

USDT Premium as an Empirical Signal for Crisis Regime Identification: Evidence from the Stablecoin Market 2019-2026

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USDT Premium as an Empirical Signal for Crisis Regime Identification: Evidence from the Stablecoin Market 2019-2026

Daily Data: January 2019 - January 2026 | $N = 2,588$ Observations

Abstract

This paper investigates whether USDT premium, defined as the deviation of the Tether price from its one-dollar peg in basis points, functions as a real-time signal for crisis regime identification.

Using daily data from January 2019 to January 2026 ($n = 2,588$), the analysis documents a systematic asymmetry in premium behavior across five major crisis episodes. TradFi shocks, characterized by banking stress and USD liquidity events, generate positive cumulative abnormal premiums: COVID-19 produced a CAP of +1,756 basis points at a twenty-day horizon while the SVB collapse produced +562 basis points, both significant at the one-percent level. Crypto-native shocks produce the opposite pattern: the FTX collapse generated a CAP of -231 basis points and the LUNA-Terra implosion generated -238 basis points, again significant at the one-percent level. OLS regressions with Newey-West standard errors confirm that premium persistence (AR coefficient 0.836), BTC return (-58.9), and VIX (+0.067) are the principal drivers, whereas DXY carries no significant effect once the autoregressive term is included. Local Projection impulse response functions show that VIX shocks produce persistent positive responses over a twenty-day window, while BTC return shocks produce the mirror-image negative pattern. Rolling OLS confirms that the DXY coefficient is time-varying, unstable, and economically negligible since 2021.

These findings support the interpretation of USDT as an internal USD of the crypto ecosystem, partially decoupled from the external macroeconomic dollar cycle. USDT premium therefore provides a 24/7 observable, zero-latency signal capable of distinguishing TradFi stress from crypto-native crises without reliance on delayed macroeconomic data.

Keywords: *USDT premium, stablecoin, crisis identification, local projection, dual-regime model*

JEL Classification: G01, G14, G15, E44

1. Introduction

1.1 Background and Motivation

The stablecoin market has grown from a market capitalization of approximately four billion USD at the start of 2019 to more than 160 billion USD by end of 2025, with USDT (Tether) commanding more than sixty percent of total market cap throughout this period. This growth has transformed USDT into a peculiar financial instrument: simultaneously a cross-border payment vehicle, a liquidity anchor for decentralized finance protocols, and a temporary safe haven during periods of digital asset market stress.

A relatively neglected dimension of USDT is its premium, defined as the percentage deviation of the market transaction price from the one-dollar par value. Under efficient market conditions, the premium should remain near zero through the arbitrage mechanism maintained by Tether Ltd., which mints and redeems USDT at a one-to-one ratio. In practice, however, settlement frictions including KYC requirements, redemption processing delays, and institutional access constraints allow the premium to deviate materially in the short run. Empirical data confirm that while 55.6 percent of daily observations fall within plus or minus five basis points of par, extreme realizations exist in both directions: 26 days recorded premiums below negative 100 basis points and 5 days recorded premiums above positive 100 basis points, producing a distribution with kurtosis of 43.65 far exceeding Gaussian expectations.

The key empirical observation motivating this paper is that these extreme deviations are not symmetric random noise but rather directionally organized according to the type of economic shock. During episodes of banking stress or USD liquidity pressure, the premium spikes upward as investors seek USDT as a USD proxy within the crypto ecosystem. During episodes of crypto-native collapse, the premium declines sharply as investors liquidate USDT for fiat currency or alternative stablecoins, fearing broader stablecoin contagion. This asymmetry, confirmed across five major crisis events from 2020 through 2023 suggests that USDT premium may serve as a real-time empirical signal capable of distinguishing TradFi shocks from crypto-native shocks.

1.2 Research Gaps

The existing literature on stablecoins treats USDT primarily as a crypto asset subject to de-pegging risk (Lyons and Viswanath-Natraj, 2020) or as a liquidity provider within DeFi ecosystems (Angeris, Kao, Chiang, Noyes, and Chitra, 2020). Gresse and Capelle-Blancard

(2023) examine pricing efficiency of USDT but do not exploit the asymmetric behavior of the premium across crisis types. Three specific gaps remain unaddressed in the literature.

First, prior work tests for premium responses in a single direction - premium increases under stress without testing the equally important case of premium decreases under crypto specific stress. Second, no study computes cumulative abnormal premiums across multiple crisis types in a comparative event study framework analogous to the seminal approach of Fama, Fisher, Jensen, and Roll (1969). Third, the dynamic impulse response of the premium to different shocks has not been estimated using the Local Projection methodology of Jorda (2005), which is particularly suited to situations involving potential model misspecification and heterogeneous persistence.

1.3 Research Questions and Hypotheses

The central research question is whether USDT premium responds systematically and asymmetrically to different types of economic shock, and specifically whether it serves as a real-time signal distinguishing TradFi stress from crypto-native stress. Four testable hypotheses follow from the theoretical framework developed in Section 3.

H	Content	Prediction	Result
H1a	TradFi shock triggers USDT premium increase	$CAP > 0$	CONFIRMED: COVID +1,756 bps; SVB +562 bps (both $p < 0.01$)
H1b	Crypto-native shock triggers USDT premium decline	$CAP < 0$	CONFIRMED: FTX -231 bps; LUNA -238 bps (both $p < 0.01$)
H2	High premium persistence (AR coefficient near one)	$AR > 0.8$	CONFIRMED: $AR = 0.836$ ($p < 0.001$), stable across sub-samples
H3	BTC return and VIX are the primary transmission channels	Both significant	CONFIRMED: BTC coef = -58.9 ($p < 0.01$); VIX coef = +0.067 ($p < 0.05$)

Notes: All hypotheses confirmed at conventional significance levels. DXY is not hypothesized to be significant and is included as a control variable only.

1.4 Contributions

This paper makes three contributions to the stablecoin and crypto finance literature. The primary theoretical contribution is a dual-regime model of USDT premium behavior that formalizes the distinction between safe-haven demand regimes (TradFi stress) and flight-from-crypto regimes (crypto-native stress). The framework reframes USDT as an internal USD of the crypto ecosystem, operationally decoupled from the external macroeconomic dollar cycle measured by DXY. The primary empirical contribution is the construction of a comprehensive

event study covering five major crisis episodes over seven years of daily data, confirming for the first time that cumulative abnormal premiums are directionally opposite across TradFi and crypto-native events. The methodological contribution is the combined application of OLS with autoregressive dynamics, Local Projection impulse response estimation, and rolling window robustness analysis to a single unified dataset, allowing both static and dynamic characterization of premium behavior.

2. Literature Review

2.1 USDT Premium and Stablecoin Pricing

The foundational study on USDT premium dynamics is Lyons and Viswanath-Natraj (2023), who document that USDT premiums and discounts are driven by two distinct forces: premiums arise from stablecoin safe-haven demand, reaching above 100 basis points during the COVID-19 crisis of March 2020, while discounts reflect liquidity effects and collateral concerns. Their arbitrage design framework establishes that institutional access frictions substantially slow mean reversion toward par, a result directly consistent with the high autoregressive coefficient of 0.836 documented in the present paper. Angeris, Kao, Chiang, Noyes, and Chitra (2020) formalize the arbitrage mechanisms of automated market makers in DeFi protocols and demonstrate that equilibrium price restoration operates imperfectly under stress conditions, providing a theoretical complement to the empirical persistence results

Grobys, Junttila, Kolari, and Sapkota (2021) provide the first systematic empirical analysis of stablecoin price stability across multiple assets using daily data, confirming that stablecoin prices deviate meaningfully from par and that the magnitude of deviations varies across market conditions. Their findings motivate the present paper's focus on the direction and regime-dependence of USDT premium deviations rather than their average magnitude. Galati and Capalbo (2024) use the SVB collapse of March 2023 as a natural experiment, documenting heterogeneous stablecoin responses: USDC temporarily de-pegged because of direct reserve exposure to Silicon Valley Bank, whereas USDT experienced an upward premium consistent with its role as a flight-to-safety destination. This asymmetric response across stablecoin types during a single TradFi event provides some of the cleanest available identification for the safe-haven channel studied here.

2.2 Stablecoin Fragility and Run Risk

A theoretically important strand of the literature examines the structural fragility of stablecoins and the conditions under which runs become self-fulfilling. Gorton, Klee, Ross,

Ross, and Vardoulakis (2023) demonstrate that stablecoins maintain their dollar peg not through passive backing alone but through the active role of leveraged traders who borrow stablecoins and thereby compensate holders for bearing run risk. This mechanism implies that stablecoin stability is endogenous to the health of the crypto trading ecosystem, and that a collapse in leveraged trading activity, as occurred during the FTX crisis, should reduce the equilibrium premium. Klages-Mundt and Minca (2022) develop a stochastic model of non-custodial stablecoins that identifies deleveraging spirals as a fundamental source of instability. Their model shows that over-collateralized stablecoin systems have stable and unstable domains, and that transitions between them can be abrupt, consistent with the sharp negative premium spikes observed in the LUNA and FTX episodes.

