system, modeled after its proven framework(Hui et al., 2025). Stablecoins aim to maintain price stability by emulating a currency board system, like Hong Kong's Linked Exchange Rate System, which pegs the Hong Kong dollar to the US dollar at a fixed rate. A currency board ensures stability by requiring changes in currency supply to be matched by corresponding changes in anchor currency reserves, with assets (reserves) at least equal to liabilities (circulating currency) to ensure full solvency(Genberg and Hui, 2011). According to The GENIUS ACT (signed into law by President Trump in July 2025), stablecoin issuers must adopt a similar framework, holding reserves in an anchor currency—primarily the US dollar (USD) in a 1:1 ratio with the stablecoin supply, see The White House (2025a,b). Regular audits and transparent balance sheet disclosures are required to ensure solvency and trust. So far the GENIUS ACT may reinforce market confidence and stabilizing the stablecoins' value.

Research on peg-stabilizing mechanisms, particularly for exchange rate target zones, provides a foundation for studying stablecoin price dynamics. Krugman (1991) introduced a target zone model assuming a fully credible exchange rate band, where the currency stays within bounds due to market expectations. Lo et al. (2015) and Hui et al. (2016) developed a quasi-bounded target zone model, where exchange rate dynamics follow a mean-reverting square root process, driven by the mean-reverting property of fundamental dynamics (e.g., demand). Specifically for stablecoins, Hui et al. (2025) provides a robust framework for analyzing stablecoin price stability through quasi-bounded models, emphasizing arbitrage, interventions, and mean-reverting fundamentals.

According to Ma et al. (2025), the stablecoin market operates through three key players: issuers, with a small group of authorized arbitrageurs, and a large pool of secondary market traders. Issuers create stablecoins backed 1:1 by collateral (such as USD) and allow only arbitrageurs to mint new coins by depositing $1 or redeem coins for $1. Arbitrageurs, often just a handful per month (e.g., six for USDT), are the sole link between the issuer and the secondary market. They can buy undervalued stablecoins there and redeem them at the issuer for $1, or mint new coins and sell them at a premium, thereby correcting price deviations. While numerous and competitive secondary market traders only trade among themselves and usually have no direct access to minting or redemption, see Figure 2.

From this layer structure, fluctuations in the U.S. Dollar Index (DXY) impact the stablecoin ecosystem through three potential distinct channels. At the core arbitrage level, a "closed" USD loop exists between issuers and authorized arbitrageurs, where arbitrage activities are driven by deviations in secondary market prices, thereby insulating the process from direct interference by DXY movements. On the demand side, DXY fluctuations significantly influence secondary market user behavior by altering the exchange rate costs for non-USD users to acquire stablecoins. If a US-based individual or corporation rotates away from a USD

money market fund or bank deposit (secondary market) into USD backed stablecoins, this would be currency neutral as it would not create new FX demand but rather represents an internal USD transfer from one form to another(to a digital USD), so this special channel rules out DXY fluctuations. At the systemic stability level, DXY variations affect the valuation and liquidity of reserve assets, as well as the global attractiveness of USD-denominated assets, directly constraining issuers' reserve management costs and the system's solvency.
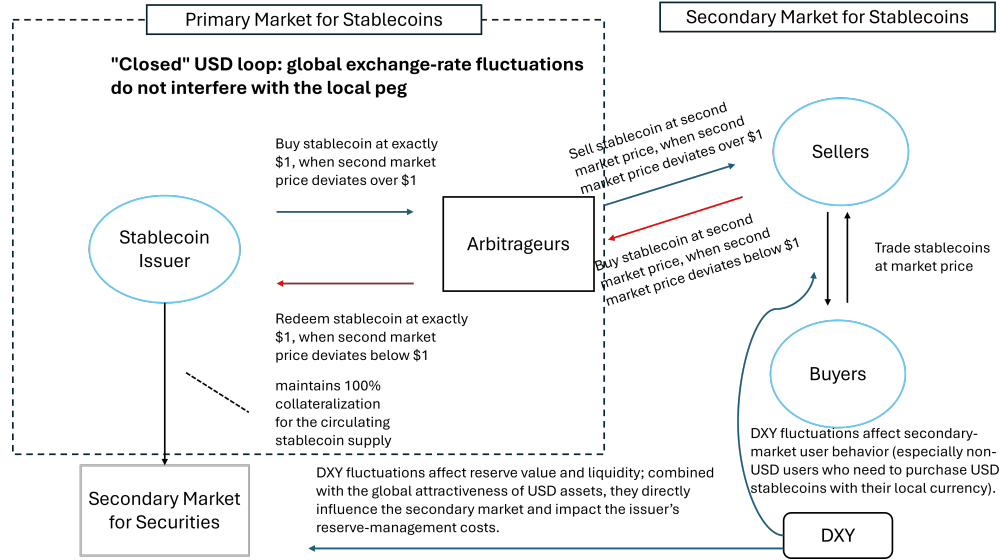

Figure 3: The Design of Fiat-backed Stablecoins as Ma et al. (2025) with DXY Fluctuations

2.1 Stablecoin Market Segmentation and Data

Existing literature has extensively analyzed three major stablecoins that employ distinct mechanisms to maintain their dollar peg. The two dominant stablecoins, USDC and USDT, are pegged to the US dollar through reserves held in fiat money as their backing. In contrast to the centralized, fiat-backed models of USDT and USDC, DAI operates as a decentralized stablecoin whose value is stabilized through a crypto-collateralization mechanism, predominantly using USDC as collateral.

The collapse of Silicon Valley Bank (SVB) on March 10, 2023, triggered a classic stablecoin de-pegging event. Circle (the issuer of USDC) held \$3.3 billion in deposits at SVB, with significant exposure to the bank's failure. As SVB collapsed, uncertainty surrounding these deposits caused USDC to lose its 1:1 dollar peg, with its value dropping to \$0.88. DAI was also influenced by its Peg Stability Module mechanism, mirrored USDC's fluctuations. Meanwhile USDT, unaffected by SVB exposure, consistently held its dollar peg during the event. Such events are rare and driven by exogenous shocks, making the volatility of these stablecoins inconsistent and event-specific rather than intrinsic. When constructing a GARCH model or other mean-reverting models for financial time series analysis, using USDC and DAI as primary assets may not be robust and reliable due to their specific market behaviors.

Tether (USDT), the longest-standing and largest stablecoin by circulation volume, has remained largely stable during various stablecoin crises, though brief deviations occurred during events like the TerraUSD collapse in May 2022 and the FTX collapse in November 2022. This long-term stable price performance provides rich market data, effectively reflecting market sentiment and crisis impacts, making it a reliable sample for studying stablecoin price behavior. The GENIUS ACT also could enhance USDT's credibility by enforcing stricter reserve and transparency requirements, potentially stabilizing its peg during crises and making USDT's price data an excellent subject for analyzing the impact of regulatory policies on stablecoin stability.

Empirical literature also prefers USDT as the representative stablecoin for research. Hui et al. (2025) explored how stablecoin market liquidity and Bitcoin price volatility impacted Tether's price dynamics and peg-stabilizing mechanism. These findings highlight the interplay of market factors and stabilizing mechanisms in maintaining Tether's peg. Building on this, my empirical analysis also focuses on Tether's price data to investigate its price dynamics and peg stability, extending the understanding of how market conditions and external shocks influence stablecoins' behavior to USD exchange rate fluctuations.

2.2 Volatility Spillover from USD to USDT

As for the overall price volatility of Tether (USDT), despite the absence of an explicit trading band(like USD/HKD is supposed to be in the range of [7.75,7.85], see Hui et al. (2025)), USDT typically trades within a narrow range around its "1:1 USD peg". Some analysis of its price data reveal that the 0.5th and 99.5th percentiles of its empirical distribution are 0.94 and 1.03, respectively. Supporting this, S&P Global
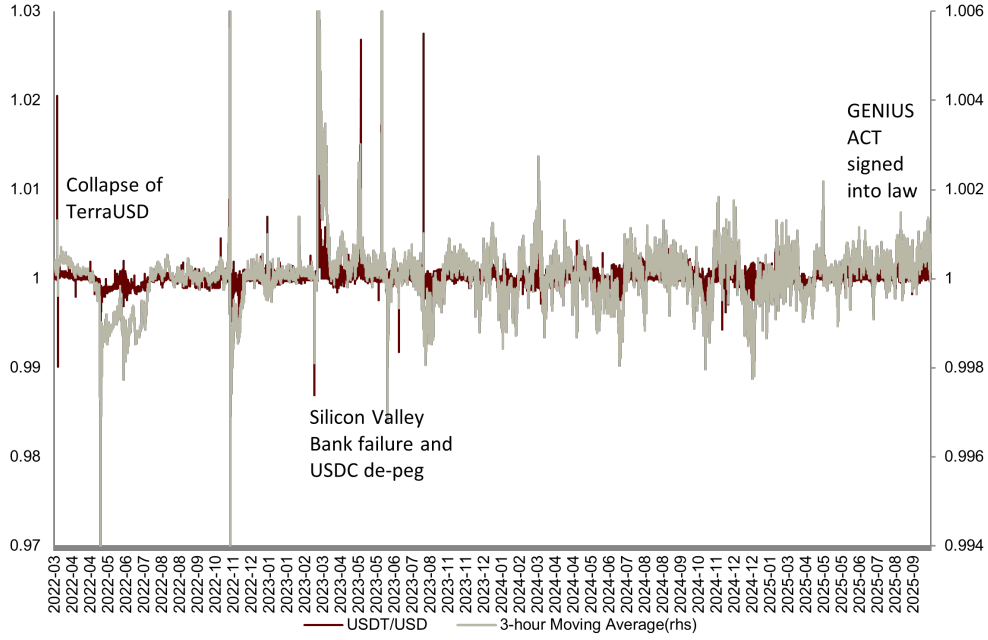
Figure 4: Closing Price of Tether/USD in 10-minute Frequency and Corresponding 3-hour Moving Average
Sources: Bloomberg

(2023a,b) documented that major stablecoins, including USDT, experienced minimum prices between 0.85 and 0.98 during a recent two-year period, with USDT's low at 0.95, which is a historical fluctuation pattern to capture normal fluctuations of USDT while respecting its peg. Numerous factors drive USDT's price dynamics within this range, including market liquidity, investor sentiment, and macroeconomic conditions. Some studies have developed theoretical and empirical models to analyze this volatility, providing insights into the mechanisms governing stablecoin price stability and deviations.

Shocks to the collateral assets of stablecoins or severe liquidity disruptions often lead to direct and significant de-pegging, causing them to completely break their peg. Such event-driven deviations (e.g., the SVB bank collapse) are outside the scope of this paper. This paper studies the liquidity of USDT in the market under normal conditions, so a natural approach is to examine their trading counterparts. Currently, apart from limited cross-border payment, the primary role of stablecoins is to facilitate the purchase of on-chain cryptocurrency assets (such as BTC and ETH), which are challenging and even costly to acquire directly with cash. Typically, investors first purchase stablecoins with cash and then use these stablecoins for on-chain transactions in the crypto market. Many studies explore how fluctuations in the cryptocurrency market influence the stability mechanisms of USDT to the US dollar. Research by Xie et al. (2021), Wang et al. (2020), Baur and Hoang (2021), Barucci et al. (2022), and Díaz et al. (2023) indicate that fiat-money backed stablecoins, notably USDT, serve as safe-haven assets for crypto investments. Furthermore, the evolving interplay between USDT and Bitcoin highlights a dynamic connection between stablecoins' safe-haven characteristics and Bitcoin's volatility over time. Specifically, during times of significant Bitcoin

volatility a flight-to-safety occurs. As investors seek shelter, capital flows into stablecoins, thereby driving up their prices. While some argue that cryptocurrency market volatility does not spill over to stablecoin prices, as contended by Lyons and Viswanath-Natraj (2023).

In essence, crypto market volatility spillovers pose a threat to the peg of stablecoins. The booms and busts of cryptocurrency markets, driven by a complex interplay of internal factors, always further impact stablecoins' demand then their volatility, as they serve as key enablers of crypto market transactions Ahmed and Aldasoro (2025). Grobys et al. (2021) identify a Granger-causal relationship between Bitcoin's price volatility (BTCvol) and fluctuations in stablecoin prices, including Tether (USDT). In addition, Lyons and Viswanath-Natraj (2023) explore several underlying factors driving USDT's premiums and discounts, such as volatility in the BTC/USDT trading pair and concerns over insufficient collateral reserves. Macro-financial dynamics also exert both direct and indirect influence on stablecoins. For example, shifts in interest rates alter the opportunity cost of holding stablecoins Eichengreen et al. (2025). As imperfect substitutes for traditional money market instruments, stablecoins give rise to an inconvenience yield. This yield signifies a required risk premium, compelling stablecoin-based lending rates to exceed their conventional counterparts. Ultimately, this interest rate sensitivity can transmit to the stablecoins themselves, amplifying their price deviations from the peg, especially during periods of monetary tightening or easing.

