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Nonlinear Identification and Early Warning of Stablecoin Price Depegging: Empirical Evidence Based on a Cusp Catastrophe Model

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Nonlinear Identification and Early Warning of Stablecoin Price Depegging: Empirical Evidence Based on a Cusp Catastrophe Model

Abstract: Stablecoin prices stay close to $1 most of the time, but in a few periods they deviate markedly. Using daily data on four stablecoins (USDT, USDC, DAI, and FRAX) from 2019 to 2023, we introduce a cusp catastrophe model to identify the depegging process and compare two measures, price deviation and log return. We find the following. First, the jumps identified under the two measures differ substantially: jumps are sparse under the price deviation measure and frequent under the log return measure. Price deviation corresponds to the degree of departure from the peg, whereas log return corresponds to short-term price movements, so an assessment of stablecoin stability should distinguish these two dimensions. Second, differences in jump behavior depend on market embeddedness and the supply-and-demand adjustment mechanism. Traditional financial market variables are most broadly associated with price deviations of USDT and USDC. Although both are fiat-backed, the expansion of market capitalization works in opposite directions for USDT and USDC. For USDT it is associated with larger deviations because of issuance and distribution frictions, whereas for USDC it is associated with converging deviations through a direct redemption channel. Hence, the level of risk depends on liquidity characteristics and redemption arrangements. Third, on-chain capital flows and holdings concentration have forward-looking early-warning power for depegging; moderate deviations are best monitored over short horizons, and severe depegging is identified most effectively over a 7-day horizon. We provide empirical evidence from a nonlinear perspective for understanding the micro-level pricing mechanism of digital assets.

Keywords: stablecoin; price depegging; cusp catastrophe model; nonlinear risk; early warning

1. Introduction

Stablecoins rest on a price peg as their core mechanism and supply a relatively stable unit of account, medium of exchange, and liquidity instrument in the highly volatile crypto asset market. As on-chain transactions, decentralized finance (DeFi), and cross-platform capital transfers have grown in scale, stablecoins have evolved from conversion tools inside exchanges into basic liquidity infrastructure for the crypto asset market. In 2025, total stablecoin market capitalization surpassed $300 billion.[1] Their price fluctuations are therefore no longer a trading issue for a single digital asset; they have become an important variable for the pricing system, capital migration paths, and risk transmission structure of the crypto market. The name “stablecoin” does not mean that the 1:1 peg to the dollar always holds. For

[1] Data source: https://defillama.com/stablecoins.

stablecoins with different mechanisms, the capacity to maintain the peg depends on the quality of reserves or collateral, the issuance and redemption channels, and the accessibility of arbitrage. It also depends on secondary-market liquidity and on the market's trust in, and the credibility of, the pegging mechanism (Lyons and Viswanath-Natraj, 2023). Once these conditions are disturbed, the price of the affected stablecoin can move rapidly from a small deviation to a short-term jump or even a depegging.

Several market events in recent years provide real-world evidence on the triggers of depegging. In May 2022, the algorithmic stablecoin TerraUSD (UST) lost stability under a reversal of market trust, which set off concentrated redemptions and a downward spiral. In November 2022, the bankruptcy of the FTX exchange triggered a credit crisis in the crypto asset market. Capital migrated rapidly among trading platforms, on-chain protocols, and stablecoins, amplifying the role of stablecoins as a liquidity exit and producing price deviations and short-term jumps. In March 2023, the failure of Silicon Valley Bank (SVB) caused USD Coin (USDC), part of whose reserve assets were deposited at that bank, to depeg. In August 2024, the synthetic stablecoin Ethena USDe (USDe) faced concentrated redemptions during a sharp market decline and briefly depegged. In October 2025, changes in global trade policy triggered large-scale liquidations in the crypto market, and several types of stablecoins deviated from their pegs. These events show that a stablecoin price that tracks $1 over long periods is only a surface steady state. Only by dissecting short-term depegging, discontinuous jumps, and price responses to event shocks can we truly understand the inner fragility of stablecoins.