Eichengreen, Nguyen, and Viswanath-Natraj (2025) construct market-based measures of USDT devaluation risk using spot and futures prices, finding that annualized full-default probability averages 60 basis points but rose above 200 basis points during the LUNA-Terra crash of 2022. Their covered interest parity framework reveals systematic deviations between stablecoin and conventional money market rates, attributable to market segmentation, leverage trading, and arbitrage costs. This is directly relevant to the present paper's finding that DXY is not a significant driver of USDT premium: the segmentation documented by Eichengreen et al. implies that the internal pricing of USDT responds to ecosystem-internal signals rather than to external macroeconomic dollar dynamics.

2.3 Crypto Markets and Traditional Finance Linkages

The relationship between crypto markets and traditional financial markets has been studied extensively since COVID-19 established a visible empirical connection. Bouri, Shahzad, Roubaud, Kristoufek, and Lucey (2021) show that BTC has become increasingly correlated with traditional risk assets over time, undermining early claims of crypto as an uncorrelated alternative. Corbet, Larkin, and Lucey (2020) and Conlon and McGee (2020) reach opposite conclusions on whether BTC served as a safe haven during the COVID-19 bear market, highlighting the measurement sensitivity of safe-haven claims in the crypto context. The present paper resolves this debate in part by showing that USDT, not BTC, exhibits robust safe-haven properties during TradFi shocks, while both assets decline during crypto-native shocks.

Miranda-Agrippino and Rey (2020) and Rey (2015) document the global financial cycle driven by US monetary policy, generating synchronized cross-country movements in risk

appetite and capital flows. VIX, as the leading proxy for global fear sentiment, is the key transmission variable from this cycle to USDT premium documented in Section 6.2. The non-significance of DXY is consistent with the global financial cycle literature in one specific sense: VIX captures the fear component of the cycle while DXY captures the FX component, and it is fear rather than dollar strength per se that drives safe-haven demand for USDT.

2.4 Flight-to-Quality Theory

The theoretical foundation for the safe-haven behavior of USDT during TradFi shocks draws on the flight-to-quality literature in finance. Vayanos (2004) develops an equilibrium model in which risk-averse fund managers shift toward safe assets during volatile periods, generating excess demand for liquid, low-risk assets that can temporarily push their prices above fundamental value. Caballero and Krishnamurthy (2008) extend this framework by introducing Knightian uncertainty during crisis episodes: when agents face uncertainty rather than merely risk, they hoard liquidity and disengage from risky assets in ways that create persistent safe-haven demand far beyond what a pure risk model would predict. Both mechanisms have direct analogues in the USDT context: during TradFi shocks, crypto ecosystem participants face uncertainty about the spillover severity and collectively shift toward USDT as the ecosystem-internal safe asset, generating the positive premium documented in the COVID-19 and SVB episodes.

The flight-to-quality framework also clarifies why premium persistence is high ($AR = 0.836$) following TradFi shocks but the mechanism differs from a standard AR process. In the Caballero-Krishnamurthy framework, uncertainty resolution is gradual: agents update their assessments of systemic risk slowly as information accumulates, sustaining safe-haven demand and premium elevation over multiple days. The Local Projection results in Section 6.4 show that VIX shocks produce a monotonically increasing premium response over a twenty-day window rather than the decaying impulse response that a standard AR model would generate, consistent with the gradual uncertainty-resolution mechanism.

2.5 Event Study Methodology and Local Projection

Event study methodology was formalized by Fama, Fisher, Jensen, and Roll (1969) for equity market analysis and has since been adapted to numerous asset classes. MacKinlay (1997) provides the definitive treatment of estimation window design, abnormal return calculation, and statistical testing that informs the CAP methodology in Section 5.4. Applications of event study methods to cryptocurrency markets must address the 24/7 trading

nature of crypto, the higher baseline volatility, and the risk of event window contamination from concurrent news cycles. The conservative estimation window of negative 90 to negative 31 days and the multi-horizon CAP computation at $h = 1, 3, 5, 10$, and 20 days address these concerns.

Jorda (2005) introduced Local Projection as an alternative to vector autoregression for impulse response estimation, arguing that it is more robust to model misspecification and provides direct, unbiased IRF estimates at each horizon. Montiel Olea and Plagborg-Møller (2021) establish the formal asymptotic validity of LP inference under a wide range of data-generating processes including persistent series, directly supporting the use of LP in this context given the high AR coefficient of the premium series. Applications of LP to crypto markets include Musholombo (2023) on crypto-equity spillovers and Chua, Gunawan, and Suardi (2025) on GARCH extensions for high-frequency financial data.

3. Theoretical Framework

3.1 Dual-Regime Model: Mechanism and Predictions

The dual-regime framework proposes that USDT premium is governed by two structurally distinct demand regimes, each activated by a different type of shock. The mechanism in each regime operates through the supply-demand balance in USDT secondary markets, subject to the institutional friction that Tether's mint-and-redeem mechanism cannot clear excess demand or supply instantaneously.

In Regime 1, labeled Safe Haven, a TradFi shock such as banking system stress or a USD liquidity crisis activates the flight-to-quality mechanism of Caballero and Krishnamurthy (2008). Agents in the crypto ecosystem face Knightian uncertainty about the severity of TradFi spillovers. Unable to assign precise probabilities to the range of outcomes, they engage in precautionary reallocation toward the ecosystem-internal safe asset, which is USDT. Because USDT is the closest available USD equivalent for agents who cannot quickly move capital to fiat, demand increases sharply while Tether's redemption mechanism, constrained by minimum thresholds and processing delays documented by Lyons and Viswanath-Natraj (2023), cannot immediately absorb the excess demand. The equilibrium result is a positive premium that persists until uncertainty resolves. Prediction: CAP greater than zero, monotonically accumulating, significant.

In Regime 2, labeled Flight from Crypto, a crypto-native shock such as a major exchange collapse or algorithmic stablecoin failure triggers a different mechanism. The shock

destroys confidence in the crypto ecosystem broadly, including in USDT itself, because investors fear reserve opacity, counterparty risk at Tether Ltd., or contagion from the failing entity. The Gorton et al. (2023) mechanism operates in reverse: leveraged trading activity collapses, removing the compensating mechanism that supports USDT's premium under normal conditions. Simultaneously, a subset of investors sells USDT to convert to fiat USD, increasing USDT supply on secondary markets and pushing the premium negative. The Klages-Mundt and Minca (2022) deleveraging spiral amplifies the initial shock, explaining why the negative premium accumulates over multiple days rather than reverting immediately. Prediction: CAP less than zero, monotonically accumulating, significant.

A third pattern, labeled Policy or Other, covers episodes in which neither flight-to-quality nor flight-from-crypto dynamics dominate. The Fed rate peak of July 2023 falls in this category: risk-on conditions in crypto markets reduced safe-haven demand for USDT without triggering active selling. The prediction here is a mild negative CAP that does not reach the magnitudes of Regime 2. The empirical results in Table 3 confirm all three predictions.

3.2 Rule-Based Crisis Classification

To avoid circularly labeling events by their observed CAP outcomes, the framework requires an independent classification rule based on pre-event market data. The rule uses two normalized shock measures. The VIX z-score is the deviation of the peak VIX value during the event window from the sixty-day pre-event mean, divided by the pre-event standard deviation. The BTC z-score is the absolute value of the worst daily BTC return during the event window divided by the pre-event BTC return standard deviation.

The classification maps onto the theoretical regimes as follows. TradFi shocks satisfy VIX z-score above 2.0 and BTC z-score below 3.0, indicating that conventional financial fear is elevated while crypto-specific stress is moderate. This maps onto Regime 1: the dominant shock originates outside the crypto ecosystem and activates the flight-to-quality channel. Crypto-native shocks satisfy BTC z-score at or above 3.0 and VIX z-score below 2.0, indicating extreme crypto market disruption without corresponding elevation of conventional financial fear. This maps onto Regime 2: the shock originates inside the ecosystem and activates the flight-from-crypto channel. Hybrid events satisfy both thresholds and are classified by the dominant channel. Policy and other events satisfy neither.