Following the approach of Abdi and Ranaldo (2017), this paper utilizes the closing price of the spot USDT index. The 10-minute frequency data covering from 1/1/2024, to 10/1/2025 was obtained from the Bloomberg Terminal. It is notable that the data for 1/19/2025 is missing. In addition to the price data, we further control for the scale effect of USDT, as its market size may systematically affect the relationships under investigation following Ahmed and Aldasoro (2025) and Aldasoro, Iñaki et al. (2025), which aggregate the market capitalization of the six largest stablecoins collected from CoinMarketCap. These daily capitalization are subsequently dis-aggregated and matched with 10-minute frequency USDT price data for our analysis. Also following the methodology of Aldasoro, Iñaki et al. (2025), we construct a series of cryptocurrency shocks derived from the unforecastable component of returns based on the Bloomberg Galaxy Bitcoin Index (similar to BGCI and we call this index BGCI). This shock series controls the idiosyncratic yet persistent impulses that drive crypto market cycles, thereby sharpening our identification of USDT-specific dynamics.

The U.S. Dollar Index (DXY) is also supposed to influence USDT's price volatility, complicating its ability to maintain a 1:1 USD peg within its typical trading range. As a barometer of the dollar's global strength, DXY fluctuations alter the opportunity cost of holding non-yielding USDT, with a rising DXY diminishing demand, while a declining DXY enhances USDT's appeal as a stable store of value. Given USDT's primary role in facilitating cryptocurrency purchases, DXY-driven shifts in crypto market dynamics—where a stronger dollar often suppresses Bitcoin demand and a weaker dollar spurs it—can lead to increased USDT demand or redemptions and cause price deviations. Moreover, DXY volatility disrupts crypto market liq-

uidity, widening the BTC/USDT bid-ask spread and hindering arbitrage mechanisms critical to stabilizing USDT's peg, as noted in studies like Abdi and Ranaldo (2017). These macro-financial dynamics, shaped by monetary policy and economic conditions, underscore the DXY's pivotal role in challenging USDT's price stability, as highlighted by Ahmed and Aldasoro (2025) and Aldasoro, Iñaki et al. (2025).

Variable Construction. In Lyons and Viswanath-Natraj (2023), as well as Ahmed and Aldasoro (2025), stablecoin peg stability is measured in absolute price deviations from \$1: $dt = |1 - p_t|$, where dt is the minute, hourly, or daily price deviation and p_t is the closing price of the stablecoin corresponding to the same frequency. While this study utilizes 10-minute frequency USDT closing price data, denominated in USD, obtained from the Bloomberg Terminal, covering the period from January 1, 2024, to October 1, 2025, denoted by p_t at time t. Given USDT's peg to one USD, the deviation at each 10-minute interval is defined as the percentage USDT depegged from 1 USD

$$Dev_t = (p_t - 1) \times 100$$

Aldasoro, Iñaki et al. (2025) provide methods for handling control variables in digital currency analysis, including the (log) of the US dollar nominal effective exchange rate (NEER). In this paper, we also apply the logarithm to the DXY index which we need to study.

2.3 A Class of GARCH(1,1) Models for USDT and DXY Index

To analyze the volatility characteristics of the deviation series over the full sample, this study employs a class of GARCH(1, 1) models with method of Bollerslev (1986). Its mean equation is specified as a white noise process, or an AR(1) process,. Regarding the distributional assumption of the residuals, we estimate two alternative specifications: one assumes the conditional residuals follow a normal distribution, while the other assumes a Student's t-distribution. This approach aims to compare the impact of different distributional assumptions on the model estimation results. For white noise mean equation model, it is specified as:

$$Dev_t = \mu + \epsilon_t,$$
$$\epsilon_t = \sigma_t z_t, \quad z_t \sim N(0,1)(\text{or } t(\nu)),$$
$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

The parameters and variables are defined as follows: Dev_t represents the percentage deviation of USDT at time t, μ is the constant term in the conditional mean equation, and ϵ_t denotes the residuals. The term σ_t^2 is the conditional variance implied by GARCH model at time t, while z_t is the standardized residual, an i.i.d. random variable following either a standard normal distribution, $N(0,1)$, or a standardized Student-t distribution $t(\nu)$, where ν is the degrees of freedom parameter capturing fat tails. In the variance equation, ω (where $\omega \geq 0$) is the constant intercept, α (where $\alpha \geq 0$) measures the short-term impact of past shocks (the ARCH effect), and β (where $\beta \geq 0$) captures the persistence of past volatility (the GARCH effect), see Nelson (1990).

To capture the potential autocorrelation characteristics of the deviation series—that is, the possibility that the current period's deviation is influenced by its prior state—this study further constructs a GARCH(1, 1) model with a first-order autoregressive (AR(1)) process as its mean equation. This specification allows the current level of the series to depend directly on its preceding observation, thereby providing a more accurate characterization of the dynamics of its conditional mean. The model is specified as follows:

$$Dev_t = \mu + Dev_{t-1} + \epsilon_t,$$

$$\epsilon_t = \sigma_t z_t, \quad z_t \sim N(0, 1)(\text{or } t(\nu)),$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2$$

Based on the estimation results of the four models (Table 1), the model with a white noise mean equation and residuals follows a Student-t distribution with 7.87 degrees of freedom, which exhibits thinner tails, resembling a normal distribution. Consequently, this model is excluded first, as the use of a Student-t distribution is redundant for modeling the residuals. In contrast, the model with an AR(1) mean equation and residuals follows a Student-t distribution with 2 degrees of freedom, which effectively captures the heavy-tailed nature of USDT price deviations, with lower AIC and BIC values indicating superior model fit. The pronounced ARCH effect suggests that USDT volatility is primarily driven by short-term events, likely due to the short-term clustering of price deviations triggered by market liquidity shocks or investor selling pressures as noted by Abdi and Ranaldo (2017), which rapidly amplify price deviations. These shocks prompt swift repricing of market conditions, but their impact is short-lived and decays quickly (given the 10-minute data frequency, an alpha of 0.9 implies rapid decay). The model's weaker GARCH effect indicates low persistence of long-term volatility, reflecting the effectiveness of USDT's peg-stabilizing mechanism, particularly through arbitrage that swiftly corrects deviations (Ma et al., 2025). This volatility pattern underscores USDT's role as a stable transaction medium in crypto markets, where price dynamics are predominantly driven by short-term market shocks rather than long-term volatility trends.

Table 1: Estimation Results of GARCH$(1,1)$ Models with Different Specifications

Parameter	White Noise Mean Equation		AR(1) Mean Equation	
	Normal	Student's t	Normal	Student's t
μ	0.0123	9.93×10^{-3}	8.64×10^{-3}	-8.01×10^{-3}
	$(1980)^{***}$	$(135)^{***}$	$(1870)^{***}$	$(-5.87)^{***}$
	[0.000]	[0.000]	[0.000]	[0.000]
ϕ	$-$	$-$	0.866	0.985
	$-$	$-$	$(1910)^{***}$	$(2320)^{***}$
	$-$	$-$	[0.000]	[0.000]
ω	5.99×10^{-6}	4.64×10^{-6}	5.56×10^{-6}	2.01×10^{-4}
	$(30.2)^{***}$	$(44.6)^{***}$	$(11.2)^{***}$	$(63.9)^{***}$
	[0.000]	[0.000]	[0.000]	[0.000]
α	0.0598	0.149	0.0554	0.9
	$(2020)^{***}$	$(59.6)^{***}$	$(1600)^{***}$	$(99)^{***}$
	[0.000]	[0.000]	[0.000]	[0.000]
β	0.935	0.85	0.939	0.0987
	$(3870)^{***}$	$(327)^{***}$	$(17000)^{***}$	$(34.4)^{***}$
	[0.000]	[0.000]	[0.000]	[0.000]
ν	$-$	7.87	$-$	2.39
AIC	-3.413715	-3.531844	-3.985391	-4.877042
BIC	-3.413484	-3.531555	-3.985102	-4.876695

Note: This table presents the estimation results of the GARCH$(1,1)$ models. Values in parentheses are t-statistics, and values in square brackets are p-values. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.
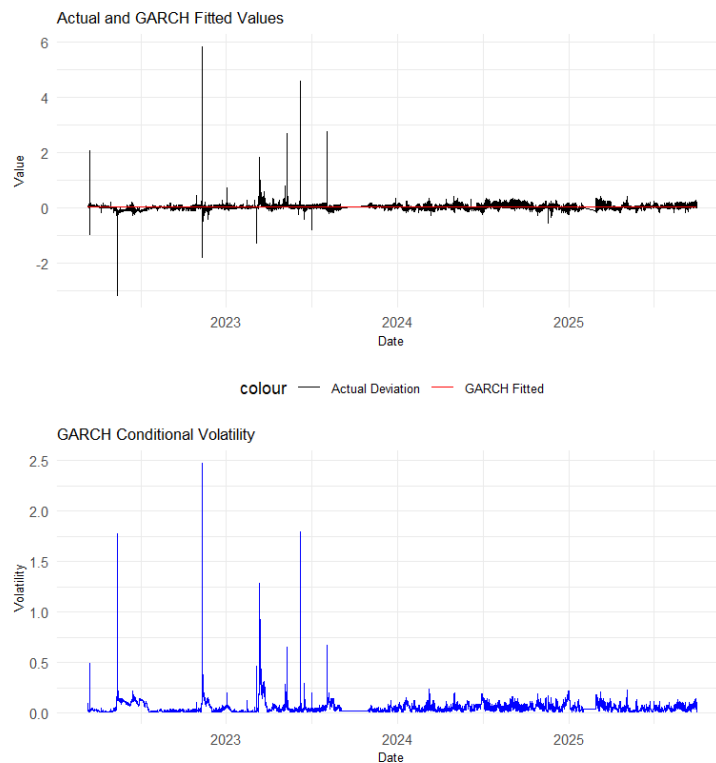
Figure 5: GARCH(1,1) Model of USDT With White Noise Mean Equation, Normal Distribution for Residuals.
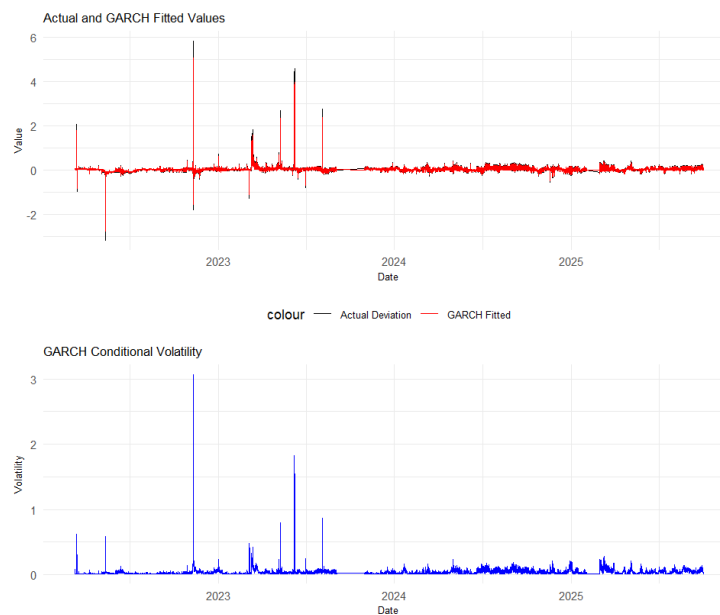**Sources:** Bloomberg

Figure 6: GARCH(1,1) Model of USDT With AR(1) Mean Equation, Normal Distribution for Residuals.
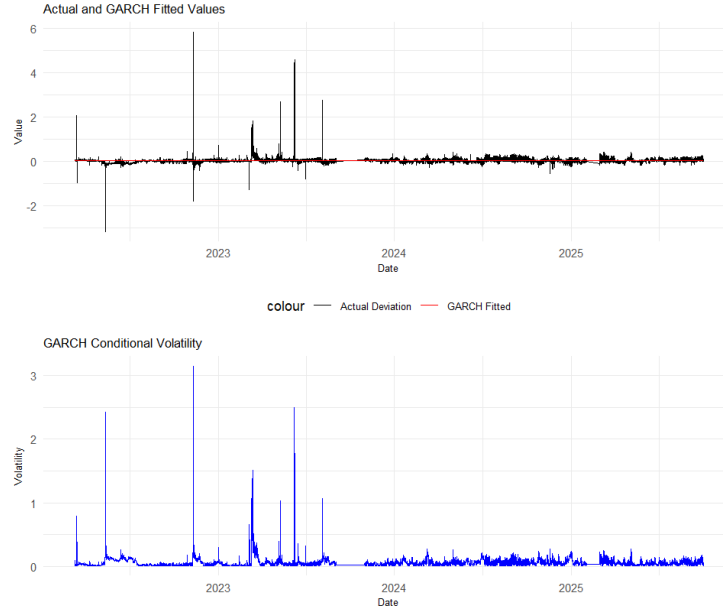**Sources:** Bloomberg