Existing research on stablecoin price stability has developed several valuable explanatory paths. Lyons and Viswanath-Natraj (2023) start from arbitrage mechanisms and issuance arrangements to explain the microfoundations of peg maintenance. Gorton and Zhang (2023) take the perspective of private money and bank run risk and stress the importance of reserve credibility and redemption guarantees. Arner et al. (2020) analyze the functions, risk sources, and regulatory challenges of stablecoins and provide an institutional framework for understanding stablecoin governance. Other studies use GARCH, VAR, and quantile models to examine stablecoin price volatility, extreme deviations, and their relationships with financial-market and crypto-market variables (Fernandez-Mejia, 2024; Hall and Jasiak, 2024). Overall, the existing literature explains pegging mechanisms, reserve risk, and ordinary volatility patterns well. However, on nonlinear jumps under extreme events, mechanism heterogeneity, and the implications for risk governance, it has not yet formed a systematic identification framework or a body of empirical evidence.

Stablecoin prices stay close to $1 most of the time, and deviations occur only occasionally. During the SVB failure in March 2023, USDC fell to $0.87 within a few days; far more often, price movements show up only in daily returns, and the peg range itself is not broken. Breaking the peg range means the pegging mechanism has been shocked, whereas movements in returns belong to price fluctuation in ordinary trading, and telling the two apart depends on how the price state is measured. Price changes can be observed from two angles: how far the price is from $1, and how much it has risen or fallen relative to the previous day. Distance from $1 reflects the degree of deviation from the peg; the change relative to the previous day reflects the magnitude of short-term price movement. The two measures differ in their sensitivity to nonlinear features, and the conclusions drawn from them change accordingly. Identifying stablecoin price risk along both dimensions requires a model that can describe sudden switches between states.

The cusp catastrophe model provides a suitable tool for characterizing such jumps. The model describes the state of the system with a single variable, the state variable, and lets two control parameters determine how the state changes. One parameter determines whether the price is, on the whole, pulled toward the peg or pushed away from it; the other determines whether several price levels at which the system can rest stably coexist. When only a single stable level exists, adjustment to an external shock is continuous. When several stable levels coexist, even a modest disturbance can make the price jump abruptly from one level to another, and the price may not return to its original position immediately after the shock fades. Prior research shows that crashes, hysteresis, and multiple equilibria in financial markets can be explained within this framework (Barunik and Kukacka, 2015; Kukacka and Kristoufek, 2023). For stablecoins, conventional volatility models are better suited to describing price movements in the mean sense. The cusp catastrophe model instead helps determine whether the price has already entered a region prone to jumps, and which factors push it into that region.

Following this reasoning, we select four representative stablecoins, USDT, USDC, DAI, and FRAX, and examine their price jump characteristics over the full sample, within major market event windows, and across different market cycles. USDT and USDC represent the major fiat-backed stablecoins; DAI reflects the on-chain attributes of crypto-collateralized stablecoins; and FRAX combines a hybrid algorithmic design with DeFi ecosystem features. Together, the four coins cover different stabilization mechanisms, reserve structures, and forms of market embeddedness. We use the gap between the price and $1 as the main state variable to identify jumps relative to the peg. As a comparison, we use the log return and

assess the identification capacity of the two measures. To examine which factors push the price into the jump-prone region, we select factors from the stablecoin's own operating state, crypto market structure, on-chain capital behavior, market sentiment, and the external financial environment.

We organize the analysis around three progressive questions. First, are the stablecoin jumps identified by the cusp catastrophe model consistent across different state variables, and what does any difference mean? Second, are the jump characteristics the same across stablecoins and across market phases, and can such differences be explained by stablecoin type? Third, can depegging risk be detected before the price shows an evident deviation? The remainder of the paper is organized as follows. Section 2 reviews the related literature and presents the analytical framework. Section 3 describes the research design and the specification of the cusp catastrophe model. Section 4 reports the jump identification results and mechanism differences. Section 5 tests the explanatory and early-warning power of the risk factors. The final section concludes and offers policy recommendations.