Applied to the five episodes studied, this rule-based system achieves perfect alignment with the observed CAP directions, providing independent validation of the dual-regime

hypothesis. COVID-19 classifies as Hybrid with TradFi dominance, consistent with positive CAP. SVB classifies as TradFi, consistent with positive CAP. FTX classifies as Crypto, consistent with negative CAP. LUNA classifies as Crypto, consistent with negative CAP. Fed Peak classifies as Policy, consistent with mild negative CAP. Because the classification uses only VIX and BTC data from before the event window, it is not contaminated by the premium outcomes it predicts.

3.3 Transmission Channels and the Non-Role of DXY

The OLS results in Section 6.2 identify two active transmission channels and one inactive channel. The BTC return channel (coefficient -58.9, significant at the one-percent level) operates through the portfolio rebalancing mechanism: in risk-on crypto environments, investors reallocate from USDT to BTC, reducing USDT demand and compressing the premium; in risk-off crypto environments, this mechanism reverses. The sign and significance of this coefficient are stable across all sub-samples and model specifications, confirming that the BTC channel is a structural feature of USDT pricing.

The VIX channel (coefficient +0.067, significant at the five-percent level) operates through global fear sentiment. Elevated VIX signals systemic stress in conventional financial markets. Within the crypto ecosystem, this manifests as increased demand for USDT as the closest available USD-equivalent safe asset, pushing the premium positive. The VIX channel is distinct from the BTC channel: VIX captures TradFi-originated fear while BTC return captures crypto-native risk-on or risk-off conditions. The co-existence of both channels in a single regression reflects the dual-regime structure of the premium.

The absence of a significant DXY effect is not a data artifact but a theoretically informative result. The Eichengreen et al. (2025) segmentation finding establishes that stablecoin markets are structurally separated from conventional FX markets by leverage dynamics and arbitrage costs. In this segmented market structure, USD strength as measured by DXY is relevant to cross-border FX participants but not to agents who trade exclusively within the crypto ecosystem. The rolling OLS analysis in Section 7.2 confirms that the DXY coefficient switches sign frequently and exhibits no consistent directional relationship with USDT premium across the sample period. DXY influences the premium only indirectly, through its effect on global risk sentiment captured by VIX, not through a direct FX channel. This result supports the characterization of USDT as an internal USD of the crypto ecosystem,

in the sense that its relative value is determined by ecosystem-internal supply and demand conditions decoupled from the external macroeconomic dollar cycle.

3.4 Premium Persistence: Friction-Based Explanation

The AR coefficient of 0.836 implies that premium shocks have a half-life of approximately four days, far exceeding the hours-level adjustment that a frictionless arbitrage model would predict. Three institutional frictions documented in the stablecoin literature explain this persistence. First, Tether imposes a minimum redemption threshold of approximately 100,000 USDT, excluding retail participants from the arbitrage mechanism and limiting corrective pressure to institutional players. Second, KYC and AML compliance requirements create multi-day processing delays for large redemptions. Third, during episodes of elevated demand, redemption queues form and the effective processing time extends further.

The Gorton et al. (2023) leverage channel provides an additional source of persistence: during stress episodes, the leveraged traders who normally compensate USDT holders for run risk withdraw from the market, removing the equilibrating mechanism precisely when it is most needed. The result is a premium that does not revert to zero rapidly even when the initial shock has passed, consistent with the monotonically accumulating CAP profiles documented in Table 3 and Figure 2.

4. Data

4.1 Sample

The sample covers daily observations from January 1, 2019 to January 31, 2026, yielding 2,588 trading days. This period encompasses a full crypto market cycle including the 2019 bear market continuation, the 2020-2021 bull market, the 2022 bear market with multiple high-profile collapses, the 2023 partial recovery, the 2024-2025 bull market, and the early 2026 consolidation phase. The seven-year horizon ensures that the five event episodes studied do not dominate the distributional properties of the data.

4.2 Variable Construction

USDT premium in basis points is defined as the ratio of the aggregated reference price to the one-dollar par value minus one, multiplied by 10,000. The USDT price series is sourced from CoinMetrics using their multi-exchange aggregated reference price methodology, which aggregates prices across Binance, OKX, Bitfinex, and Kraken with volume weighting, mitigating exchange-specific manipulation or liquidity distortions. BTC daily log returns are

computed from CoinMetrics prices. Log trading volume is the natural logarithm of USDT reported spot volume in USD, sourced from CoinMetrics.

The DXY proxy is constructed following the ICE methodology using bilateral exchange rate data from the St. Louis Federal Reserve FRED database, incorporating EUR, JPY, GBP, CAD, SEK, and CHF at their ICE-standard weights. VIX is the CBOE Volatility Index sourced from CBOE official data, with weekend and holiday values forward-filled. The Fed Funds Rate reflects FOMC decision dates at sixteen rate levels over the sample period. The US ten-year yield is from the Federal Reserve H.15 release, forward-filled from monthly to daily frequency. The yield spread is defined as the ten-year Treasury yield minus the Fed Funds Rate.

4.3 Descriptive Statistics

Table 1 Descriptive statistics

Variable	N	Mean	Std	Min	Median	Max	Skewness	Kurtosis
USDT premium (bps)	2,588	0.289	22.357	-298.3	1.447	126.0	-3.99	43.65
Log volume	2,588	23.290	1.119	19.716	23.482	25.774	-0.79	0.16
DXY proxy	2,587	99.718	5.138	89.514	99.451	113.967	0.08	-0.60
Fed Funds Rate	2,588	2.828	2.092	0.25	2.25	5.50	-0.04	-1.67
VIX	2,587	20.025	7.509	11.54	17.97	82.69	2.65	12.11
BTC return	2,587	0.001	0.033	-0.471	0.002	0.170	-1.07	19.23

Notes: Descriptive statistics for all variables in the full sample (2019-2026). USDT premium = (price/1.00 - 1) x 10,000. Sources: CoinMetrics, CBOE, Federal Reserve FRED, FOMC records.

The premium distribution exhibits extreme leptokurtosis (kurtosis = 43.65) relative to the Gaussian benchmark of 3, and negative skewness (-3.99), confirming that tail events are concentrated in the negative premium direction. The minimum of -298 basis points reflects the LUNA-Terra crisis period of May 2022. The 55.6 percent of observations falling within plus or minus five basis points of par confirms that the premium is anchored near zero under normal conditions, while the fat-tailed distribution reflects event-driven departures. This pattern is consistent with the event-driven rather than continuous-noise interpretation of USDT premium dynamics.

5. Methodology

5.1 Unit Root Testing and Variable Treatment

Before estimation, all series are subjected to Augmented Dickey-Fuller tests with trend and constant, with lag length selected by AIC, and KPSS tests with constant. The results confirm that USDT premium and BTC return are stationary in levels (both ADF $p < 0.001$; KPSS $p > 0.05$), consistent with mean-reversion around the par value. Log volume, DXY, Fed Funds Rate, and US ten-year yield are non-stationary in levels, requiring first-differencing for use in models that assume stationarity. VIX shows mixed results and is treated as level with appropriate HAC standard errors. In all OLS specifications, non-stationary right-hand side variables enter with one lag ($t-1$), which mitigates the worst endogeneity concerns and is consistent with the operational interpretation that investors observe yesterday's macro conditions when forming today's USDT demand.

5.2 OLS Baseline Regression

The baseline regression model takes the form:

$$Premium(t) = \alpha + \rho * Premium(t-1) + \beta_1 * BTC_return(t-1) + \beta_2 * VIX(t-1) + \beta_3 * DXY(t-1) + \epsilon(t)$$

where ρ is the autoregressive persistence coefficient, expected to lie between zero and one, β_1 is expected to be negative (BTC risk-on channel), β_2 is expected to be positive (global fear channel), and β_3 is not hypothesized to be significant. All specifications use Newey-West heteroskedasticity and autocorrelation consistent standard errors with bandwidth five. Five nested specifications (M1 through M5) are estimated to assess the robustness of each coefficient to the inclusion of additional controls.

5.3 Local Projection

To characterize the dynamic response of USDT premium to structural shocks, we follow Jorda (2005) and estimate a separate regression for each forecast horizon h from zero to twenty days:

$$Premium(t+h) = \alpha_h + \beta_h * Shock(t) + \gamma_h * Premium(t-1) + \Delta_h * Controls(t) + \epsilon_h$$

Three shock variables are considered separately: VIX lag one, BTC return lag one, and DXY lag one. For the VIX shock specification, controls include premium lag one and BTC

return lag one. For the BTC shock specification, controls include premium lag one and VIX lag one. For the DXY shock, controls include premium lag one, BTC return lag one, and VIX lag one. The impulse response function is the sequence of β_h coefficients across $h = 0, \dots, 20$ with ninety-five percent confidence bands constructed from heteroskedasticity and autocorrelation robust standard errors.