Figure 7: GARCH(1,1) Model of USDT With White Noise Mean Equation, Student-t Distribution for Residuals.
Sources: Bloomberg
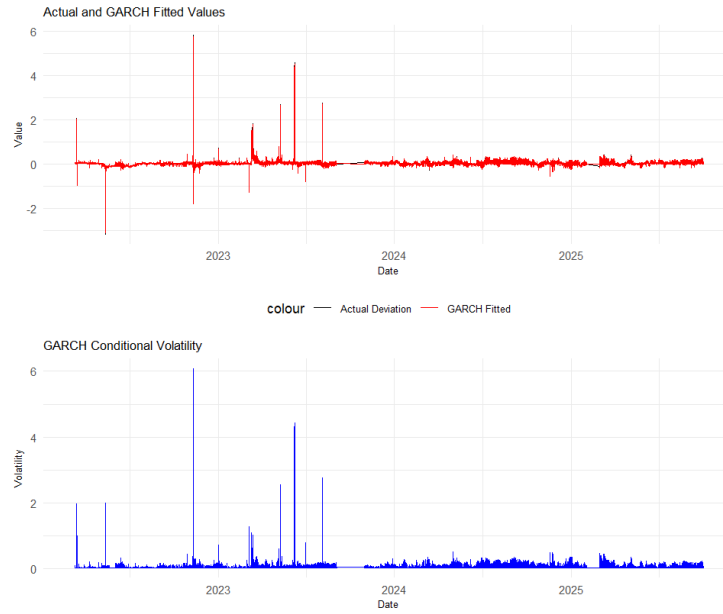
Figure 8: GARCH(1,1) Model of USDT With AR(1) Mean Equation, Student-t Distribution for Residuals.
Sources: Bloomberg

To examine the spillover effect of the U.S. Dollar Index on USDT volatility, this paper incorporates $\log(\text{DXY})$ as an exogenous variable into the variance equation of the GARCH(1,1) model. This specification is motivated by the following considerations: first, the Dollar Index, serving as a proxy for the macroeconomic

environment, primarily exerts its influence by altering market participants' risk expectations rather than directly impacting the short-term price pegging of stablecoins; second, existing literature demonstrates that the transmission of external macroeconomic shocks to cryptocurrency markets predominantly manifests as volatility effects, with stablecoins exhibiting limited sensitivity to fundamentals except for short-term interest rates (Aldasoro, Iñaki et al., 2025); and finally, the Student-t distribution is employed for residuals to ensure robustness. Generally, the model is specified as:

$$Dev_t = \mu + Dev_{t-1} + \epsilon_t,$$

$$\epsilon_t = \sigma_t z_t, \quad z_t \sim N(0, 1),$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \gamma \Delta log(DXY_t)$$

Where $\Delta log(DXY_t)$ is the first-order difference to make ensure DXY Index is a stationary time series without trends. It appears that the US dollar index has a limited effect on the volatility of USDT within the GARCH(1,1) model framework.

Table 2: Estimation Results of GARCH$(1, 1)$ Models with log(DXY) in Variance Equation

| | Student's t Distribution for Residuals | |
Parameter	White Noise Mean Equation	AR(1) Mean Equation
μ	0.0098	-0.0078
	$(146.63)^{***}$	$(-5.665)^{***}$
	$[0.000]$	$[0.000]$
ϕ	$-$	0.985
	$-$	$(2331)^{***}$
	$-$	$[0.000]$
ω	4×10^{-6}	1.7×10^{-4}
	$(8.04)^{***}$	$(58.25)^{***}$
	$[0.000]$	$[0.000]$
α	0.28	0.999
	$(31.68)^{***}$	$(93.78)^{***}$
	$[0.000]$	$[0.000]$
β	0.78	0.1694
	$(137.2)^{***}$	$(44.62)^{***}$
	$[0.000]$	$[0.000]$
γ	0.000	0.000
	(6×10^{-6})	(2×10^{-6})
	$[0.9999]$	$[1.000]$
ν	5.848	2.364
AIC	-3.542	-4.8881
BIC	-3.5416	-4.8877

Note: This table presents the estimation results of the GARCH$(1, 1)$ models. Values in parentheses are t-statistics, and values in square brackets are p-values. $*$, $**$, and $***$ denote statistical significance at the 10%, 5%, and 1% levels, respectively.

According to Hui et al. (2025), there are precedents for shifts in USDT's volatility mechanism, such as transfers between blockchains, policy changes, or simply the rise in circulating scale. This paper further

discusses the relationship between the 3-month stablecoin market cap growth rate and the 3-month DXY growth rate, finding no correlation before 2024, but a strong correlation emerging after 2024—see Figure 9. In 2022–2023, the stablecoin market was dominated by internal crypto ecosystem events, including the May 2022 TerraUSD (UST) collapse, which caused stablecoin market cap to plummet from approximately \$140 billion to below \$120 billion, followed by the June FTX bankruptcy that intensified panic, leaving market cap lingering around \$130 billion. In 2023, the market recovered slowly but remained influenced by Bitcoin halving expectations and regulatory uncertainty. Meanwhile, in 2022, the DXY rose from 95 at the start of the year to a September peak of 114 (during the Fed's rate-hiking cycle), yet stablecoin market cap declined over the same period as investors sold crypto assets for safety, fleeing into traditional dollar assets rather than stablecoins. These events were not driven by macroeconomic dollar drivers. From 2024 onward, stablecoin reserve assets shifted more toward U.S. Treasuries. At that time, the high-interest-rate environment under the Fed (federal funds rate at 4.5%–5.25% in 2024) enabled stablecoin issuers to earn higher yields, attracting capital inflows. When the DXY strengthened (reflecting rising Treasury yields and enhanced dollar appeal), stablecoin demand surged.

The Dynamic Conditional Correlation GARCH (DCC-GARCH) model is particularly well-suited for examining the volatility spillover effects from the U.S. Dollar Index (DXY) to Tether (USDT), as it allows the conditional covariance matrix of the dependent variables to follow a flexible dynamic structure while permitting the conditional mean to adhere to a vector autoregressive (VAR) framework, see Engle (2002) and Tse and Tsui (2002). This dynamic structure effectively captures the time-varying correlations between DXY and USDT, enabling a more precise analysis of how macroeconomic shocks, proxied by DXY fluctuations, transmit volatility to USDT's price dynamics. Compared to static or simpler GARCH models, the DCC-GARCH approach better accounts for the evolving interdependencies in cryptocurrency markets, offering a robust framework to quantify the spillover effects while accommodating the heavy-tailed characteristics of USDT returns, as supported by the use of Student-t distributed residuals in related studies.
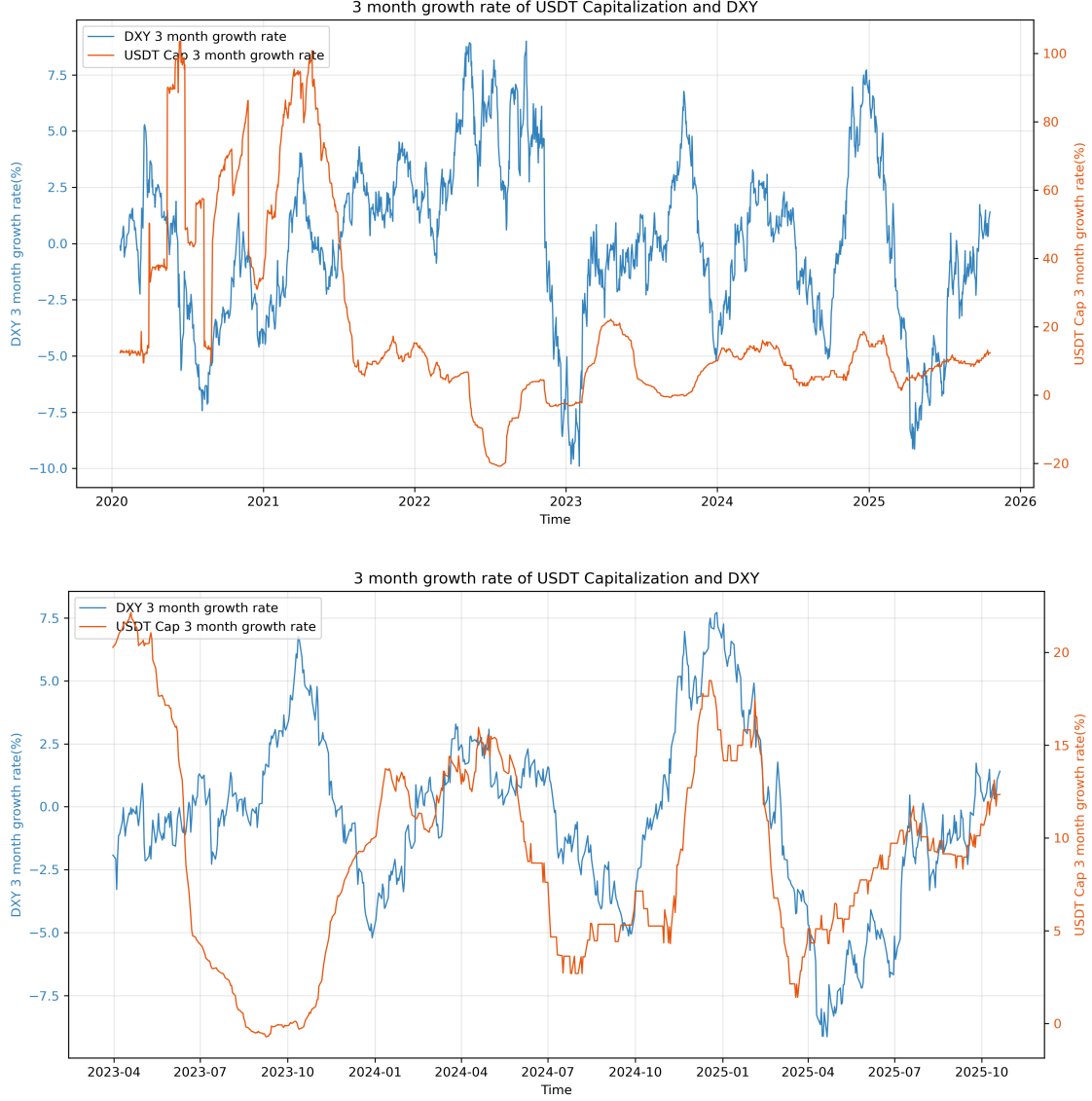
Figure 9: Comparison of DXY and USDT Capitalization 3-Month Growth Rates
Sources: Bloomberg, CoinMarketCap

The general Multi-variate GARCH model about USDT and DXY can be written as:

$$y_t = \mu + Cx_t + \epsilon_t$$

$$\epsilon_t = H_t^{\frac{1}{2}} \nu_t$$

Where y_t is a m-vector of dependent variables, C is a $m \times k$ parameter matrix, x_t is a k-vector of explanatory variables, possibly including lags of y_t, H_t is the time-varying conditional covariance matrix, and ν_t is a m-vector of zero-mean, unit-variance i.i.d. innovations.

In our case $y_t = \begin{bmatrix} Dev_t \\ \Delta log(DXY_t) \end{bmatrix}$, μ is the drift vector, $\mu_t = \begin{bmatrix} \mu_0 \\ \mu_1 \end{bmatrix}$, and Mean Equations of Dev_t and

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$log(DXY_t)$ follow AR(1) process, so parameter matrix is a diagonal matrix, $C_t = \begin{bmatrix} \phi_0 & 0 \\ 0 & \phi_1 \end{bmatrix}$.

Directly modeling H_t faces the issue of excessive parameter dimensionality. The Dynamic Conditional Correlation (DCC) model can substantially reduce the number of parameters to be estimated, this model may be written as:

$$y_t = \mu + Cy_{t-1} + \epsilon_t$$

$$\epsilon_t = H_t^{\frac{1}{2}} \nu_t$$

$$H_t = D_t^{\frac{1}{2}} R_t D_t^{\frac{1}{2}}$$

$$R_t = diag(Q_t)^{-\frac{1}{2}} Q_t diag(Q_t)^{-\frac{1}{2}}$$

$$Q_t = (1 - a - b)\bar{Q} + a\hat{\epsilon}_{t-1}\hat{\epsilon}_{t-1}^T + bQ_{t-1}$$

Where D_t is a diagonal matrix of conditional variances estimated by AR(1) processes for each variable, R_t is a matrix of conditional quasicorrelations, and $\hat{\epsilon}_t$ is a vector of standardized residuals, $D_t^{-\frac{1}{2}}\epsilon_t$. $\bar{Q}$ is the unconditional mean of Q_t.

Table 3: DCC-GARCH Estimation Results

Parameter	Estimate	Std. Error	t-value	p-value
Dev_t				
μ	-0.00804	0.00105	-7.68	0.000
ϕ	0.98501	0.00047	2080.87	0.000
ω	0.00020	0.00001	35.02	0.000
α	0.90035	0.00512	175.89	0.000
β	0.09865	0.00615	16.04	0.000
$\Delta log(DXY_t)$				
μ	0.00000	0.00000	-0.34	0.736
ϕ	0.00217	0.00392	0.55	0.580
ω	0.00000	0.00000	0.00	1.000
α	0.05006	0.00171	29.22	0.000
β	0.89994	0.00254	354.01	0.000
DCC				
a	0.04682	0.00364	12.86	0.000
b	0.95266	0.00372	255.99	0.000
Observations		174,116		
Log-likelihood		-3.75×10^{10}		
AIC		431,045		

From Table 3, it can be observed that the ARCH coefficient of Dev_t is very high, indicating that market shocks have a very large impact on the volatility of stablecoins. The GARCH coefficient is low, suggesting that the long-term memory of volatility is weak. For the DXY index change ($\Delta \log(DXY_t)$), the p-values for both the μ (intercept) and φ (autoregressive coefficient) are greater than 0.1: these two coefficients are insignificant. The log daily changes in the DXY index show no significant trend or autocorrelation, resembling more of a random walk process, and do not require stationarity treatment. Its ARCH term value is small, indicating that market shocks have an influence on the volatility of the DXY index, but the degree of impact is minor. The GARCH coefficient is significant and very high, suggesting that the volatility of the DXY index has strong persistence, which is consistent with the characteristics of typical financial time series. The ARCH effect coefficient of the DCC is relatively small; if the residuals of Dev_t and $\Delta \log(DXY_t)$ experience abnormal volatility simultaneously, their conditional correlation may rise in the short term. The GARCH effect coefficient is significant and very high, indicating that the conditional correlation is highly persistent. Once the level of correlation changes, it tends to persist for a long time. Just as shown in Figure 9, regarding stablecoin market capitalization and the DXY index growth rate, once a positive correlation begins, it may last for several years.