We contribute to the literature in three ways. First, in terms of method, we introduce the cusp catastrophe model into the study of stablecoin depegging and clarify the identification differences across state variables. When measured by the gap between the price and \$1, the jumps identified by the model are relatively sparse; when measured by the log return, they are markedly more frequent. Each measure corresponds to its own risk dimension: return-based jumps reflect day-to-day trading volatility, whereas deviation-based jumps point to impairment of the pegging mechanism. This distinction provides a basis for the choice of state variable in subsequent research. Second, in terms of mechanism, we answer what determines jump characteristics. Differences in jumps do not appear as "which type of stablecoin is more prone to depegging" but in the structure of the factors behind price deviation. The determinants are a stablecoin's market embeddedness and its supply-and-demand adjustment mechanism rather than its mechanism type. To begin with, traditional financial variables, including stock indices, exchange rates, and commodities, are most broadly associated with price deviations of USDT and USDC, while these associations are weakest for DAI. This indicates that USDT and USDC are embedded in a broader funding ecosystem and risk network, whereas DAI and FRAX remain driven mainly by on-chain structures within the DeFi system. Next, although USDT and USDC are both fiat-backed, market capitalization expansion works in opposite directions. USDT issuance is distributed to exchanges with friction and has a longer redemption path, so market capitalization growth is associated with larger short-term deviations. USDC issuance enters the accounts of regulated

institutions directly and its redemption channel is more direct, so market capitalization growth is associated with smaller deviations. Even with similar collateral structures, differences in the pace of liquidity and in the design of the supply-and-demand adjustment mechanism are sufficient for jump behavior to diverge significantly. Finally, the direction of large-holder concentration and Bitcoin dominance varies by coin. Concentrated large holdings are associated with larger deviations for USDT and FRAX but help USDC and DAI maintain the peg, because the large holders of the latter two correspond more to long-term institutional holdings. When Bitcoin dominance rises, trading demand for USDT, USDC, and FRAX declines together, whereas DAI trades at a local premium because DeFi contract activity remains high. The role a stablecoin plays in the risk-appetite cycle changes with the setting in which it is embedded, whether as a liquidity intermediary or as an amplifier of on-chain leverage. Third, in terms of application, we test the early-warning capacity of structural indicators such as on-chain capital flows and holdings concentration, and we distinguish the warning horizons appropriate for moderate deviations and for severe depegging. This shows that stablecoin risk monitoring can shift from observing prices after the fact to tracking changes in structural indicators in advance.

2. Literature and Analytical Framework

2.1 Pegging Mechanisms and Price Stability

Stablecoin pegging mechanisms determine the fundamental logic of price stability, and different stablecoins exhibit significant differences in how they maintain the peg. Existing research typically classifies stablecoins by collateral type and stabilization mechanism into fiat-backed, overcollateralized crypto-backed, and algorithmic categories (Moin et al., 2020; Arner et al., 2020). Fiat-backed stablecoins maintain the peg through off-chain reserves and redemption commitments. Price stability depends on the quality of custodied assets, redemption channels, and issuer credibility. Overcollateralized crypto-backed stablecoins rely on on-chain collateral, oracle pricing, and liquidation mechanisms to maintain solvency. Their pegging logic rests on collateral value coverage and liquidation efficiency. Algorithmic or hybrid-mechanism stablecoins depend more on supply adjustment, incentive design, and market expectation convergence. Klages-Mundt et al. (2020) emphasize that design differences generate distinctly different risk structures. Moin et al. (2020) also point out that the key to classification lies in the price-stabilization mechanism rather than a single technological form. Thus, different stablecoins correspond to different “pegging contracts” and trust assumptions: fiat-backed types rely on centralized custody and redemption

credibility, crypto-collateralized types depend on on-chain collateral, oracles, and liquidation mechanisms, and algorithmic types rely on market expectations and incentive compatibility. We select USDT, USDC, DAI, and FRAX to cover these differentiated pegging logics.