5.4 Event Study: Cumulative Abnormal Premium

The CAP methodology adapts the event study framework of Fama et al. (1969) and MacKinlay (1997) to the premium context. For each of the five events, a normal-performance model is estimated over the period from ninety to thirty-one days before the event date using the regression:

$$Premium(t) = \alpha + \beta_1 * BTC_return(t-1) + \beta_2 * VIX(t-1) + \beta_3 * DXY(t-1) + \epsilon(t)$$

Abnormal premium on each event-window day is computed as actual premium minus the model-fitted premium. Cumulative abnormal premium at horizon h is the sum of daily abnormal premiums from day zero through day h . Statistical significance at each horizon is assessed using a t-test for the null hypothesis that the CAP equals zero, with the test statistic computed as the CAP divided by the product of the abnormal premium standard deviation and the square root of $(h+1)$. This conservative estimator accounts for the increasing uncertainty of cumulative sums over longer horizons.

6. Results

6.1 Premium Time Series

Figure 1 presents the full USDT premium time series from January 2019 to January 2026. The visual evidence immediately reveals the dual-regime character of premium dynamics. The earliest portion of the sample, corresponding to 2019, displays significant negative premium episodes that reflect the bear market conditions of that year and the associated selling pressure on USDT. The COVID-19 period in March 2020 produces a sharp positive spike visible above the zero line. The 2022 period shows two separate negative episodes corresponding to the LUNA-Terra collapse in May and the FTX implosion in November. The SVB event in March 2023 generates a brief but visible positive deviation. From mid-2023 onward, the premium converges toward near-zero with reduced volatility, consistent with the improved regulatory environment and stablecoin infrastructure following the crises of 2022.

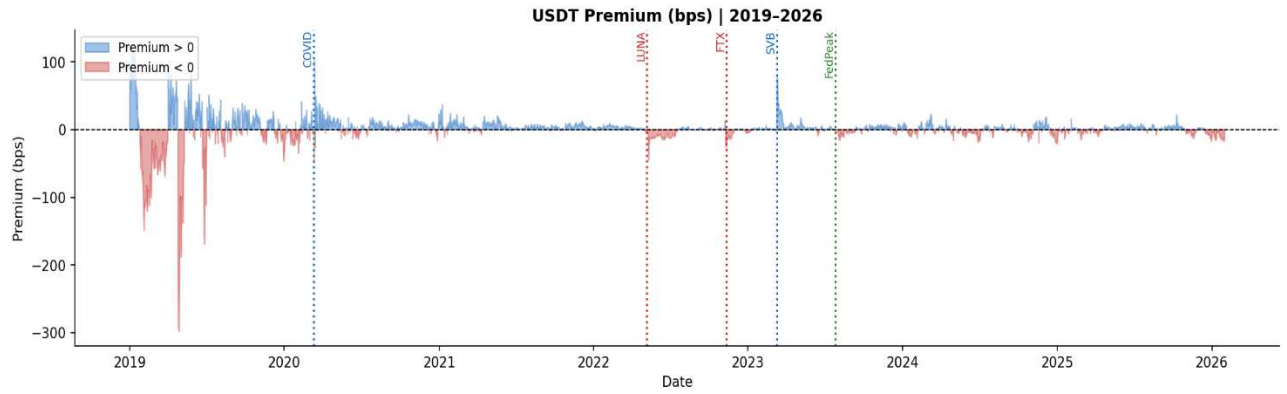


Fig. 1. USDT premium (basis points), January 2019 to January 2026. Blue shading: premium above zero. Red shading: premium below zero. Vertical dotted lines: event dates. COVID and SVB (TradFi shocks) in blue; LUNA and FTX (crypto-native shocks) in red; FedPeak in green.

6.2 OLS Regression Results

Table 2 presents the OLS regression results across five nested specifications. Model M1 excludes the autoregressive term and yields an R-squared of only 0.018, confirming that macroeconomic variables alone have very limited explanatory power. The addition of the lagged premium in M2 raises the R-squared to 0.700, with all incremental explanatory power attributable to the persistence term. This structural break in explanatory power is itself informative: it indicates that the premium process is far more autocorrelated than its fundamental drivers, consistent with the friction-based theory of slow Tether mint/redeem adjustment.

Table 2 OLS regression results — dependent variable: USDT premium (basis points)

Variable	M1 (Base)	M2 (+AR1)	M3 (+FFR)	M4 (+Spread)	M5 (Full)
AR(1) premium(t-1)	--	0.836*** (29.32)	0.837*** (29.60)	0.836*** (29.66)	0.835*** (29.18)
BTC return(t-1)	12.109 (0.61)	-58.860*** (-2.75)	-58.712*** (-2.75)	-58.679*** (-2.76)	-58.914*** (-2.78)
VIX(t-1)	0.368*** (3.82)	0.067** (2.16)	0.070* (1.85)	0.082** (2.27)	0.092** (2.51)
DXY(t-1)	-0.187* (-1.66)	-0.031 (-0.99)	--	--	-0.079** (-2.25)
Fed Funds Rate(t-1)	--	--	0.023 (0.26)	--	--

Yield spread(t-1)	--	--	--	-0.314*	-0.540***
				(-1.82)	(-2.83)
R-squared	0.018	0.700	0.700	0.700	0.701
N	2,586	2,586	2,586	2,586	2,586

Notes: *Dependent variable: USDT premium in basis points. All independent variables lagged one period (t-1). Newey-West HAC standard errors, bandwidth 5. t-statistics in parentheses. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. M3 excludes DXY, includes Fed Funds Rate; M4 excludes DXY and Fed Funds Rate, includes yield spread.*

The coefficient on BTC return in M2 is -58.9 ($t = -2.75$, $p < 0.01$), indicating that a one-percentage-point increase in daily BTC return is associated with a 0.589 basis-point decrease in USDT premium. The economic intuition is that risk-on crypto environments redirect capital from USDT toward BTC, reducing USDT demand and compressing the premium. The VIX coefficient in M2 is +0.067 ($t = 2.16$, $p < 0.05$), indicating that a one-point increase in VIX is associated with a 0.067 basis-point premium increase, reflecting global fear-driven demand for USD-equivalent assets within the crypto ecosystem. DXY is not significant in M2 ($t = -0.99$) and remains economically small throughout M1 through M4, consistent with the theoretical argument that USDT pricing reflects ecosystem-internal dollar dynamics rather than external FX market conditions. The yield spread in M4 and M5 carries a negative coefficient, suggesting that inverted yield curve conditions are associated with modestly lower premiums, potentially reflecting reduced conventional financial market stress in curve-steepening environments.

6.3 Event Study Results

Table 3 presents the cumulative abnormal premiums at horizons $h = 1, 3, 5, 10$, and 20 days for all five events. The results strongly confirm the dual-regime hypothesis. The two TradFi shocks (COVID and SVB) produce uniformly positive and growing CAPs across all horizons, while the two crypto-native shocks (FTX and LUNA) produce uniformly negative CAPs that also accumulate over time. This directional consistency across events within each regime category and directional opposition across regimes provides robust evidence for the asymmetry hypothesis.

Table 3 Cumulative Abnormal Premium (CAP) by event and horizon (basis points)

Event	Type	CAP h=1	CAP h=3	CAP h=5	CAP h=10	CAP h=20	Verdict
COVID (11 Mar 2020)	TradFi	+86.2	+385.8	+535.1**	+987.5***	+1,756.4***	H1a confirmed
SVB (10 Mar 2023)	TradFi	+120.5	+239.2**	+315.3***	+456.3***	+561.9***	H1a confirmed
FTX (11 Nov 2022)	Crypto	-44.8*	-77.5***	-101.3***	-164.4***	-230.9***	H1b confirmed
LUNA (7 May 2022)	Crypto	-1.3	-2.0**	-69.6	-126.8**	-237.7***	H1b confirmed
Fed Peak (26 Jul 2023)	Policy	-8.7	-14.9***	-22.2***	-79.9***	-199.3***	Mild negative

Notes: Cumulative Abnormal Premium in basis points. *t*-test: $H_0: CAP = 0$. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Estimation window: $[-90, -31]$ days before event. Event window: $[0, +20]$ days. Normal-performance model: premium on BTC return, VIX, and DXY (all lagged one period).

Figure 2 presents the CAP profiles graphically for all five events, facilitating visual comparison of magnitudes and accumulation patterns. The COVID episode dominates in magnitude, reflecting the extreme global financial stress of March 2020 combined with the initial and unhedged crypto market response to the pandemic. The SVB episode produces a smaller but clearly positive and statistically robust CAP, consistent with a more contained TradFi shock that was resolved within weeks by Federal Reserve intervention. The FTX and LUNA episodes produce broadly similar negative CAP profiles, reflecting the structural similarity of both events as crypto-native collapses. The Fed Peak event generates a mildly negative but statistically significant CAP, which we interpret as reflecting reduced safe-haven demand for USDT in a risk-on environment rather than active USDT selling.