Building on the generalized impulse response function (GIRF) framework established by Koop et al. (1996), this paper analyzes the J-step-ahead impact of shocks in $\Delta \log(DXY_t)$ on Dev_t using methods of Diebold and Yilmaz (2012) and Diebold and Yılmaz (2014), given our DCC-GARCH model, which is called Volatility Impulse Response Function (VIRF). The J-step-ahead Volatility Impulse Response Function of $\log(DXY_t)$ to Dev_t is expressed as:

$$\Lambda_t = E(H_{t+J,12}|\nu_{2,t} = \lambda_{2,t}, F_{t-1}) - E(H_{t+J,12}|\nu_{2,t} = 0, F_{t-1})$$

where $\lambda_{2,t}$ is a vector with a one at the 2^{2th} position and zero otherwise, this is a one standard deviation shock to the variable $\Delta \log(DXY_t)$. And H_{t+J} is the covariance matrix of both $\Delta \log(DXY_t)$ and Dev_t, the element H_{12} is in this matrix

$$\begin{bmatrix} H_{11} & H_{12} \\ H_{21} & H_{22} \end{bmatrix}$$

This variable measures the covariance between $\Delta \log(DXY_t)$ and Dev_t at J periods after the shock arrives.

The historical VIRF leverages the model's historical data and estimated parameters to trace how shocks of $\Delta \log(DXY_t)$ influence the system's covariance matrix over time. The historical VIRF incorporates the shock sequences (e.g., residuals) with actual data, thereby providing a dynamic analysis more closely aligned with historical scenarios. This historical VIRF can quantify how a specific DXY shock (e.g., a sudden increase in the DXY on a particular day in 2024) impacts the volatility of USDT price deviations ($Dev_t = p_t - 1$) over

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subsequent intervals, such as 8 hours through the channel of covariance. In March 2025, amid expectations of tariff policies under the Trump administration, global trade uncertainty escalated, eroding the appeal of the U.S. dollar as a safe-haven asset and triggering a rapid decline in the Dollar Index. A one-standard-deviation shock to $\Delta \log(DXY_t)$ causes a sharp spike in the covariance between $\Delta \log(DXY_t)$ and USDT deviations within 8 hours, indicating strengthened correlation and rapid "contagion" of DXY volatility to stablecoins. This is likely driven by the high liquidity of the crypto market, where algorithmic trading and arbitrage mechanisms enable near-instantaneous transmission, see Divakaruni and Zimmerman (2025). Overall, the dollar's weakness during this period quickly exerts pressure on stablecoins: most are backed by dollar-denominated assets (such as short-term Treasury bills). When the DXY falls dramatically, the relative value of these reserves depreciates, potentially sparking redemption panic. In other periods, USDT's reserve management, arbitrage mechanisms, market segmentation, and differences in the macroeconomic environment effectively buffer dollar index (DXY) volatility during normal times.

The dynamic correlation time series indicate that the impact of DXY shocks on USDT prices was generally modest for most of the sample period since in Figure 5 the dynamic correlation coefficient occasionally exceeded 0.5 and remained very close to zero in most instances.

Dynamic Conditional Correlation: log_DXY vs USDT_Deviation
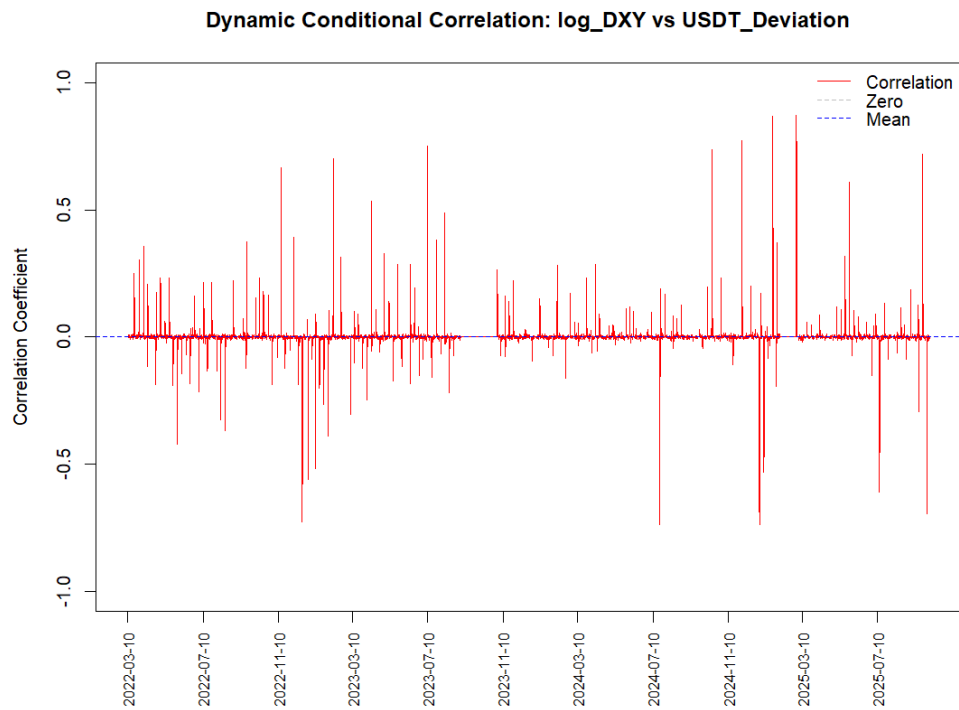

Figure 10: Dynamic Correlation Coefficient of DCC-GARCH Model with DXY Index and USDT Deviation
Sources: Bloomberg
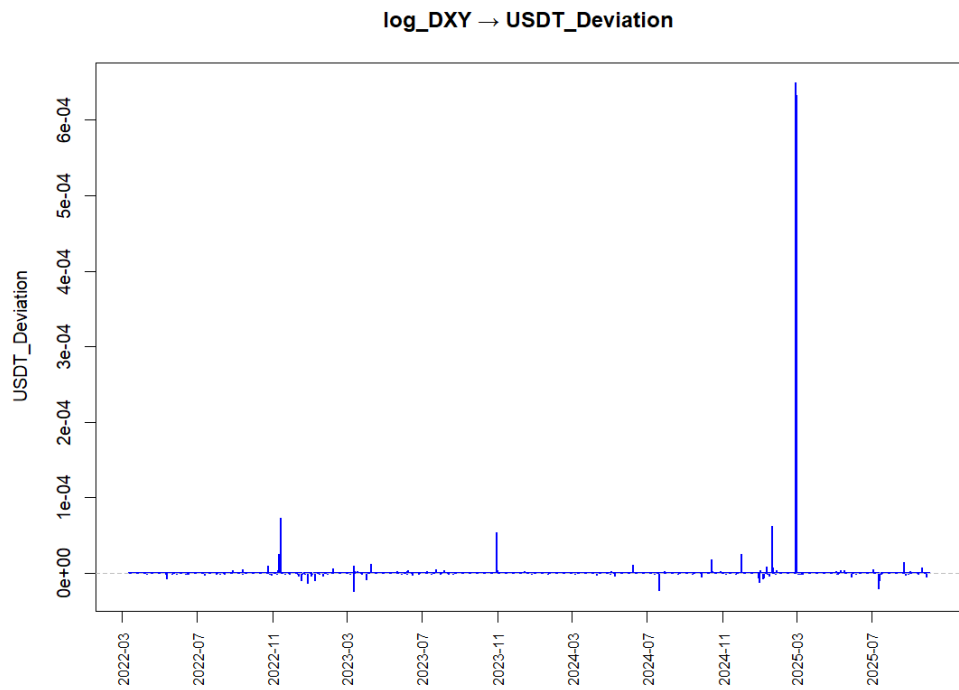
log_DXY → USDT_Deviation

Figure 11: Volatility Impulse Response Function of DCC-GARCH Model
Sources: Bloomberg

2.4 A Markov Regime-switching GARCH Model of USDT

According to the findings of the previous subsection, the conditional volatility of USDT exhibits distinct volatility mechanisms before and after 2024, suggesting a potential structural shift in market dynamics. To further investigate this phenomenon and enhance the model's explanatory power, this study partitions the full sample into two subsamples—pre-2024 and post-2024—and conducts separate GARCH models to capture the distinct volatility characteristics and their underlying drivers in each period.

Table 4: Comparison of GARCH$(1,1)$ Models: Pre- vs. Post-2024 Periods

Mean Equation Setting	Pre-2024 Period		Post-2024 Period	
	With AR(1) Mean	Constant Mean	With AR(1) Mean	Constant Mean
Mean Equation				
μ	-0.007128***	0.010326***	-0.008614***	0.007222***
ar_1	0.988147***	$-$	0.980469***	$-$
Variance Equation				
ω	0.000131***	0.000004***	0.000283***	0.000033***
α_1 (ARCH)	0.863228***	0.153920***	0.920498***	0.214847***
β_1 (GARCH)	0.135772***	0.845079***	0.078502***	0.784153***
$\alpha_1 + \beta_1$ (Persistence)	0.999000	0.998999	0.999000	0.999000
Distribution				
Shape (ν)	2.520***	9.487***	2.314***	6.009***
Tail Fatness	Extreme	Near-Normal	Extreme	Moderate
Goodness-of-Fit				
Log-Likelihood	$227{,}101.3$	$169{,}574.4$	$197{,}840.3$	$138{,}498.3$
Akaike (AIC)	-5.2507	-3.9206	-4.5159	-3.1614
Residual Diagnostics				
Std. Residuals (LB)	**Serial Correlation**	**Serial Correlation**	**Serial Correlation**	**Serial Correlation**
Sq. Residuals (LB)	✓	✓	**ARCH**	**ARCH**
ARCH-LM Test	✓	✓	**ARCH**	**ARCH**
Sign Bias Test	✓	✓	**Asymmetry**	**Asymmetry**

Note: Table compares four sGARCH$(1,1)$ models with Student's t errors. 'Std. Residuals (LB)' refers to the Ljung-Box test on standardized residuals (significant p-value indicates remaining serial correlation). 'Sq. Residuals (LB)' and 'ARCH-LM Test' check for remaining ARCH effects (✓ indicates the null of no effects is not rejected). 'Sign Bias Test' checks for leverage effects (✓ indicates no significant asymmetry). Persistence levels are exceptionally high in all models. *** indicates statistical significance at the 0.1% level.

Table 5: Parameter Estimates with Robust Standard Errors and Statistical Significance

Parameter	Pre-2024 Period		Post-2024 Period	
	With AR(1)	Constant Mean	With AR(1)	Constant Mean
μ (mean)	-0.0071***	0.0103***	-0.0086***	0.0072***
Robust S.E.	(0.0016)	(0.0004)	(0.0014)	(0.0019)
ar_1	0.9881***	–	0.9805***	–
Robust S.E.	(0.0007)	–	(0.0012)	–
ω (constant)	0.0001***	0.0000	0.0003***	0.0000***
Robust S.E.	(0.0000)	(0.0000)	(0.0000)	(0.0000)
α_1 (ARCH)	0.8632***	0.1539***	0.9205***	0.2148***
Robust S.E.	(0.0140)	(0.0223)	(0.0124)	(0.0209)
β_1 (GARCH)	0.1358***	0.8451***	0.0785***	0.7842***
Robust S.E.	(0.0169)	(0.0248)	(0.0087)	(0.0230)
shape (ν)	2.520***	9.487***	2.314***	6.009***
Robust S.E.	(0.0126)	(0.4894)	(0.0062)	(0.2691)

Note: This table reports parameter estimates with robust standard errors in parentheses.
$^{*}p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$. The estimate for ω in the Pre-2024 Constant Mean model is not statistically significant at conventional levels.