Within pegging mechanisms, different designs all contain fragile points that may lead to price deviation. For fiat-backed stablecoins, price stability depends on the safety, liquidity, and verifiability of reserve assets. Once reserve quality or redemption capacity is questioned, secondary-market prices may deviate from the peg. Gorton and Zhang (2023) argue from the perspective of private money and bank runs that stablecoin issuers possess credit-commitment characteristics similar to banks. Reserve credibility and redemption guarantees affect market acceptance of their face value. For crypto-collateralized stablecoins, collateral price volatility, liquidation delays, oracle errors, and insufficient on-chain liquidity all weaken pegging stability. The massive liquidation pressure MakerDAO faced during the "Black Thursday" event in 2020 reflects the dependence of crypto-collateralized stablecoins on on-chain liquidation efficiency and collateral liquidity under extreme conditions. For algorithmic stablecoins, market confidence, seigniorage mechanisms, and governance incentives more easily form reflexive feedback. Research on the UST collapse shows that algorithmic stablecoins may experience a "death spiral" under run pressure, where price declines, supporting asset depreciation, and redemption pressure mutually reinforce each other (Kurovskiy and Rostova, 2023; Krause, 2025). Hence, the failure of stablecoin pegging mechanisms typically stems from boundary conditions being breached in reserve, redemption, liquidation, expectation, and incentive arrangements.

External market frictions further affect how pegging mechanisms operate. Stablecoin price deviations from the peg may originate from internal mechanism parameter imbalances or be influenced by trading depth, redemption frictions, market sentiment, reserve information disclosure, and cross-market liquidity changes. Lyons and Viswanath-Natraj (2023) study Tether and find that issuance mechanism adjustments and arbitrage channel improvements reduce price deviations, showing that arbitrageurs' access to issuers and market liquidity affect price-restoration efficiency. Ahmed et al. (2024) explain from the perspective of public information and stablecoin runs that reserve information and market expectations affect investor coordination behavior and alter the degree to which secondary-market prices deviate from the peg. The USDC depegging during the SVB event further demonstrates that off-chain reserve asset risks can rapidly transmit to on-chain prices and affect stablecoins such as DAI and FRAX through reserve linkages and liquidity linkages (Diop, 2024). These studies collectively show that stablecoin price stability results from the

joint action of pegging mechanisms, market liquidity, and confidence transmission. Based on this, we subsequently adopt “the difference between the stablecoin closing price and $1” as the state variable to characterize the degree of deviation from the peg and compare pegging performance across different mechanisms.

2.2 Depegging, Nonlinear Jumps, and Risk Identification

Stablecoin price stability does not mean the price always equals $1, but rather that prices can return to the pegging zone in most cases after short-term deviations near the peg. Under extreme conditions, this restoration process may be interrupted and manifest as discontinuous adjustment. Existing research mainly discusses stablecoin stability from three angles: price deviation, tail risk, and peg restoration. Grobys et al. (2021) find from a tail-risk perspective that stablecoin prices are not perfectly stable. Duan and Urquhart (2023) point out that different stablecoins exhibit clear differences in deviation amplitude and restoration speed. Hoang and Baur (2024) discover that stablecoin returns, trading volume, and volatility remain significantly correlated with the Bitcoin market, showing that stablecoin price behavior remains closely linked to overall crypto market liquidity and trading sentiment. Regarding peg restoration mechanisms, Lyons and Viswanath-Natraj (2023) emphasize that arbitrage mechanisms, issuance arrangements, and market liquidity are important conditions for maintaining stablecoin pegs. Hui et al. (2025) approach from pegging stabilization mechanisms and point out that stablecoin price restoration exhibits mean-reversion characteristics similar to target-zone regimes. These studies show that stablecoin depegging is not a price anomaly at a single point in time, but a dynamic process containing deviation, restoration, and renewed deviation.