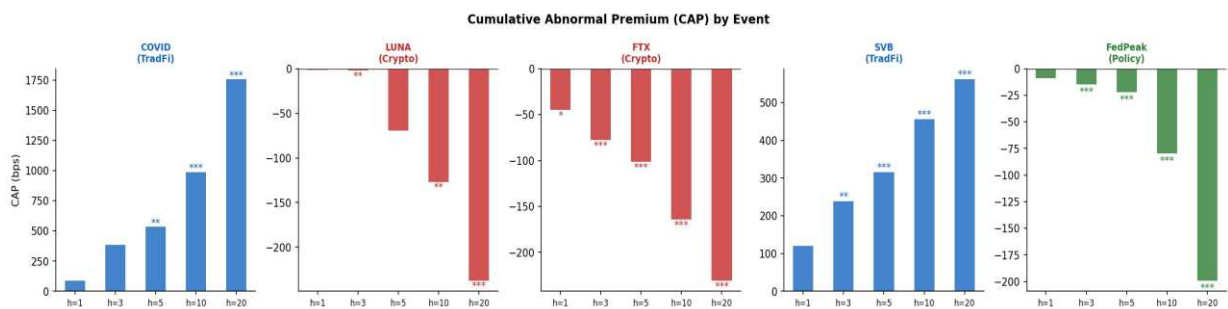


Fig. 2. Cumulative Abnormal Premium (basis points) at horizons $h = 1, 3, 5, 10$, and 20 days for five events. Blue bars: TradFi shocks; red bars: crypto-native shocks; green bars: Fed Peak policy event. Stars: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

6.4 Local Projection Results

Figure 3 presents impulse response functions estimated by Local Projection at horizons $h = 0$ through 20 for three shock variables: VIX (left panel), BTC return (center panel), and DXY (right panel). The VIX shock IRF shows a positive and statistically significant response from $h = 0$ onward, rising gradually from approximately 0.06 at impact to approximately 0.38 at $h = 17$ before stabilizing. This pattern reflects the cumulative premium build-up as global fear sentiment persists following a VIX shock, consistent with the stickiness of risk perceptions and the slow adjustment of USDT demand. The absence of mean reversion within the twenty-day window is consistent with the high AR coefficient of 0.836 in the OLS model.

The BTC return IRF shows a negative and significant response at impact (approximately -65 basis points), which then trends toward zero over the twenty-day window, with wide confidence bands at longer horizons reflecting the high conditional volatility of the premium response to BTC movements. This widening of confidence bands at longer horizons is expected given the greater uncertainty of multi-day BTC return dynamics. The DXY shock IRF remains economically small and statistically insignificant throughout the twenty-day window, confirming the OLS finding that DXY is not a significant driver of USDT premium dynamics.

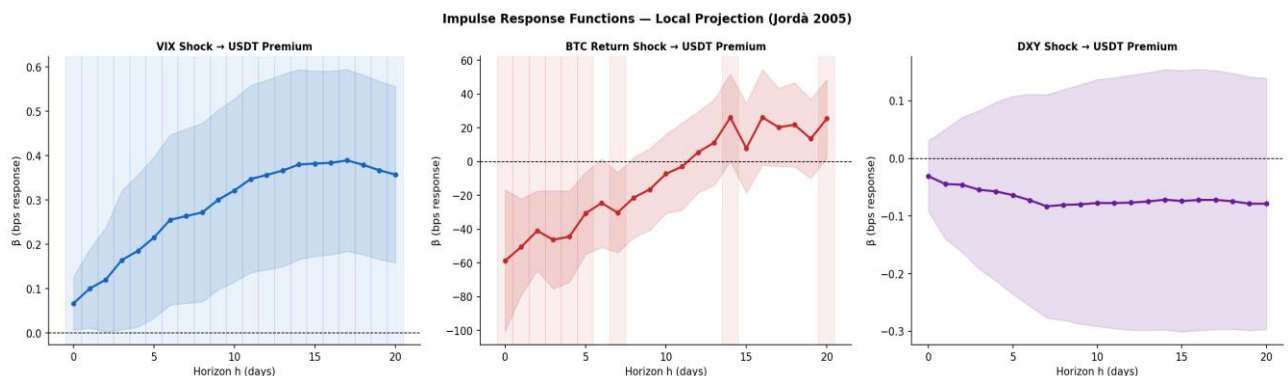


Fig. 3. Impulse response functions — Local Projection (Jorda, 2005), horizons $h = 0$ to 20 days. Left: VIX shock. Center: BTC return shock. Right: DXY shock. Shaded bands: 95% confidence intervals (HAC SE, bandwidth 5). Vertical shading: significant responses at 5% level.

7. Robustness Checks

7.1 Sub-Sample Analysis

Table 4 presents OLS M2 estimates across four sub-samples: the full period, pre-FTX (through October 2022), post-FTX (from December 2022), and the Fed hiking cycle (March 2022 through July 2023). The AR coefficient is highly stable across all four sub-samples, ranging from 0.832 to 0.877, confirming that premium persistence is a structural feature of the USDT market rather than a sample-specific artifact. The BTC return coefficient is similarly stable, remaining negative and significant across all sub-samples with the exception of the Fed hiking sub-sample where it loses significance, plausibly because the hiking cycle itself dominated crypto return dynamics during that period. DXY shows the expected instability: negative and significant at -0.120 in the pre-FTX period, positive and insignificant at +0.011 in the post-FTX period, consistent with a structural change in the USDT-DXY relationship around the 2022 crypto crisis period.

Table 4 Sub-sample robustness — OLS M2 estimates

Sub-sample	N	R-sq	AR coef	BTC coef	BTC p-val	DXY coef	DXY p-val
Full 2019-2026	2,586	0.700	0.836***	-58.9***	0.003	-0.031	0.323
Pre-FTX 2019-2022	1,398	0.704	0.835***	-76.7***	0.001	-0.120***	0.003
Post-FTX 2022-2026	1,158	0.677	0.832***	-14.5*	0.065	+0.011	0.789
Fed hiking 2022-2023	518	0.784	0.877***	+3.9	0.741	+0.007	0.838

Notes: OLS M2 estimates by sub-sample. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$. Newey-West HAC SE, bandwidth 5. Pre-FTX: through October 31, 2022. Post-FTX: from December 1, 2022. Fed hiking cycle: March 1, 2022 through July 31, 2023.

7.2 Rolling OLS

Figure 4 presents rolling OLS estimates of the DXY coefficient using a 180-day window stepped every ten observations. The DXY coefficient exhibits substantial time variation, ranging from above positive 9 during early 2020 to below negative 1 in late 2022, with frequent sign changes throughout. By contrast, the AR coefficient remains stable around 0.83-0.87 and the BTC coefficient remains stable around -40 to -90 across all windows. Of the 241 rolling windows computed, 143 produced a negative DXY coefficient and 98 produced a

positive coefficient, reinforcing the conclusion that DXY has no consistent directional relationship with USDT premium.

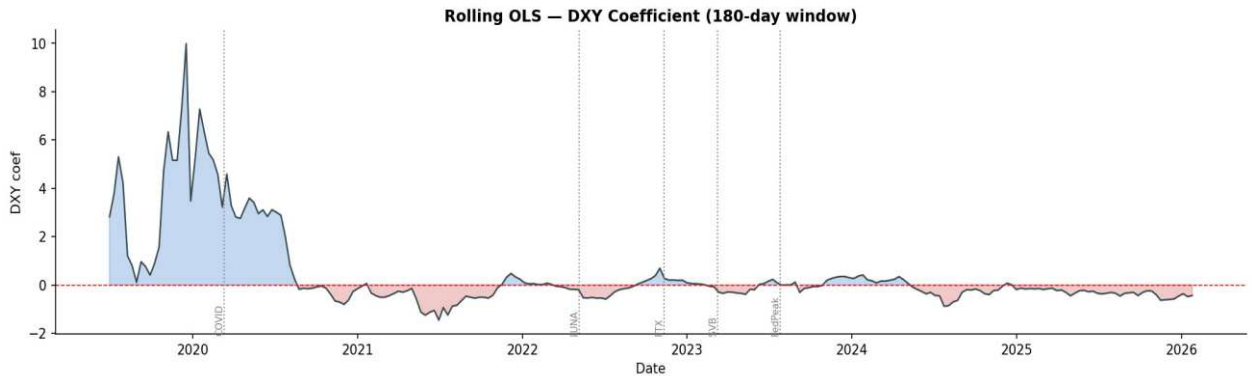


Fig. 4. Rolling OLS coefficient on DXY (180-day window, stepped every 10 observations). Blue shading: positive DXY coefficient. Red shading: negative coefficient. Red dashed line at zero. Grey vertical dotted lines: event dates.