Based on the GARCH(1,1) model analysis of USDT stablecoin deviations from its 1 USD peg, this study identifies a significant structural change around 2024. Also according to evidence that a stronger arbitrage mechanism buffers USDT against negative crypto market shocks, Hui et al. (2025) test the hypothesis that Tether(USDT)'s blockchain migration weakens the volatility spillover from Bitcoin by broadening its investor base. The results from their regime-switching cointegration model support this, showing a reduced spillover effect after the migration and potential regime-switching characteristics of USDT do exist. This suggests that greater investor access improves Tether's peg efficiency by insulating it from market downturns. Empirical results indicate that pre-2024 volatility dynamics were predominantly driven by persistent factors (high β_1), with a symmetric process and adequate model specification, suggesting that USDT deviations during this period primarily exhibited a mean-reverting process with long memory. However, post-2024, the volatility mechanism undergoes a fundamental shift, with news shocks exerting a significantly stronger influence (α_1 dominance) with a marked increase in tail risk (the shape parameter ν of residuals turns to be smaller which means fat tail distribution), indicating that USDT deviations become more sensitive to immediate market information and exhibit a higher probability of extreme deviations. Furthermore, serial correlation in the standardized residuals across all models suggests potential misspecification in the mean equation. These findings highlight the potential evolution of stablecoin volatility mechanisms in response to changing market dynamics.

To investigate the volatility dynamics of USDT, this paper has to identify transitions from tranquil to turbulent regimes since volatility model with a single regime seems hard to capture USDT's dynamics. Our evidence indicates stablecoins may follow the pattern of fluctuations of general currencies, which means

that small deviations correspond to low volatility (tranquil regime), while large deviations align with high volatility (turbulent regime), with volatility varying across these states. These two states can transit into each other, and the transition probability can be either exogenous or endogenous; for instance, certain macroeconomic or financial market factors may increase the probability of transitioning from a low-volatility to a high-volatility state. However, according to existing research, the endogenous mechanism for USDT's state transition is relatively ambiguous. Therefore, this paper assumes the transition probabilities are fixed values to be estimated.

To capture these dynamics, we employ a GARCH regime-switching model with time-varying transition probabilities driven by macroeconomic and financial indicators, such as the U.S. Dollar Index (DXY) and BTC/USDT bid-ask spreads. While such models have been applied to equity markets, interest rates, and exchange rates, see Hamilton and Susmel (1994) and Brunetti et al. (2007).

This paper focuses on the volatility of USDT, specifically examining the special phases where its price undergoes significant fluctuations. Our modeling strategy is based on the following empirical characteristics: first, small price fluctuations are typically accompanied by low market volatility (normal or tranquil state), while large price movements often coexist with high volatility (turbulent state); second, volatility exhibits clear heteroskedasticity across different states. This necessitates the use of a GARCH model with regime switching for analysis, given regime-switching volatility models have been widely applied in fields such as stock markets Hamilton and Susmel (1994), short-term interest rates Gray (1996) and exchange rates Calvet et al. (2006).

The Markov-switching model adopted in this study is built upon two fundamental assumptions. First, the volatility process is governed by two distinct regimes: a high-volatility state and a low-volatility state. Second, periods of high volatility correspond to larger deviations in the mean process, whereas low-volatility periods are associated with smaller deviations. To estimate the model, we employ the R package `MSGARCH`, which implements the Markov-switching GARCH framework developed by Haas et al. (2004). Let s_t denote the latent state variable at time t, where $s_t = 1$ represents the low-volatility (stable) regime and $s_t = 2$ corresponds to the high-volatility regime. The key parameters— μ, ω, α, β and shape parameter ν —are state(regime)-dependent, leading to the following specification:

$$\text{Dev}_t = \mu_{s_t} + \epsilon_t, \tag{1}$$

$$\epsilon_t = \sigma_{t,s_t} z_t, \quad z_t \sim t(\nu_{s_t}), \tag{2}$$

$$\sigma_{t,s_t}^2 = \omega_{s_t} + \alpha_{s_t} \epsilon_{t-1}^2 + \beta_{s_t} \sigma_{t-1,s_t}^2 \tag{3}$$

The dynamics of the discrete state variable s_t are modeled as a first-order Markov chain. Its evolution is governed by the transition probability matrix $\mathbf{P}$:

$$\mathbf{P} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \tag{4}$$

where $p_{ij} = \Pr(s_t = j \mid s_{t-1} = i)$ denotes the probability of transitioning from state i to state j at any time, which means each element of transition matrix is constant and doesn't change over time. Thus, p_{11} represents the probability of remaining in the low-volatility regime, p_{12} is the probability of transitioning from low to high volatility, p_{21} denotes the probability of shifting from high to low volatility, and p_{22} is the probability of persisting in the high-volatility regime.

Table 6: Markov-Switching GARCH Model Estimation Results

Parameter	Regime 1 (Low Volatility)		Regime 2 (High Volatility)	
	Estimate	Std. Error	Estimate	Std. Error
ω	0.0000 ***	(0.0000)	0.0000 ***	(0.0000)
α_1	0.8021 ***	(0.1967)	0.0199	(0.1252)
β_1	0.1949 ***	(0.0036)	0.9800 ***	(0.0000)
shape (ν) Significance	99.7853 ***	(0.2806)	99.9920 ***	(0.1904)
AIC	-627376.6			
BIC	-627275.9			

Note: This table reports parameter estimates with standard errors in parentheses. Significance levels: $^*p < 0.05$, $^{**}p < 0.01$, $^{***}p < 0.001$.

with transition probability matrix $\mathbf{P}$:

$$\mathbf{P} = \begin{bmatrix} 0.8975 & 0.1025 \\ 0.283 & 0.717 \end{bmatrix} \tag{5}$$

Time series analysis of USDT price deviations from its pegged level based on the Markov-Switching Generalized Autoregressive Conditional Heteroskedasticity (MS-GARCH) model reveals significant dual-regime nonlinear characteristics in its price formation process. Table 6 presents the estimation results of the MS-GARCH model. In the low-volatility regime, the shock coefficient α_1 is 0.8021 and significant at the 1% level, indicating that innovations exert a substantial impact on conditional variance, while the persistence(GARCH) coefficient β_1 is 0.1949 and also significant, suggesting a relatively limited spillover effect from past volatility. In the high-volatility regime, α_1 drops to 0.0199 and becomes insignificant, implying that external shocks have negligible influence on market fluctuations; in contrast, β_1 reaches 0.98 and is highly significant, revealing that volatility dynamics in this regime are predominantly driven by their

own lagged components. The model successfully captures the distinct characteristics of the two regimes: like classical asset prices, USDT prices(deviations) are also sensitive to news shocks during low-volatility periods, whereas high-volatility periods exhibit significant persistence clustering. Furthermore, the estimated shape parameters ν for both regimes are highly significant and extremely large (approaching 100). This indicates that, after separately controlling for the idiosyncrasies of the low- and high-volatility regimes, the conditional residuals distribution within each regime approximates a normal distribution. This statistically validates the model specification: the heavy-tailed characteristics exhibited by the overall deviation series primarily stem from the mixture distribution of different volatility regimes, rather than the distributional properties within any single regime. Therefore, the model successfully captures the volatility regime-switching characteristics.

As shown in the Figure 12, the smoothed state probability time series trajectory clearly illustrates structural transitions between a low-volatility stable regime (probability values close to 1) and a high-volatility stress regime (probability values close to 0). Empirical results indicate that when the system is in the stable regime, the deviation of USDT's actual price from its peg significantly narrows, with conditional volatility remaining low and stable, reflecting strong anchoring stability. Conversely, during periods of sharp declines in state probability, conditional volatility exhibits typical clustering behavior, and the amplitude of price deviations widens synchronously, indicating phased pressure on the stablecoin's anchoring mechanism due to market liquidity shocks or confidence disturbances.
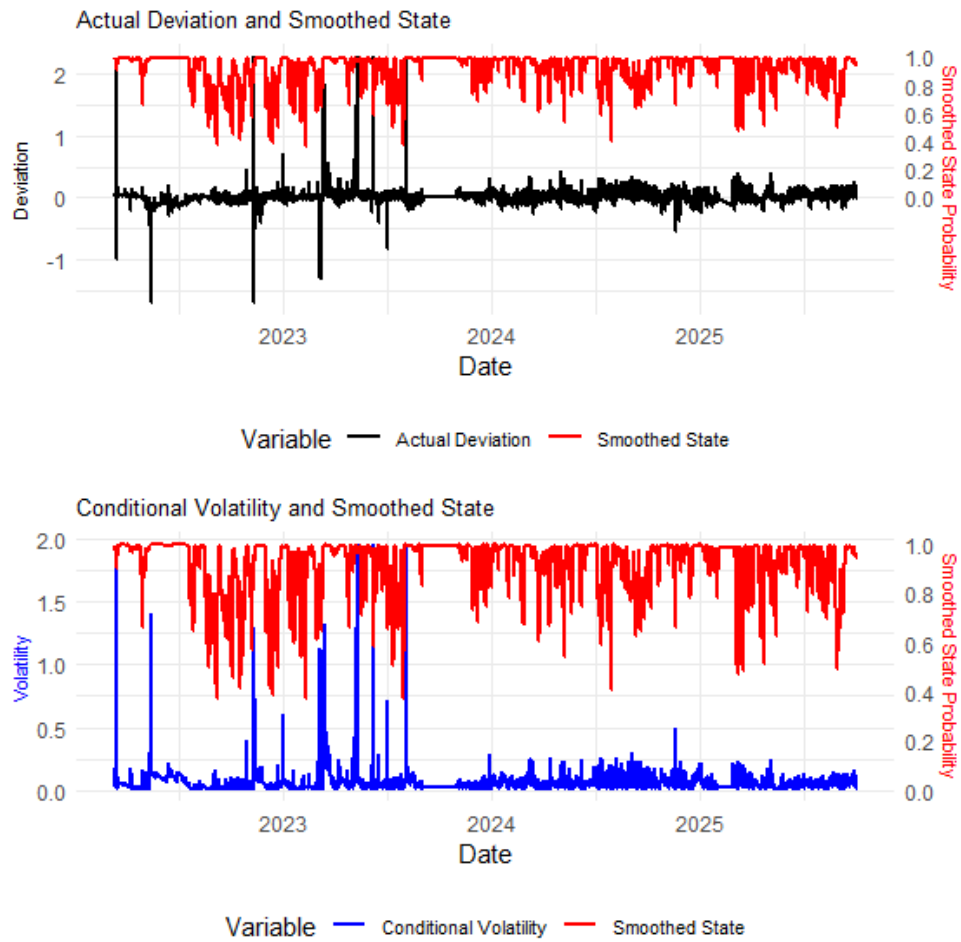
Figure 12: Regime-Switching Characteristics of USDT's Price Deviation from Peg and Conditional Volatility
Sources: Bloomberg

This study employs the MS-GARCH model to analyze the full-sample data of USDT from early 2024 to October 2025. The primary advantage of this approach lies in its ability to leverage regime-switching mechanisms to effectively distinguish conditional volatility under stable and volatile states, thereby providing a more precise characterization of the volatility dynamics across the entire sample. To further investigate the drivers of volatility, we use the conditional volatility (denoted by CV_t in the regression equation) estimated from the MS-GARCH model as the dependent variable and incorporate the logarithmic change in the US Dollar Index, $\Delta \log(DXY_t)$, as the primary explanatory variable reflecting dollar fluctuations. Relevant control variables are included in the regression analysis to systematically elucidate the underlying mechanisms influencing USDT price volatility.

Following the framework of Hui et al. (2025), this study incorporates the logarithm of USDT circulating supply $\log(Cir_t)$ as a control variable in the regression model to account for the potential effects of changes in investor concentration and USDT supply on conditional volatility. Further analysis suggests that an increase in USDT's issuance scale is typically accompanied by a broader base of holders, which not only enhances the diversity of market participants but also significantly improves USDT's trading liquidity. Theoretically, heightened liquidity helps mitigate price volatility pressures, thereby contributing to the stabilization of USDT's price around its \$1 peg.

Furthermore, this study supposes that overall cryptocurrency market fluctuations can significantly impact the anchoring mechanism of stablecoins, given Ahmed and Aldasoro (2025). However, due to the absence of ten-minute frequency data for the Bloomberg Galaxy Crypto Index, we employ the ten-minute frequency data of the Bloomberg Galaxy Bitcoin Index as a proxy variable to capture high-frequency market booms and busts, thereby enabling a more precise analysis of the potential impact of market fluctuations on USDT's price anchoring.

The Regression model is set as:

$$CV_t = \beta_0 + \beta_{dxy}\Delta \log(DXY_t) + \beta_{cir} \log(Cir_t) + \beta_{BGCI}\Delta \log(BGCI_t) + \epsilon_t \qquad (6)$$

The Table 7 suggests that the circulating supply (or market capitalization) of USDT exerts a significant negative effect on its price volatility, indicating that a larger circulating supply is associated with greater price stability for USDT. In contrast, the US dollar index (DXY) exhibits a negative but statistically insignificant impact on USDT volatility. Furthermore, fluctuations in the broader cryptocurrency market appear to have neither a significant nor consistent effect on USDT's price volatility.

Table 7: Linear Regression Results: Conditional Volatility on DXY, Circulation and BGCI variables

Variable	Coefficient	Std. Error	t-statistic	p-value
β_0	0.2816***	(0.0104)	27.13	≤0.001
β_{dxy}	-0.1178	(0.4087)	-0.29	0.773
β_{cir}	-0.0188***	(0.0009)	-21.36	≤0.001
β_{BGCI}	-0.0001	(0.0007)	-0.08	0.933
Observations	70,631			
R-squared	0.0064			
Adjusted R-squared	0.0064			
F-statistic	152.2*** (p ≤ 0.001)			

Notes: Standard errors in parentheses; *** denotes significance at the 0.1% level.