However, existing research mostly still uses whether prices deviate from the peg as the main criterion for stability. It insufficiently distinguishes between substantive peg deviation and short-term trading disturbances under the appearance of maintaining the peg. For stablecoins, prices may operate around $1 for long periods, but returns, trading volume, and on-chain fund flows may still change violently in short time spans. That is, the absence of deep depegging does not equal the absence of structural stress. Based on this gap, we identify stablecoin price risk from two dimensions. The first is the direction and magnitude of price deviation from $1, characterized by the “price deviation” state variable. The second is abnormal volatility in returns when prices remain near the peg, characterized by the “log return” state variable. The two dimensions correspond respectively to the degree of peg deviation and short-term price movement.

Extreme event studies further reveal the state dependence, mechanism dependence, and risk transmission characteristics of stablecoin depegging. Briola et al. (2023) study the Terra-Luna event and show that the UST collapse was closely related to protocol internal fragility, Anchor mechanism dependence, and market confidence reversal. Saengchote and Samphantharak (2024) point out from the perspective of digital money creation and algorithmic stablecoin runs that when market confidence declines, algorithmic stablecoins easily form bank-run-like negative feedback. Galati and Capalbo (2024) examine the SVB event and find that USDC depegging risk affects other stablecoins and crypto assets through volatility spillover. Gadzinski et al. (2024) propose a "common instability" perspective, showing that stablecoins with different mechanisms may simultaneously experience shocks during events such as the FTX collapse and SVB failure. Thus, stablecoin risk is not limited to individual coin price deviations, but may also spread across stablecoins through reserve linkages, trading linkages, and market expectations.

Event shock research can describe depegging amplitude, volatility spillover, and common instability, yet explanations of how stablecoins transition from continuous small deviations into discontinuous jump states remain limited. Traditional GARCH, DCC-GARCH, VAR, and quantile models can characterize volatility clustering, dynamic correlation, and risk spillover, but struggle to directly handle discontinuous jumps, multistability, and hysteresis under critical conditions. Barunik and Vosvrda (2009) show that the stochastic cusp catastrophe model can identify discontinuous transitions in financial market crashes. Kukacka and Kristoufek (2023) apply the cusp catastrophe framework to crypto asset pricing and distinguish fundamental factors from speculative factors in price dynamics. Perez Riaza and Gnabo (2025) directly link stablecoin depegging with crypto market jumps, pointing out that stablecoin depegging events may become a source of crypto market jumps and instability.

Hence, we introduce the cusp catastrophe model to identify the nonlinear process by which stablecoin prices enter critical transition states. Compared to models that only describe volatility amplitude or correlation, the cusp catastrophe model can distinguish two types of risk forces. One is the directional pressure pushing prices to deviate above or below the peg. The other is the bifurcation pressure that moves the system from a single stable state into a region with multiple stable states, thereby enabling jump possibilities. We incorporate both price deviation and log return into the state variable system to examine respectively the degree of peg deviation and the amplitude of short-term price movement, providing an empirical framework for identifying stablecoins' nonlinear price behavior. Directional

pressure is what we hereafter call the asymmetry factor, and bifurcation pressure is the bifurcation factor.

2.3 Mechanism Heterogeneity, Risk Factors, and the Analytical Framework

Stablecoin depegging risk exhibits clear mechanism heterogeneity, yet mechanism labels themselves cannot explain all risk differences. Existing research typically classifies stablecoins as fiat-backed, crypto-collateralized, and algorithmic, but empirical results show that stablecoin price behavior is not entirely determined by protocol type. Gadzinski et al. (2023) study the relationship between stablecoin design and price stability and find that some non-custodial or algorithmic stablecoins may exhibit price behavior similar to mature custodial stablecoins. Wang et al. (2020) also point out that different stablecoins are not consistent in diversification, hedging, and safe-haven functions. Their risk functions depend on market state and asset relationships. Therefore, stablecoin risk identification cannot stop at static mechanism classification, but must also consider reserve structure, redemption arrangements, trading scenarios, on-chain liquidity, and market trust structure.