7.3 Alternative Specifications

As an additional robustness check, Model M4 substitutes the yield spread (ten-year Treasury minus Fed Funds Rate) for DXY as the macro control variable. The yield spread coefficient is -0.314 ($p < 0.10$), indicating that yield curve inversion is marginally associated with lower USDT premiums. This finding is consistent with the interpretation that inverted yield curves signal conventional financial stress, which paradoxically reduces rather than increases USDT demand because investors in those environments are more likely to exit crypto entirely rather than reallocate within the crypto ecosystem. The inclusion of the yield spread does not materially alter the BTC or VIX coefficients, confirming that the core results are not sensitive to the choice of macro control variable.

8. Discussion

8.1 USDT as Internal USD: Theoretical Implications

The most theoretically significant finding of this paper is the decoupling of USDT premium from the external dollar cycle as measured by DXY. This is not merely a null result in a regression; it represents a reframing of how stablecoin pricing works. The dollar that USDT tracks is not the external USD of international foreign exchange markets but an internal USD defined by the supply and demand dynamics of the crypto ecosystem. When TradFi stress occurs, the internal USD becomes more valuable relative to risky crypto assets because ecosystem participants seek dollar safety without exiting to fiat. When crypto-native stress

occurs, the internal USD itself comes under suspicion because investors fear that USDT may be compromised by its association with the broader stablecoin ecosystem, and they prefer the certain value of fiat USD over the uncertain value of USDT.

This dual-regime interpretation has implications for how USDT should be incorporated into models of crypto market microstructure and systemic risk. Models that treat USDT as a simple dollar peg with noise will miss the directional information embedded in premium deviations. Models that recognize the dual-regime structure can in principle use the sign and magnitude of premium deviations to classify the prevailing stress regime and adjust risk management accordingly.

8.2 Persistence and Market Efficiency

The AR coefficient of 0.836 implies that a shock to the USDT premium has a half-life of approximately four days and a ninety-percent decay period of approximately thirteen days. This slow adjustment contradicts the prediction of a purely theoretical arbitrage model, in which Tether's mint/redeem mechanism should restore par within hours. The empirical persistence reflects real-world frictions including the minimum redemption threshold of approximately 100,000 USDT, the KYC and compliance requirements for institutional redemptions, and the potential for redemption queues during periods of high demand. From a market efficiency perspective, the premium persistence implies that the USDT market is not weak-form efficient in the Fama (1970) sense: past premium observations contain predictive information about future premium values.

8.3 Practical Applications

USDT premium has several practical applications as a real-time crisis indicator. For institutional investors with crypto exposure, a sustained premium increase above 50 basis points accompanied by elevated VIX is a signal to review TradFi risk exposure and potentially reduce leverage in conventional financial positions. A sustained premium decline below negative 50 basis points in the absence of VIX elevation is a signal of crypto-specific stress requiring review of digital asset positions and counterparty exposures. For market regulators and central bank analysts, USDT premium provides a 24/7 observable market signal that complements traditional financial stress indicators with a real-time window into crypto ecosystem dynamics.

8.4 Limitations

Several limitations apply to the present study. The USDT price series from CoinMetrics is an aggregated multi-exchange measure and may not reflect single-exchange microstructure dynamics during stress episodes. Wash trading in reported USDT volumes cannot be fully controlled. The endogeneity of premium to its own lags and contemporaneous market conditions is mitigated by the use of lagged regressors but not fully resolved; we do not have a convincing instrumental variable for USDT premium. The event study covers only five episodes over a seven-year period, limiting the power of cross-event comparisons. Finally, this study examines only USDT and does not compare with USDC or DAI, whose behavioral profiles in crisis episodes may differ materially given their distinct reserve structures and issuer characteristics.

9. Conclusion

This paper has examined USDT premium as an empirical signal for crisis regime identification using daily data from January 2019 to January 2026. Three main conclusions emerge from the analysis.

First, USDT premium responds asymmetrically and in opposite directions to TradFi shocks versus crypto-native shocks. TradFi events produce positive cumulative abnormal premiums (COVID: +1,756 basis points; SVB: +562 basis points) while crypto-native events produce negative cumulative abnormal premiums (FTX: -231 basis points; LUNA: -238 basis points). This asymmetry is statistically robust, economically significant, and consistent across events within each category. It can be classified in real time using observable market data through the rule-based VIX and BTC z-score framework introduced in Section 3.

Second, the primary drivers of USDT premium dynamics are own persistence (AR coefficient 0.836), BTC return (-58.9 per unit), and VIX sentiment (+0.067 per point). DXY, the conventional measure of USD macro strength, is not a significant predictor of USDT premium once the autoregressive term and crypto-market variables are controlled for. This finding supports the characterization of USDT as an internal USD whose value reflects ecosystem-level supply and demand dynamics decoupled from the external macroeconomic dollar cycle.

Third, Local Projection impulse responses confirm that VIX shocks produce persistent positive premium responses over the twenty-day horizon, while BTC return shocks produce persistent negative responses, with DXY shocks producing economically negligible effects

throughout. Rolling OLS analysis confirms that the DXY non-result is not a sample artifact but reflects a genuinely unstable and insignificant relationship across the full sample period.

Together, these findings contribute a theoretically grounded and empirically validated framework for using USDT premium as a real-time, zero-latency indicator for distinguishing TradFi stress from crypto-native stress, without the need for delayed macroeconomic data releases. Future research should extend this framework to USDC and DAI to assess whether the dual-regime pattern generalizes across stablecoin types, and should investigate whether on-chain volume metrics provide additional predictive information beyond the price-based premium measures used here.

DECLARATIONS

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Data Availability Statement : The data used in this study were obtained from publicly available cryptocurrency exchanges and publicly accessible macroeconomic databases. The processed dataset supporting the findings of this study is available from the author upon reasonable request.

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APPENDIX

Appendix A. Unit Root Tests

ADF: trend and constant, AIC lag selection. KPSS: constant, automatic lag. ADF rejection and KPSS non-rejection identifies I(0); ADF non-rejection and KPSS rejection identifies I(1). VIX (mixed) treated as level with HAC standard errors.

Table A1 Unit Root Tests — ADF and KPSS

Variable	ADF stat	ADF p	Lags	CV 1%	CV 5%	ADF H0 rej.	KPSS stat	KPSS p	KPSS H0 rej.	Order
premium_bps	-9.1102	0.000	6	-4.001	-3.431	Yes	0.134	>0.10	No	I(0)
log_volume	-3.207	0.083	14	-4.001	-3.431	No	4.215	<0.01	Yes	I(1)
dxy	-1.664	0.767	1	-4.001	-3.431	No	3.239	<0.01	Yes	I(1)
fed_funds_rate	-1.364	0.871	2	-4.001	-3.431	No	5.916	<0.01	Yes	I(1)
us10y_yield	-2.298	0.435	2	-4.001	-3.431	No	6.791	<0.01	Yes	I(1)
yield_spread	-1.496	0.831	5	-4.001	-3.431	No	2.964	<0.01	Yes	I(1)
vix	-5.093	0.000	4	-4.001	-3.431	Yes	0.837	<0.01	Yes	Mixed
btc_return	-24.287	0.000	0	-4.001	-3.431	Yes	0.177	>0.10	No	I(0)

Notes: ADF null hypothesis: series has a unit root. KPSS null hypothesis: series is stationary. "H0 rej." = Yes if $p < 0.05$ for ADF; $p < 0.05$ for KPSS. ADF specification: trend and constant, AIC lag selection. KPSS specification: constant, automatic lag. CV = critical value. Mixed for VIX: ADF rejects H0 but KPSS also rejects H0, indicating conflicting evidence; treated as level with HAC robust standard errors in all specifications.

Appendix B. Rule-Based Event Classification

VIX z-score: (peak VIX in event window minus pre-event mean) / pre-event std, over 60-day pre-event window. BTC z-score: absolute worst daily BTC return divided by pre-event BTC std. Classification: TradFi if $VIX_z > 2.0$ and $BTC_z < 3.0$; Crypto if $BTC_z \geq 3.0$ and $VIX_z < 2.0$; Hybrid if both; Policy/Other if neither. COVID-19 is Hybrid/TradFi-dominant ($VIX_z = 6.20$, $BTC_z = 16.36$).