3 Reserve Composition as a Determinant of Stablecoin Stability

Considering that stablecoins are denominated in US dollars, it's not surprising that they can effectively hedge against the impact of the US dollar's appreciation or depreciation. They tend to remain pegged to the 1 USD parity even when the dollar fluctuates. From the perspective of a currency peg, maintaining a fixed exchange rate against the US dollar depends on the issuing institution's timely market interventions to stabilize the exchange rate. Of course, it also depends on the economic fundamentals of the economy using that currency. If the economy itself suffers a major financial or economic shock, the currency is likely to break its peg.

This leads us to examine the financials of Tether Limited who is the issuer of USDT. Tether's large holdings of highly liquid dollar assets effectively hedge against the impact of USD exchange rate fluctuations on USDT's price. While the evolution of its reserve structure particularly the shift in liquidity composition may be the key reason behind USDT's significantly reduced depegging risk in recent years. A clear piece of evidence is that since 2024 USDT has demonstrated much greater stability in maintaining its peg. Therefore, this paper shifts the focus away from conventional macroeconomic indicators. Instead, it seeks to understand the deeper logic behind stablecoin depegs by examining the inherent properties of stablecoin reserve and the structural characteristics of the stablecoin market.

3.1 U.S. Stablecoin Legislation and Reserve Asset Evolution

Since 2022, the U.S. Senate has been working to establish a comprehensive regulatory framework for digital assets, including cryptocurrencies and stablecoins. They want to bring digital assets into the existing financial system while balancing innovation, consumer protection, and market integrity. As a series of bills(or Acts) have been introduced in Congress, the reserve requirements for dollar stablecoins have also been gradually evolving. The collaboration between Lummis and Gillibrand marks the first serious attempt by the U.S. Congress to establish a clear framework for regulating the cryptocurrency industry, particularly stablecoins. S. 2281, the Lummis-Gillibrand Responsible Financial Innovation Act, underwent a hearing

on October 26, 2023, but ultimately did not pass Congress.[5] Prior to the Lummis-Gillibrand Responsible Financial Innovation Act, which mandated high-quality liquid assets for payment stablecoin issuers, Tether had held substantial amounts of gold, Bitcoin, and corporate bonds. These holdings in corporate bonds had previously led to price fluctuations in USDT due to default risks.

The Lummis-Gillibrand Payment Stablecoin Act further narrowed the scope of eligible reserve assets for stablecoin issuers. However, after its introduction in 2024, it did not advance in Congress and remained stalled, mainly due to the election cycle and the subsequent congressional recess.[6]. Now under GENIUS ACT[7], stablecoin issuers must hold 1:1 reserves for any stablecoins issued. These reserves can be held in physical currency, US treasury bills, repurchase agreements and other low-risk assets approved by regulators. Issuers are required to report reserve composition and are subject to regular audits by registered public accounting firms.
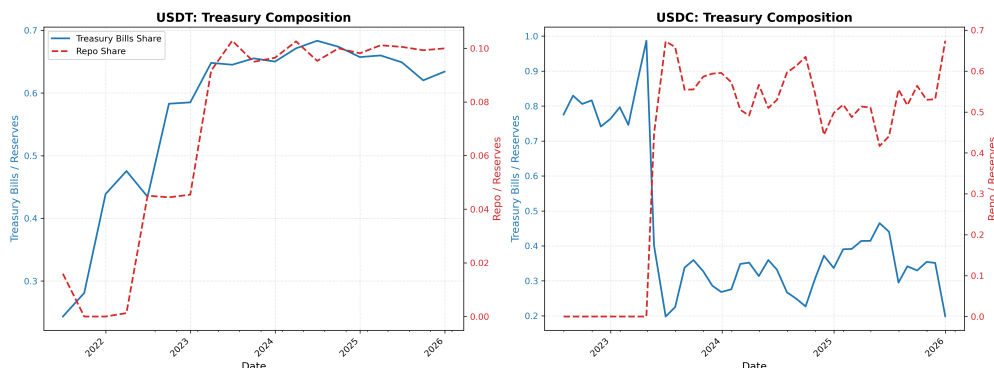

Figure 13: Increasing Share of U.S. Treasury Bill–Linked Assets in USDT and USDC Reserve
Sources: https://tether.to/en/transparency/?tab=reports
and https://www.circle.com/transparency

According to Figure 13, since 2021 there is a clear trend in stablecoin reserves: both USDT and USDC have been steadily increasing their holdings of U.S. Treasury bills and related short-term instruments like overnight repurchase agreements. In simpler terms, a growing chunk of the money backing these digital dollars is now tied up in U.S. government debt or very short-term loans secured by it. This shift is heavily influenced by U.S. policy. Starting with the Trump administration, there's been a push for stablecoins to act as a new source of demand for Treasuries, helping to alleviate the government's debt burden. That's why you see these assets becoming a more prominent part of their reserves.

Take USDC for example, interest rates on reverse repos and U.S. Treasury bills have been significantly higher than those associated with bank deposits for the past several years, which is reflected in the substantial

[5]Cynthia M. Lummis and Kirsten Gillibrand, *Responsible Financial Innovation Act*, S.2281, 118th Cong. (2023), introduced July 12, 2023, https://www.congress.gov/bill/118th-congress/senate-bill/2281. Hearing held October 26, 2023, by the Senate Committee on Banking, Housing, and Urban Affairs.

[6]Cynthia M. Lummis and Kirsten Gillibrand, *Lummis-Gillibrand Payment Stablecoin Act*, S.4155, 118th Cong.(2024), introduced April 17,2024, https://www.congress.gov/bill/118th-congress/senate-bill/4155.

[7]*GENIUS Act*, Pub. L. No. 119-27, 119th Cong. (enacted July 18, 2025), https://www.congress.gov/bill/119th-congress/senate-bill/1582.

allocation of USDC reserves to reverse repos and U.S. Treasury bills, see Copic (2025). Circle's USDC illustrates this vulnerability: from 2022–2024, interest on reserve assets contributed 95 to 99 percent of its total revenue, per its S-1 filing[8]. This change in the composition of reserve assets may impact the price deviation of USDC.

3.2 Data Selection and Empirical Analysis

This paper adopts the framework of Foley et al. (2025), employing four main categories of explanatory variables for stablecoin deviations: trading price and volume, market information, sentiment, and volatility. Building upon this foundation, we incorporate additional variables related to the stablecoin's market structure and its own reserve composition to analyze the reasons behind its deviation from par.

Given the paper's focus on stablecoins with extensive historical data and well-established financial auditing, the explanatory variables consist of the daily prices of USDT and USDC, obtained from CoinMarketCap. Then we use the same deviation measurement

$$dev_t = |p_t - 1| \times 100$$

where p_t is daily stablecoin price. This paper also downloaded the market capitalizations of major stablecoins with longest history (including USDT, USDC, DAI, FUSD) as well as the total market capitalization of the crypto market from CoinMarketCap, as shown in Figure 14.

As overall crypto trading and Market Cap increase, so does the demand for stablecoins as a medium of exchange and source of liquidity, showing that stablecoins play a crucial role as a bridge between fiat currencies and the wider crypto ecosystem (European Systemic Risk Board, 2025). Since traders often hold stablecoins to facilitate crypto trading. Given that traders often hold stablecoins to facilitate crypto trading, we naturally consider the first explanatory variable for stablecoin stability to be market capitalization. Due to network effects, larger stablecoins appear more resilient to various shocks, with better liquidity, lower trading friction, and stronger trader confidence that reduces panic selling. To ensure the variable is stationary, our first explanatory variable is the ratio of stablecoin market cap to total crypto market cap. For USDT, this ratio has risen from 2.22% in August 2022 to 6.3% in January 2026.

However, a direct OLS regression suffers from a severe endogeneity problem. The logic is straightforward: if a stablecoin frequently or significantly deviates from its $1 peg, it will lose market trust and demand. Consequently, its market cap growth will be constrained, and its share of the overall crypto market is unlikely to increase. This reverse causality must be addressed.

This paper uses two Instrumental Variables from studies (European Systemic Risk Board, 2025) and (Kim, 2025). The first IV is the log of overall crypto market cap. This works because when the total crypto

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[8]As filed with the Securities and Exchange Commission on April 1, 2025. Available at: https://www.sec.gov/Archives/edgar/data/1876042/000119312525070481/d737521ds1.htm

market grows, trading activity increases, which naturally leads to more stablecoin usage, thus raises the ratio of the stablecoin's market cap to the overall crypto market cap. However, if just one stablecoin (like USDT) loses its peg slightly, it doesn't really change the value of the entire crypto market. This helps us isolate the cause-and-effect relationship. The second IV is stablecoin DAI market cap over overall crypto market cap. Since USDT and USDC are reserve-backed stablecoins, which maintain a reserve of fiat currency-denominated financial assets to back the coins traded in the market. While Dai is an algorithmic stablecoin that uses smart contracts to effectively perform open market operations to maintain the coin's price stability. DAI is a clean Instrumental Variable. For one thing, its peg mechanism is completely different from USDT and USDC. If USDT and USDC lose their peg and get suppressed in market cap because of reserve issues (through the burning of stablecoins or a temporary halt in minting), the spillover effect on DAI will be very limited. In fact, DAI has almost no correlation with reserve-related explanatory variables, because it doesn't tie to any reserve assets at all. That's why its exogeneity is more solid.

Figure 14: Market Capitalization of the Crypto Market and Stablecoins
Sources: CoinMarketCap

The second explanatory variable is also derived from market capitalization: the Herfindahl-Hirschman Index (HHI) for major stablecoins since 2021-06. This index measures market concentration (and conversely, the degree of competition) in the stablecoin market. Historically the stablecoin market has been highly concentrated dominated by USDT and USDC, often resulting in HHI levels fluctuating between 0.45 to 0.6(see Figure:??). Greater competition reflected in a lower HHI may enhance stablecoin's stability by reducing reliance on any single issuer and also fostering more resilient peg mechanisms. This effect could become particularly relevant under the GENIUS Act, which prohibits stablecoin issuers from paying interest (or yield) to holders, thereby eliminating yield-based incentives that previously allowed some issuers to attract and retain market share through returns on reserves. In a non-interest-bearing regime, competitive dynamics driven by factors like transparency, regulatory compliance, and operational reliability are likely to play a larger role in promoting peg stability.

The Herfindahl-Hirschman Index (HHI) for the four major stablecoins (USDT, USDC, DAI, FDUSD) is calculated as follows:

$$HHI = s^2_{\text{USDT}} + s^2_{\text{USDC}} + s^2_{\text{DAI}} + s^2_{\text{FDUSD}}$$

where s_i denotes the market share (in percentage terms) of stablecoin i within this subset, defined as

$$s_i = \frac{\text{Market Cap}_i}{\sum_{j \in \{\text{USDT, USDC, DAI, FDUSD}\}} \text{Market Cap}_j}$$

Market shares are derived from circulating supply or market capitalization data (e.g., from CoinMarketCap, CoinGecko, or DefiLlama), ensuring $\sum s_i = 100\%$.
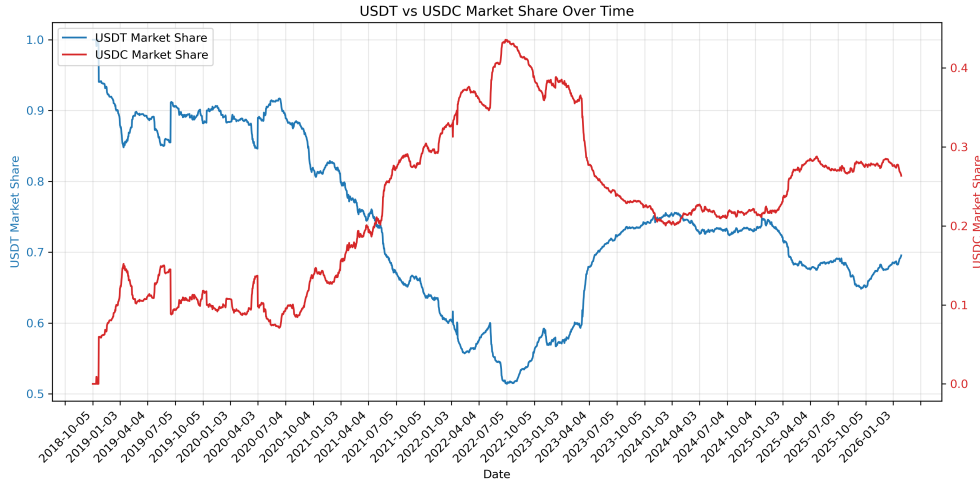