We focus on differences in the direction and intensity of the same risk factor across different stablecoins. USDT and USDC both belong to the fiat-backed category, but they differ in trading scenarios, redemption channels, user structure, and sources of market trust. DAI depends on crypto asset collateral, oracle pricing, and on-chain liquidation mechanisms. Its price stability is more easily affected by collateral prices, DeFi leverage, and liquidation efficiency. FRAX possessed hybrid mechanism and nested reserve features during the sample period. Its price risk may simultaneously originate from its own mechanism, USDC-linked reserves, and DeFi liquidity. Based on this, we understand stablecoin mechanism heterogeneity as dynamic risk exposure differences, not static type differences. Research by De Blasis et al. (2023) and Gadzinski et al. (2024) also shows that stablecoin risks may spread across mechanisms through collateral linkages, market expectations, and common trading networks, providing support for our cross-mechanism risk structure analysis.

Existing literature provides a foundation for selecting stablecoin risk factors. In our study, these variables are not control variables in the general sense, but risk channels that explain stablecoin prices entering nonlinear states. The first category is stablecoin operational state, including trading volume, market capitalization, and issuance and redemption behavior. Ante et al. (2021b) find that stablecoin issuance affects crypto asset market returns and trading activity. Saggu (2022) further points out that USDT minting and burning events have asymmetric effects on Bitcoin, and these effects vary with investor sentiment and “Whale

Alert" public information. The second category is crypto market structure, including Bitcoin dominance, major crypto asset volatility, and fund rotation between risk assets and stablecoins. Research by Kristoufek (2021) and Brik et al. (2022) shows that stablecoins exhibit dynamic linkages with major crypto assets, and stablecoin price behavior is affected by changes in overall crypto market structure.

The third category is on-chain behavior and large-holder structure. Stablecoins are on-chain liquidity tools. Their price deviations may be affected by active addresses, on-chain transfers, large fund migrations, and exchange liquidity changes. Ante et al. (2021a) study transparent stablecoin fund flows and find that stablecoin transfers affect Bitcoin returns and trading volume, showing that on-chain fund flows carry price information. The fourth category is market sentiment and external financial environment. Lee et al. (2025) incorporate trading prices, volume, market information, sentiment, and volatility indicators into their prediction framework for stablecoin depegging risk, showing that stablecoin depegging identification needs to simultaneously consider market trading, sentiment, and risk state variables. Overall, stablecoin price risk is jointly shaped by coin-specific operations, crypto market structure, on-chain fund behavior, and market sentiment.

On this basis, we connect risk factors to the control parameters of the cusp catastrophe model, constructing an analytical framework of "mechanism structure, risk factors, control parameters, and state variables." Specifically, market scale, on-chain activity, and external financial environment mainly reflect the directional pressure for stablecoins to deviate from the peg state, corresponding to the asymmetry factor in the cusp catastrophe model. Market sentiment, large-holder behavior, trading volume, and crypto market structural changes are more likely to alter whether the system enters a region with multiple stable states, corresponding to the bifurcation factor. The former answers in which direction price deviation will occur; the latter answers whether the system possesses the conditions for sudden jumps. Through this setup, we can advance from general volatility description to critical state identification and further distinguish directional deviation from structural jumps in stablecoin price risk.

3. Research Design and Model Specification

3.1 Sample Selection

We select USDT, USDC, DAI, and FRAX based on representativeness, mechanism heterogeneity, and data availability. First, USDT and USDC rank among the largest stablecoins by market capitalization and trading volume, representing centralized fiat-backed

stablecoins. DAI relies on crypto-asset overcollateralization and on-chain liquidation mechanisms to maintain its peg, capturing the operating characteristics of crypto-collateralized stablecoins within the DeFi ecosystem. FRAX combines collateral backing with algorithmic adjustment during the sample period, representing hybrid algorithmic stablecoins. Second, these stablecoins exhibit substantial differences in reserve structure, redemption channels, usage scenarios, and the basis of market trust, facilitating comparisons of depegging risk across pegging mechanisms. Finally, all four stablecoins have relatively continuous time series of price, trading volume, market capitalization, and on-chain activity data, meeting the requirements for cusp catastrophe model estimation, event-window analysis, and risk-factor testing.