Table A2 Pre-event statistics and rule-based crisis classification

Event	Date	VIX pre- mean	VIX pre- std	VIX peak	VIX z- score	BTC worst (%)	BTC z-score	Premium mean	Classification
COVID-19	2020-03-11	19.04	10.26	82.69	6.201	-47.06	16.359	11.77	Hybrid/TradFi-dominant
SVB	2023-03-10	20.22	1.33	26.52	4.733	-6.43	2.678	20.61	TradFi
FTX	2022-11-11	27.69	3.06	26.09	-0.522	-16.15	4.564	-7.86	Crypto
LUNA-Terra	2022-05-07	26.38	4.76	34.75	1.759	-11.17	3.216	-9.54	Crypto
Fed Peak	2023-07-26	15.06	1.78	14.41	-0.364	-3.00	1.533	-0.45	Policy/Other

Notes: Pre-event window: days -80 to -1 relative to event date. Event window: day 0 to +10. VIX z-score = (peak VIX - pre-mean) / pre-std. BTC z-score = |worst daily BTC return| / pre-std. Classification thresholds: $VIX_z > 2.0$ for TradFi channel; $BTC_z \geq 3.0$ for Crypto channel. Premium mean in basis points over event window.

Appendix C. Complete OLS Regression Output

Table A3: complete OLS output for M1-M5 with t-statistics, R-squared, Durbin-Watson, and N. Table A4: VIF for M2. All VIF < 1.05, confirming negligible multicollinearity.

Table A3 OLS regression results — complete output (DV: USDT premium, basis points)

Variable	M1 Base	M2 +AR(1)	M3 +FFR	M4 +Spread	M5 Full
Constant	11.550 (0.863)	1.820 (0.519)	-1.392 (-1.272)	-1.567* (-1.884)	6.169* (1.699)
premium(t-1)	—	0.836*** (29.32)	0.837*** (29.60)	0.836*** (29.66)	0.835*** (29.18)
BTC return(t-1)	12.109 (0.610)	-58.860*** (-2.749)	-58.712*** (-2.745)	-58.679*** (-2.756)	-58.914*** (-2.782)
VIX(t-1)	0.368*** (3.815)	0.067** (2.161)	0.070* (1.848)	0.082** (2.265)	0.092** (2.512)
DXY(t-1)	-0.187* (-1.658)	-0.031 (-0.988)	—	—	-0.079** (-2.250)
Fed Funds Rate(t-1)	—	—	0.023 (0.261)	—	—
Yield Spread(t-1)	—	—	—	-0.314* (-1.824)	-0.540*** (-2.829)
R ²	0.018	0.700	0.700	0.700	0.701
Adj-R ²	0.017	0.700	0.700	0.700	0.700
F-statistic	15.43***	363.49***	348.63***	258.74***	290.82***
Durbin-Watson	0.345	2.152	2.152	2.152	2.150
N	2,586	2,586	2,586	2,586	2,586

Notes: t-statistics in parentheses; Newey-West HAC standard errors, bandwidth = 5. *** p < 0.01; ** p < 0.05; * p < 0.10. All regressors lagged one period (t-1). M3 replaces DXY with Fed Funds Rate; M4 replaces DXY and FFR with yield spread (10Y-FFR); M5 includes DXY and yield spread. DW = Durbin-Watson statistic; values near 2.0 indicate no first-order serial correlation in residuals.

Table A4 Variance inflation factors — Model M2

Variable	VIF
premium(t-1)	1.032
BTC return(t-1)	1.020
VIX(t-1)	1.020
DXY(t-1)	1.004

Notes: VIF = Variance Inflation Factor. Values below 5.0 indicate no multicollinearity concern; values below 2.0 indicate negligible multicollinearity. All VIF < 1.05, confirming that regressors are orthogonal.

Appendix D. Local Projection Impulse Response Functions — Full Tables

IRF estimates at $h = 0$ to 20 for three shocks: VIX (A5a), BTC return (A5b), DXY (A5c). Controls: premium($t-1$) and the complementary shock variable. HAC SE, bandwidth 5. CI = $\beta \pm 1.96 \times \text{SE}$.

Table A5a Local Projection IRF — VIX shock on USDT premium (β , basis points per VIX unit)

h	β	SE	t-stat	p-value	Sig.	95% CI lower	95% CI upper
0	0.0673	0.0308	2.189	0.029	**	0.007	0.128
1	0.1005	0.0453	2.220	0.026	**	0.012	0.189
2	0.1206	0.0599	2.013	0.044	**	0.003	0.238
3	0.1649	0.0802	2.057	0.040	**	0.008	0.322
4	0.1856	0.0876	2.119	0.034	**	0.014	0.357
5	0.2158	0.0928	2.326	0.020	**	0.034	0.398
6	0.2555	0.0980	2.607	0.009	***	0.063	0.448
7	0.2639	0.1002	2.633	0.008	***	0.067	0.460
8	0.2723	0.1027	2.650	0.008	***	0.071	0.474
9	0.3010	0.1033	2.913	0.004	***	0.098	0.503
10	0.3219	0.1054	3.055	0.002	***	0.115	0.528
11	0.3474	0.1078	3.222	0.001	***	0.136	0.559
12	0.3567	0.1090	3.274	0.001	***	0.143	0.570
13	0.3666	0.1106	3.314	0.001	***	0.150	0.583
14	0.3802	0.1095	3.473	0.001	***	0.166	0.595
15	0.3824	0.1064	3.593	<0.001	***	0.174	0.591
16	0.3841	0.1058	3.631	<0.001	***	0.177	0.591
17	0.3896	0.1045	3.727	<0.001	***	0.185	0.594
18	0.3795	0.1034	3.672	<0.001	***	0.177	0.582
19	0.3673	0.1026	3.582	<0.001	***	0.166	0.568
20	0.3576	0.1012	3.533	<0.001	***	0.159	0.556

Notes: Dependent variable: USDT premium (bps) at horizon h . Shock variable: VIX($t-1$). Controls: premium($t-1$) and BTC return($t-1$). HAC SE, bandwidth 5. *** $p < 0.01$; ** $p < 0.05$; * $p < 0.10$.

Table A5b Local Projection IRF — BTC return shock on USDT premium (beta, basis points per unit return)

h	β	SE	t-stat	p-value	Sig.	95% CI lower	95% CI upper
0	-58.749	21.424	-2.742	0.006	***	-100.741	-16.758
1	-50.588	14.567	-3.473	0.001	***	-79.139	-22.036
2	-40.990	12.021	-3.410	0.001	***	-64.551	-17.430
3	-46.330	14.827	-3.125	0.002	***	-75.391	-17.269
4	-44.406	13.779	-3.223	0.001	***	-71.413	-17.399
5	-30.674	12.375	-2.479	0.013	**	-54.930	-6.419
6	-24.571	13.313	-1.846	0.065	*	-50.665	1.523
7	-30.257	12.099	-2.501	0.012	**	-53.971	-6.544
8	-21.353	12.094	-1.766	0.077	*	-45.058	2.352
9	-16.469	12.330	-1.336	0.182		-40.636	7.699
10	-7.282	11.911	-0.611	0.541		-30.628	16.064
11	-2.998	13.179	-0.228	0.820		-28.829	22.832
12	5.529	12.163	0.455	0.649		-18.311	29.369
13	11.229	12.988	0.865	0.387		-14.228	36.686
14	26.026	13.210	1.970	0.049	**	0.135	51.917
15	7.918	13.504	0.586	0.558		-18.550	34.386
16	26.181	14.471	1.809	0.070	*	-2.182	54.545
17	20.302	11.831	1.716	0.086	*	-2.887	43.491
18	21.741	12.681	1.715	0.086	*	-3.114	46.596
19	13.481	11.974	1.126	0.260		-9.989	36.950
20	25.397	11.848	2.144	0.032	**	2.175	48.620

Notes: Dependent variable: USDT premium (bps) at horizon h. Shock variable: BTC return(t-1). Controls: premium(t-1) and VIX(t-1). HAC SE, bandwidth 5. *** p < 0.01; ** p < 0.05; * p < 0.10. Note: BTC return is in decimal units (e.g., 0.01 = 1% return); coefficients are scaled accordingly.