Figure 15: Market Share Evolution of USDT and USDC
Sources: CoinMarketCap

Additionally, to capture the influence of macroeconomic liquidity cycles on stablecoin peg stability, we control the global and U.S. financial conditions. As 24/7 globally traded assets, cryptocurrencies exhibit strong procyclicality with liquidity: tightening regimes induce risk aversion, reduced arbitrage capacity, and elevated depegging pressures, whereas expansive liquidity supports inflows, reserve confidence, and peg resilience. The primary control is the Bloomberg Global Liquidity Index (in the regression we use its monthly growth rate, GL_monthly_growth), which aggregates major central bank balance sheets and broad money supply (M2 equivalents) across key economies (Figure: 17). It serves as a broad proxy for global investable funds available to risk assets. For robustness, an alternative regresssion uses the Bloomberg US Financial Conditions Index (a Z-score of U.S. money, bond, and equity market stress, incorporating spreads, yields, equity valuations, and volatility). Given the USD denomination of most stablecoins and dollar-centric crypto trading, U.S. conditions may exert strong influence.
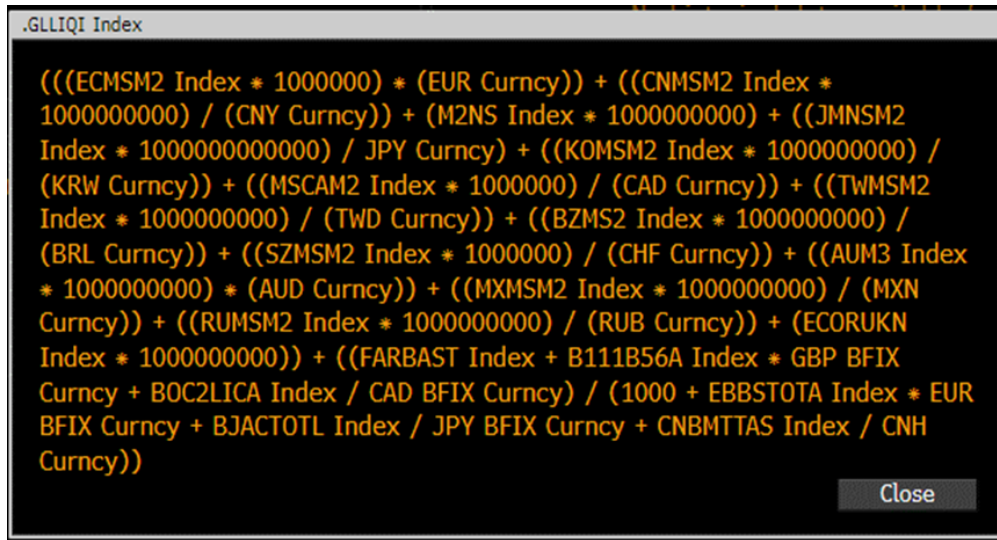
Figure 16: Bloomberg Global Liquidity Formula
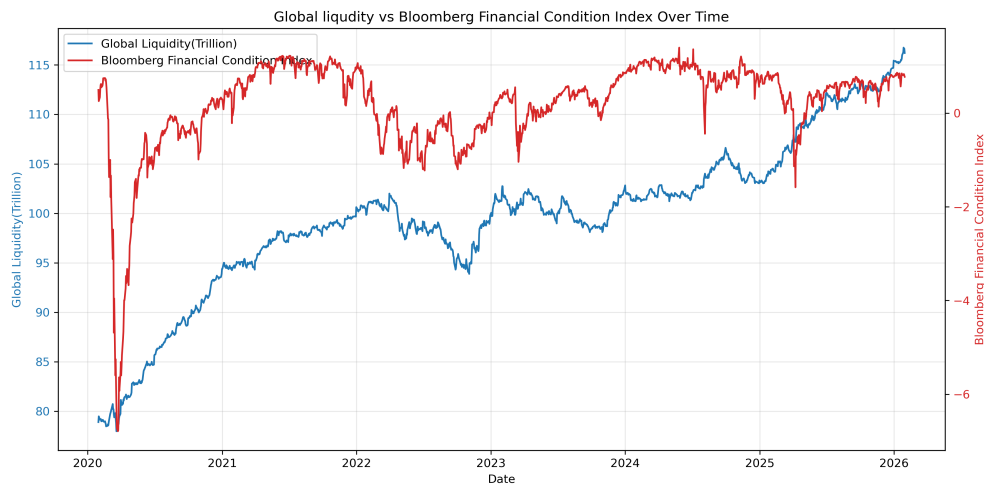**Sources:** Bloomberg

Figure 17: Bloomberg Global Liquidity and US Financial Condition Index
Sources: Bloomberg

Furthermore, the analysis focuses on variables influencing stablecoin reserve allocation decisions. These include the three-month U.S. Treasury bill yield, serving as a benchmark for risk-free returns and incentivizing issuers to shift reserves toward short-term US Treasuries during rate hikes to optimize yield without compromising liquidity. Additionally, the spread between the Secured Overnight Financing Rate (SOFR) and the Federal Reserve's Overnight Reverse Repurchase Agreement (ON RRP) rate is incorporated; a widening SOFR-ON RRP differential signals elevated funding market pressures, prompting issuers like Circle (for USDC) to favor U.S Treasury Repurchase Agreements. Complementing these are the four-week and three-month U.S. Treasury bill auction bid-to-cover ratios, which proxy market demand for short-duration Treasuries: higher ratios indicate robust investor appetite, reflecting abundant liquidity and reduced borrowing costs that facilitate greater Treasury holdings in stablecoin reserves, while lower ratios may signal tightening conditions and a pivot toward alternative cash equivalents. These indicators underscore how stablecoin reserve strategies are inexorably shaped by Treasury market dynamics, and liquidity cycles.

The most important explanatory variable is the structure of stablecoin reserves. USDT has been publishing quarterly financial audits since June 30, 2021. This paper uses the proportion of three types of assets, Treasury bills, Reverse Repo Notes, and Corporate Bonds & Precious Metals in its reserves as explanatory variables (early Tether reports combined Corporate Bonds & Precious Metals into a single category). USDC has been publishing monthly financial audits since July 31, 2022. This paper uses the proportion of Treasury bills and U.S. Treasury Repurchase Agreements in its reserves as explanatory variables.

Following (Lee et al., 2025), this paper also includes the Fear and Greed Index as a control variable. The Fear and Greed Index captures the prevailing sentiment in the Bitcoin market, condensing complex data into a straightforward meter ranging from 0 to 100. Scores from 0 to 24 indicate Extreme Fear, 25 to 46 indicate Fear, 47 to 54 represent Neutral, 55 to 75 signify Greed, and 76 to 100 denote Extreme Greed. This index serves as a concise tool for understanding investor sentiment in the cryptocurrency market. The Fear and Greed Index data is obtained from Alternative.me[9].

The two-stage OLS model is specified as

$$
dev_t = \beta_0 + \beta_{MktShare}MktShare_t + \beta_{HHI}HHI_t + \beta_L Liquidity + \beta_{SOFR}SOFR\_ONRRP + \beta_i Rate3M_t
$$
$$
+ \beta_{FGI}FearGreedIndex_t + \beta_{DXY}DXY_t + \beta_{JPY}JPY + \beta_{Gold}GoldReturn + \beta_{VIX}VIX_t
$$
$$
+ \beta_{4W}BidCover4W_t + \beta_{3M}BidCover3M_t + \beta_B BillShare_t + \beta_R RepoShare_t + \beta_C CorporateBondMetal_t + \epsilon_t
$$

$$
MktShare_t = \gamma_0 + \gamma_{DAI}DAI_t(IV1) + \gamma_{\log MC}\log(CryptoMarketCap_t)(IV2) + ExogenousVar + u_t
$$

Regression results(see Table 9) indicate that the Herfindahl-Hirschman Index (HHI) is the most robust and significant determinant of stablecoin peg deviations from \$1 parity, especially for USDT. The coefficient on HHI is positive and highly significant, indicating that higher market concentration (elevated HHI) is associated with larger deviations from the peg, while greater competition (lower HHI) suppresses deviations and enhances peg mechanism. The stabilizing role of competition may be especially pronounced under frameworks like the GENIUS Act, which prohibits interest payments on stablecoins and eliminates yield-based differentiation, redirecting competitive efforts toward perceived safety, operational reliability, and peg integrity.

Coefficients on the share of reserves held in U.S. Treasury bills (and related Treasury, repo, and reverse repo exposures) are negative and statistically significant, though weaker for USDT. Allocating a larger proportion of reserves to high-quality, short-term liquid assets such as Treasury bills and reverse repo facilities significantly reduces peg volatility. These assets offer near-zero credit and duration risk, deep market liquidity, and reliable redemption capacity, enabling issuers to meet outflows promptly, support efficient arbitrage, and maintain user confidence without forced liquidation.

Higher proportions of reserves allocated to corporate bonds and precious metals in USDT are associated with increased peg deviations (worse stability). These assets introduce greater credit, duration, and liquidity risks compared to short-term Treasuries, weakening reserve resilience and amplifying vulnerability to market shocks or redemption pressures. In contrast, the three-month U.S. Treasury bill auction bid-to-cover ratio exhibits a negative and significant coefficient for USDT peg deviations: stronger auction demand (higher bid-to-cover) enhances Treasury market liquidity, lowers trading costs&frictions, and improves the ease of reserve deployment or liquidation, thereby reducing price volatility and supporting tighter peg adherence.

Global liquidity expansion is generally associated with greater stablecoin peg stability, as evidenced by the negative and statistically significant coefficient on the liquidity measure (GL monthly growth) for USDC. However, this stabilizing effect appears less pronounced for USDT, where the corresponding coefficient is negative but statistically insignificant

3.3   Analysis of the Duration of Stablecoin Deviation Episodes

Drawing on the methodology of (Foley et al., 2025), this study collects 10-minute interval USDT price data from March 9, 2020, to October 2, 2025, estimates the 90-day rolling window standard deviation of USDT prices, and records the daily duration (measured in 10-minute intervals) during which the stablecoin price deviates beyond ± 1, ± 2, and ± 3 standard deviations within the sample period.

To identify depegging events(one event corresponds to 10 minutes), we create two dummy variables that record the depegging events. For USDT prices above the upper threshold:

$$D_t^{\text{Above}} = \begin{cases} 1 & \text{if } USDT_t > 1 + k\hat{\sigma}, \\ 0 & \text{otherwise,} \end{cases}$$

For USDT prices below the lower threshold:

$$D_t^{\text{Below}} = \begin{cases} 1 & \text{if } USDT_t < 1 - k\hat{\sigma}, \\ 0 & \text{otherwise,} \end{cases}$$

where k could be 1,2,3 for different thresholds. This study continues to employ daily frequency data for regression analysis, specifically by aggregating the total minutes of deviation for each day. The two-stage OLS model for USDT deviating duration is specified as

$$Minutes_{t,k} = \beta_0 + \beta_{MktShare}MktShare_t + \beta_{HHI}HHI_t + \beta_L Liquidity + \beta_{SOFR}SOFR\_ONRRP + \beta_i Rate3M_t$$
$$+ \beta_{FGI}FearGreedIndex_t + \beta_{DXY}DXY_t + \beta_{JPY}JPY + \beta_{Gold}GoldReturn + \beta_{VIX}VIX_t$$
$$+ \beta_{4W}BidCover4W_t + \beta_{3M}BidCover3M_t + \beta_B BillShare_t + \beta_R RepoShare_t + \beta_C CorporateBondMetal_t + \epsilon_{t,k}$$

$$MktShare_t = \gamma_0 + \gamma_{DAI}DAI_t(IV1) + \gamma_{\log MC}\log(CryptoMarketCap_t)(IV2) + ExogenousVar + u_{t,k}$$

The regression results (see Table 10) indicate that an increased proportion of Treasury bills in reserves shortens the duration for which USDT trades below both the 1-std and 2-tsd thresholds, thereby enhancing its stability. As for periods when USDT trades below 1&2- std thresholds, the 3 month Treasury bill auction bid-to-cover ratio exhibits a significantly negative coefficient. This suggests that strong demand for Treasury bills is associated with a lower likelihood of prolonged USDT depegging, whereas weaker auction demand correlates with extended periods of downward deviation.

The first key finding is that while the Fear and Greed Index is statistically insignificant in regressions using daily USDT and USDC price levels, it shows a strongly negative and significant relationship with the duration of USDT deviations below the 1-,2- and 3- std thresholds. This indicates that once USDT has begun to depeg downward, heightened fear in the cryptocurrency market tends to prolong the deviation episode, making it more difficult for USDT to return to its 1 USD parity.

For the role of market concentration in stablecoin peg dynamics, when USDT trades below its peg (downward deviations), a higher HHI (indicating greater market concentration) significantly increases the duration of deviation beyond the threshold. Conversely, when USDT trades above its peg (upward deviations), a higher HHI significantly shortens the deviation duration. This suggests that in a more competitive stablecoin market (lower HHI), USDT deviations tend to be upward rather than downward, likely reflecting

stronger demand for USDT. And USDT downward deviations are corrected more quickly, indicating that competition helps reinforce the lower bound of the peg and supports USDT's value stability.

A second key finding is the share of USDT capitalization in overall crypto market capitalization is insignificant in price-level regressions, it becomes significant in deviation-duration models. A larger USDT market share is associated with shorter durations when USDT trades above the 2&3-std thresholds, likely because USDT can be quickly issued in response to excess demand, facilitating a faster return to parity. However, when USDT trades below the 1-std threshold, a larger market share of USDT prolongs the time to re-peg. This may be attributed to the scale effect: when USDT is widely adopted, users exhibit stronger inertia and trust, making them less sensitive to minor downward deviations and thus slowing the arbitrage-driven correction process.