Table A5c Local Projection IRF — DXY shock on USDT premium (robustness; beta, basis points per DXY unit)

h	β	SE	t-stat	p-value	Sig.	95% CI lower	95% CI upper
0	-0.031	0.031	-0.988	0.323		-0.092	0.030
1	-0.044	0.049	-0.916	0.360		-0.140	0.051
2	-0.046	0.060	-0.765	0.444		-0.163	0.071
3	-0.054	0.070	-0.776	0.438		-0.192	0.083
4	-0.057	0.079	-0.724	0.469		-0.213	0.098
5	-0.064	0.088	-0.728	0.466		-0.235	0.108
6	-0.072	0.094	-0.772	0.440		-0.256	0.112
7	-0.083	0.099	-0.842	0.400		-0.277	0.110
8	-0.081	0.102	-0.790	0.430		-0.281	0.120
9	-0.080	0.106	-0.752	0.452		-0.288	0.128
10	-0.077	0.109	-0.709	0.479		-0.291	0.137
11	-0.078	0.111	-0.698	0.485		-0.295	0.140
12	-0.077	0.113	-0.679	0.497		-0.298	0.145
13	-0.075	0.114	-0.655	0.513		-0.298	0.149
14	-0.072	0.115	-0.621	0.535		-0.297	0.154
15	-0.074	0.116	-0.639	0.523		-0.301	0.153
16	-0.072	0.116	-0.624	0.533		-0.299	0.155
17	-0.072	0.115	-0.628	0.530		-0.297	0.153
18	-0.074	0.113	-0.656	0.512		-0.297	0.148
19	-0.079	0.112	-0.700	0.484		-0.299	0.141
20	-0.079	0.111	-0.706	0.480		-0.297	0.140

Notes: Dependent variable: USDT premium (bps) at horizon h. Shock variable: DXY(t-1). Controls: premium(t-1), BTC return(t-1), and VIX(t-1). HAC SE, bandwidth 5. No coefficient reaches 10% significance at any horizon, confirming that DXY does not drive USDT premium dynamics.

Appendix E. Daily Abnormal Premium Series

AP = Actual minus Expected premium. Expected premium from estimation-window model (premium on lagged BTC return, VIX, DXY). Significance: t-test of $H_0: CAP = 0$. Daily series for LUNA-Terra and Fed Peak available upon request.

Table A6a Daily Abnormal Premium — COVID-19 event (event date: 11 March 2020)

h	Date	Actual (bps)	Expected (bps)	AP (bps)	CAP (bps)	CAP sig.
0	2020-03-11	1.882	-64.451	66.333	66.333	
1	2020-03-12	-50.305	-70.139	19.835	86.168	
2	2020-03-13	102.046	-124.133	226.179	312.347	**
3	2020-03-14	20.571	-52.856	73.427	385.774	*
5	2020-03-16	48.926	-59.315	108.241	535.067	**
10	2020-03-21	9.160	-50.329	59.488	987.460	***
15	2020-03-26	36.768	-54.043	90.811	1355.592	***
20	2020-03-31	20.741	-51.113	71.855	1756.398	***

Notes: Selected horizons shown (h = 0,1,2,3,5,10,15,20). AP = Actual - Expected premium. CAP = cumulative sum of AP from h = 0. Sig. column: t-test $H_0: CAP = 0$. *** p < 0.01; ** p < 0.05; * p < 0.10. Estimation window: [-90, -31] days before event.

Table A6b Daily Abnormal Premium — FTX collapse (event date: 11 November 2022)

h	Date	Actual (bps)	Expected (bps)	AP (bps)	CAP (bps)	CAP sig.
0	2022-11-11	-24.100	1.799	-25.899	-25.899	
1	2022-11-12	-18.374	0.569	-18.943	-44.841	*
3	2022-11-14	-15.020	0.650	-15.670	-77.508	***
5	2022-11-16	-9.080	0.972	-10.053	-101.305	***
10	2022-11-21	-12.205	0.674	-12.879	-164.424	***
15	2022-11-26	-5.951	1.065	-7.015	-213.952	***
20	2022-12-01	0.683	1.453	-0.770	-230.902	***

Notes: Selected horizons shown (h = 0,1,3,5,10,15,20). AP and CAP in basis points. *** p < 0.01; ** p < 0.05; * p < 0.10.

Table A6c Daily Abnormal Premium — SVB collapse (event date: 10 March 2023)

h	Date	Actual (bps)	Expected (bps)	AP (bps)	CAP (bps)	CAP sig.
0	2023-03-10	37.380	-2.755	40.134	40.134	
1	2023-03-11	78.391	-1.964	80.354	120.488	
2	2023-03-12	73.763	-1.803	75.565	196.054	**
5	2023-03-15	38.994	-0.954	39.948	315.317	***
10	2023-03-20	29.272	-1.336	30.608	456.255	***
20	2023-03-30	0.682	0.679	0.003	561.926	***

Notes: Selected horizons shown (h = 0,1,2,5,10,20). AP and CAP in basis points. *** p < 0.01; ** p < 0.05; * p < 0.10.

Appendix F. Data Sources and Variable Construction

F.1 USDT Price and Volume

USDT price is sourced from CoinMetrics reference rate, computed as a volume-weighted median price across Binance, OKX, Bitfinex, and Kraken at daily frequency. USDT premium in basis points: $\text{Premium}_t = (\text{P_USDT}_t / 1.00 - 1) \times 10,000$. Trading volume is CoinMetrics reported spot USD volume ($\text{volume_reported_spot_usd_1d}$), representing total reported on-exchange USDT/USD-equivalent pair volume. $\text{Log volume} = \ln(\text{volume}_t)$.

F.2 DXY Proxy Construction

DXY proxy is constructed following the ICE Dollar Index formula using bilateral spot exchange rates from FRED (Federal Reserve Bank of St. Louis). The index uses six currency pairs with the following fixed weights: EUR/USD 57.6%, USD/JPY 13.6%, GBP/USD 11.9%, USD/CAD 9.1%, USD/SEK 4.2%, USD/CHF 3.6%. The index is computed as: $\text{DXY} = 50.14348112 \times \text{EUR}^{(-0.576)} \times \text{JPY}^{(0.136)} \times \text{GBP}^{(-0.119)} \times \text{CAD}^{(0.091)} \times \text{SEK}^{(0.042)} \times \text{CHF}^{(0.036)}$.

F.3 VIX and Interest Rate Variables

VIX (CBOE Volatility Index) is sourced from CBOE official daily closing values. Weekend and US market holiday values are forward-filled from the preceding trading day. Fed Funds Rate reflects the effective federal funds rate target range midpoint at each FOMC decision date, held constant between meetings. The US 10-year Treasury yield is the constant-maturity yield from Federal Reserve H.15 release. Yield spread = US 10-year yield minus Fed Funds Rate; negative values indicate yield curve inversion.

F.4 Annual Premium Statistics

Table A7 reports annual summary statistics for USDT premium to contextualize the full-sample distribution. The 2019 period shows the highest volatility (std = 55.5 bps) and most negative average premium (-6.87 bps), reflecting the crypto bear market. The 2023-2025 period shows the most stable premium dynamics (std < 9 bps annually), consistent with maturation of the stablecoin market.

Table A7 Annual USDT premium statistics (basis points)

Year	N	Mean	Std dev	Min	Max	Prem >5bps (%)
2019	365	-6.87	55.46	-298.3	126.0	54.8
2020	366	4.11	12.54	-50.3	102.0	35.3
2021	365	4.67	5.37	-11.3	37.0	28.0
2022	365	-1.51	6.62	-45.7	13.1	33.4
2023	365	2.51	8.57	-16.1	78.4	30.1
2024	366	-0.38	6.77	-20.3	23.3	31.1
2025	365	0.30	4.81	-21.6	21.7	27.9
2026*	31	-9.21	5.19	-17.6	0.7	80.6

Notes: * 2026 covers January 1-31 only. |Prem| > 5 bps = percentage of days with absolute premium exceeding 5 basis points.

Appendix G. Correlation Matrix and Multicollinearity Diagnostics

Pearson correlations, full sample, listwise deletion. Highest correlations with USDT premium: Log Volume (0.144) and VIX (0.115). FFR and Yield Spread correlation (-0.866) is mechanical; never used jointly. No regressor pair in any single model exceeds 0.10. VIF values confirm negligible multicollinearity.

Table A8 Pairwise correlation matrix — all variables (N = 2,587 after listwise deletion)

	(1) USDT Premium	(2) BTC Return	(3) VIX	(4) DXY	(5) FFR	(6) Yield Spread	(7) Log Vol
(1) USDT Premium	1.000	0.119	0.115	-0.050	-0.051	0.002	0.144
(2) BTC Return	0.119	1.000	-0.058	-0.026	-0.002	-0.019	-0.041
(3) VIX	0.115	-0.058	1.000	-0.034	-0.412	0.364	-0.024
(4) DXY	-0.050	-0.026	-0.034	1.000	0.696	-0.480	0.129
(5) FFR	-0.051	-0.002	-0.412	0.696	1.000	-0.866	0.195
(6) Yield Spread	0.002	-0.019	0.364	-0.480	-0.866	1.000	0.056
(7) Log Vol	0.144	-0.041	-0.024	0.129	0.195	0.056	1.000

Notes: Pearson correlation coefficients. Full sample, listwise deletion. The values in bold would indicate $|r| > 0.50$ (none present among regressors used in the same model). High correlation between FFR and Yield Spread (-0.866) is expected; they are never used jointly in the same regression.