Conclusion

This paper investigates what anchors the peg of the dominant fiat-backed stablecoin Tether's USDT, and, in particular, how macro-dollar conditions interact with stablecoin-specific market microstructure and reserve backing to shape time-varying deviations from par. Using a sequence of volatility models and complementary reduced-form regressions, the analysis documents a peg that is tight on average yet punctuated by short, state-contingent dislocations. It's an empirical profile consistent with rapid arbitrage around a credible redemption promise, but with occasional transitions into stress states in which deviations become more persistent.

A first set of results concerns the market-risk channel from the U.S. dollar to stablecoin pricing. Dynamic-correlation evidence indicates that the co-movement between USDT deviations and the Dollar Index is typically close to zero, but rises sharply around stress episodes; impulse responses show that a one-standard-deviation shock to dollar-index changes can generate a rapid spike in the covariance with USDT deviations within hours, consistent with high-frequency transmission through arbitrage and liquidity-sensitive order flow. A Markov regime-switching volatility specification characterizes USDT dynamics as switching between an "anchored-calm" regime and a "stress-clustered" regime: in the former, innovations matter and are quickly arbitraged away; in the latter, volatility is dominated by its own persistence, producing clustering and wider departures from par. Importantly, once regime-switching and scale are accounted for, the circulating supply (a proxy for market depth and breadth of the holder base) is the main economically meaningful predictor of conditional volatility, while contemporaneous dollar-index changes and broad crypto shocks become small and statistically insignificant. Taken together, these findings suggest that, especially in the post-2024 environment, microstructure and scale conditions dominate "normal-times" peg stability, with macro-dollar effects operating primarily through episodic, state-dependent spillovers rather than continuous pass-through.

A second set of results links peg stability to reserve composition and market structure. Motivated by

the regulatory emphasis on reserve backing and disclosure, the paper studies how balance-sheet quality and the competitive environment map into deviations from \$1 parity. In 2SLS regressions that address reverse causality between stability and market share, market concentration(measured by the Herfindahl–Hirschman Index) emerges as the most robust determinant of peg deviations, particularly for USDT: higher concentration is associated with larger deviations, while greater competition is associated with tighter adherence to par. Reserve quality matters in the expected direction. Larger shares of high-quality, short-duration, liquid assets (U.S. Treasury bills and closely related repo/reverse-repo exposures) are associated with smaller deviations, whereas greater exposure to riskier and less liquid components (corporate bonds and precious metals in USDT's disclosures) is associated with larger deviations. Measures of Treasury-market depth also enter meaningfully: stronger Treasury bill auction demand (higher bid-to-cover) is associated with smaller USDT deviations, consistent with liquidation capacity and lower market frictions strengthening the arbitrage and redemption channel.

A third contribution is to shift attention from the magnitude of deviations to their persistence. Using 10-minute USDT prices to construct daily "minutes outside thresholds" measures, the paper shows that reserve composition and market conditions shape not only whether USDT deviates, but also how quickly it re-pegs. Higher Treasury-bill shares shorten the duration of downward depegging episodes, and weaker Treasury auction demand is associated with longer spells below parity. Investor sentiment becomes more relevant precisely in stress: while the Fear–Greed index is insignificant in daily price-level regressions, it is strongly related to the duration of downward deviations—fear prolongs the re-pegging process once a depeg begins. Market structure also matters asymmetrically: higher concentration increases the duration of downward deviations but shortens upward deviations, suggesting that competition may help reinforce the lower bound of the peg by supporting demand and accelerating arbitrage when USDT trades below par. These duration results complement the regime-switching evidence by clarifying which observable market and balance-sheet variables are most closely associated with the persistence of stress states.

These findings carry several implications for market design and regulation. First, the regime-switching evidence supports viewing large fiat-backed stablecoins as de facto currency-board arrangements: when reserves are credible and arbitrage/redemption channels remain open, the peg can remain tight despite sizeable but transitory shocks. In that framing, regulation that hard-wires reserve backing, disclosure, and auditing may operate less by altering short-run volatility mechanics and more by reducing the probability and severity of transitions into stress regimes. Second, the prominence of scale and liquidity implies that policies (and business practices) that broaden the investor base and deepen secondary-market liquidity can be stabilizing even if they do not mechanically change the reserve mix. Third, the reserve-composition results provide an empirical rationale for restricting eligible reserve assets toward short-duration, high-liquidity instruments and for treating Treasury-market functioning as an input into stablecoin stability: when the liquidation technology improves (e.g., higher bid-to-cover, easier repo intermediation), peg deviations

contract.

The purpose of this paper is also to consolidate and analyze stablecoin pegging mechanism by incorporating the latest policy changes. The empirical validation of the stabilizing role of Treasury bills supports the prudential requirements proposed in legislation such as the GENIUS Act and the Lummis-Gillibrand Payment Stablecoin Act, which advocate for reserves restricted to high-quality liquid assets. The results suggest that policy interventions should prioritize the composition of reserves and the promotion of market competition over attempts to manage stablecoin volatility through direct intervention or capital controls. By mandating transparency and restricting reserves to assets with minimal credit and duration risk, regulators can effectively reduce the probability of the system transitioning into the high-volatility regime identified in this study.

In summary, this paper demonstrates that the stability of fiat-backed stablecoins is fundamentally anchored in the quality of their reserves and the liquidity of their secondary markets. While macroeconomic shocks and dollar volatility present intermittent stress tests, the resilience of the peg is ultimately determined by the issuer's adherence to a conservative, currency-board-style reserve management strategy. Future research should extend this framework to include algorithmic stablecoins and explore the systemic risk implications of the growing interconnectedness between traditional Treasury markets and the digital asset ecosystem.

Table 8: Comparison of Stablecoin Reserve Asset Requirements Across Proposed U.S. Legislation

Asset Category	Lummis-Gillibrand Responsible Financial Innovation Act (S.2281, 2023)	Lummis-Gillibrand Payment Stablecoin Act (S.4155, 2024)	Genius Act (S.1582, 2025, Became Public Law No: 119-27)
1. Cash & Central Bank Balances	(1) U.S. coins, currency, legal tender; (3) Balances at Federal Reserve banks.	(A) U.S. legal tender.	(i) U.S. currency, Federal Reserve notes, Fed account balances.
2. Bank Deposits	(2) Demand deposits at depository institutions (subject to deposit insurance limits).	(B) Insured demand deposits at a depository institution.	(ii) Insured demand deposits or shares at an insured depository institution.
3. U.S. Treasury Securities	(5) Short-term Treasury securities (original maturity ≤ 1 year).	(C) U.S. Treasury bills, bonds, or notes (maturity ≤ 90 days from purchase).	(iii) Treasury bills, notes, or bonds (remaining/original maturity ≤ 93 days).
4. Repurchase Agreements (Repo)	(6) Repo agreements backed by eligible Treasury securities.	(D) Repo agreements (maturity ≤ 7 days) backed by Treasury bills (maturity ≤ 1 year).	(iv) Overnight repos (as seller) backed by Treasury bills (maturity ≤ 93 days).
5. Reverse Repurchase Agreements	Not Specified.	Not Specified.	(v) Overnight reverse repos (as purchaser), tri-party/centrally cleared/bilateral, collateralized by Treasuries.
6. Money Market Funds	Not Specified.	Not Specified.	(vi) Registered government money market funds invested solely in assets (i)-(v).
7. Foreign Reserves	(4) Foreign withdrawable reserves (stablecoin's denomination).	Not Specified.	Not Specified.

Table 9: Stablecoin Deviation 2SLS Regression Summary

Liquidity measure	USDT		USDC	
	GL_monthly_growth	Bloomberg FC	GL_monthly_growth	Bloomberg FC
Intercept	−0.197	−0.249	1.029***	0.918*
	(0.293)	(0.253)	(0.392)	(0.376)
Stablecoin Share	3.299	2.863	−5.429	−5.599
	(3.629)	(3.512)	(4.368)	(4.260)
HHI	0.906***	0.889***	0.281	0.338
	(0.287)	(0.307)	(0.403)	(0.396)
Liquidity Measure	−0.271	0.005	−0.769**	−0.012
	(0.242)	(0.013)	(0.307)	(0.015)
SOFR_ONRRP	0.013	0.014	0.124	0.103
	(0.130)	(0.119)	(0.095)	(0.094)
VIX	0.000	0.001	0.003***	0.002
	(0.001)	(0.001)	(0.001)	(0.001)
Fear Greed Index	0.000	0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)
DXY	0.005	0.005	−0.007**	−0.006*
	(0.004)	(0.004)	(0.003)	(0.003)
JPY	−0.004	−0.004	0.001	0.001
	(0.002)	(0.002)	(0.001)	(0.001)
Gold Return	0.436	0.420	0.376	0.300
	(0.281)	(0.280)	(0.380)	(0.381)
4W Bid Cover	0.005	0.004	−0.027	−0.038*
	(0.010)	(0.009)	(0.019)	(0.018)
3M Bid Cover	−0.032***	−0.031***	0.029	0.032
	(0.012)	(0.012)	(0.018)	(0.018)
3M Treasury Bill Rate	0.031	0.028	−0.002	−0.005
	(0.021)	(0.020)	(0.015)	(0.015)
Repo Share	−1.705*	−1.610*	−0.663***	−0.672***
	(0.804)	(0.804)	(0.120)	(0.126)
Bill Share	−0.482*	−0.455*	−0.515***	−0.518***
	(0.207)	(0.220)	(0.104)	(0.112)
Corporate Bond+Precious Metal	1.055*	1.176*	–	–
	(0.417)	(0.460)		
Observations				
R-squared				

Standard errors in parentheses; ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

Table 10: IV Regression Results for Deviating Duration under Different Std Thresholds

Variable	High Thresholdss			Low Thresholds		
	1std_high	2std_high	3std_high	1std_low	2std_low	3std_low
Intercept	−188.79**	114.70**	66.06**	−411.36***	−151.63***	−28.59*
	(90.12)	(48.07)	(31.99)	(101.06)	(44.85)	(16.12)
USDT Share	−1934.19	−1771.00**	−1227.00**	3194.29**	824.93	50.10
	(1329.03)	(708.90)	(471.80)	(1490.39)	(661.45)	(237.72)
HHI	281.74***	−71.19	−82.25**	669.59***	212.14***	30.45*
	(101.33)	(54.05)	(35.97)	(113.64)	(50.43)	(18.13)
GL_month_diff	242.29***	−45.69	−74.43**	−33.74	−14.17	−10.47
	(83.63)	(44.61)	(29.69)	(93.78)	(41.62)	(14.96)
SOFR_ONRRP	94.09**	101.20***	54.43***	−2.17	64.76***	0.66
	(42.85)	(22.85)	(15.21)	(48.05)	(21.32)	(7.66)
VIX	0.56*	0.42**	0.21*	−0.39	−0.35**	−0.02
	(0.33)	(0.17)	(0.12)	(0.37)	(0.16)	(0.06)
Fear Greed Index	0.22**	0.01	−0.03	−0.52***	−0.15***	−0.03
	(0.10)	(0.05)	(0.04)	(0.11)	(0.05)	(0.02)
DXY	−3.06**	−3.10***	−1.94***	2.99*	1.28*	0.13
	(1.50)	(0.80)	(0.53)	(1.68)	(0.74)	(0.27)
JPY	2.47***	1.63***	1.06***	−0.43	−0.24	−0.02
	(0.84)	(0.45)	(0.30)	(0.95)	(0.42)	(0.15)
Gold Return	92.26	101.90*	94.28**	1.15	40.92	−16.15
	(104.60)	(55.80)	(37.13)	(117.30)	(52.06)	(18.71)
4W Bid Cover	−12.97***	−1.98	−1.68	−3.02	−1.66	−1.39*
	(4.63)	(2.47)	(1.65)	(5.20)	(2.31)	(0.83)
3M Bid Cover	−11.31**	−3.32	0.14	−15.95***	−5.09**	1.39*
	(4.61)	(2.46)	(1.64)	(5.17)	(2.30)	(0.82)
3M Rate	−11.27	−7.48	−5.41*	18.79*	5.13	−0.11
	(8.54)	(4.56)	(3.03)	(9.58)	(4.25)	(1.53)
Repo Share	−244.52	123.90	114.60	−1098.58***	−357.32***	−51.33
	(249.87)	(133.30)	(88.70)	(280.20)	(124.36)	(44.69)
Bill Share	163.50	132.80**	111.90***	−335.45***	−86.77	6.92
	(115.03)	(61.36)	(40.83)	(128.99)	(57.25)	(20.58)
Corp Bond/Precious Metal	2164.18***	559.40**	420.30***	−31.32	68.60	62.25
	(406.82)	(217.00)	(144.40)	(456.21)	(202.47)	(72.77)
Weak Instruments (F-stat)	76.67***	76.67***	76.67***	76.67***	76.67***	76.67***
Wu-Hausman (p-value)	0.00279	2.92e−06	3.90e−05	0.00449	0.228	0.863
Observations	1187	1187	1187	1187	1187	1187
R-squared	0.0721	−0.1121	−0.0822	0.0460	0.0698	0.0305

Standard errors in parentheses; ***, **, * denote significance at 1%, 5%, and 10% levels, respectively.

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