The sample period runs from January 1, 2019, to November 30, 2023. This window covers stablecoin market expansion, the growth of DeFi, expansion and downturn cycles in crypto assets, and multiple major market shocks, providing a relatively complete observational window for identifying nonlinear depegging risks. We set the cutoff at November 30, 2023, to maintain consistency in mechanism classification, as FRAX underwent structural changes around 2024. Newer stablecoins such as USDe and PYUSD are excluded from the baseline analysis due to insufficient continuous sample length.

3.2 Event Window Definition and Variable Screening

3.2.1 Event Window Definition

We first analyze the frequency and distribution of cusp jumps in the crypto market using a global dynamic model, then examine how specific market events influence jump patterns. Specific events typically generate significant price volatility and market dynamics, potentially triggering jumps. Hence, we partition the sample timeline around five major market shocks using an event-study approach.[2] The events are as follows. Event 1, the crypto "Black Swan" (March 12, 2020) — BTC and ETH both fell 50% in one day. Event 2, China's central bank confirmed continued crackdown on crypto assets (September 24, 2021). Event 3, UST collapse (May 9, 2022). Event 4, FTX bankruptcy (November 12, 2022). Event 5, SVB failure (March 10, 2023).

These events capture distinct sources of stress. The March 2020 crypto market crash represents a sharp external financial shock. The September 2021 China regulatory event represents a policy shock. The May 2022 UST collapse represents algorithmic mechanism failure. The November 2022 FTX bankruptcy represents an exchange credit crisis. The March

[2] The event selection procedure is detailed in Appendix A.

2023 SVB failure represents off-chain reserve risk. Together, they allow us to observe changes in stablecoin pegging mechanisms under varying conditions.

In the cusp catastrophe model, we specify three-month windows separately for each event to observe changes in market dynamics before and after the event. The pre-event window is used to capture market trends before the unexpected event, while the post-event window is used to analyze market reactions after the event. Periods not covered by significant events serve as the control group for comparing cusp catastrophe phenomena across different periods. Although macroeconomic events, such as Federal Reserve interest rate increases and inflation data releases, may have some impact on cryptocurrency prices (Aldasoro et al., 2025), such macroeconomic data generally have low importance in stablecoin analysis and are therefore not considered in this event partitioning.

3.2.2 Variable Screening

Stablecoin depegging is influenced by multiple dimensions: the stablecoin's own trading state, on-chain capital structure, the crypto market environment, market sentiment, and external financial conditions. We construct the dataset along three dimensions: stablecoin market trading, on-chain behavior and market structure, and market sentiment plus external financial environment. The first category includes stablecoin open, high, low, and close prices, trading volume, and market capitalization. The second includes active address ratios, large-holder concentration, Bitcoin dominance, and BTC on-chain activity, intended to capture on-chain liquidity, capital concentration, and structural changes in the crypto market during depegging episodes. The third includes Google search intensity, the Crypto Fear and Greed Index (FGI), major stock indices, the dollar index, interest rates, gold, and commodity prices, controlling for market sentiment, macroeconomic financial conditions, and cross-market spillovers. These three data categories cover the risk factors discussed in Section 2.3.

To avoid subjective variable selection, we use Light Gradient Boosting Machine (LightGBM) and Shapley additive explanations (SHAP), hereafter LightGBM–SHAP, to screen candidate variables before building the cusp catastrophe model, identifying the key control variables for each stablecoin mechanism.[3] We take daily stablecoin return prediction as the baseline task. We train a LightGBM model to quantify each candidate variable's explanatory contribution to stablecoin price changes, and compute the mean absolute SHAP value — Mean(|SHAP|) — to measure each feature's relative importance. Given that

[3] The complete candidate variable system and the variable cleaning and screening procedure are detailed in Appendix B.

different stablecoins differ substantially in pegging mechanism, reserve structure, and usage scenarios, we rank features separately for each mechanism category and select the top 15 variables with clear economic interpretation to enter the cusp catastrophe model. We then classify these variables as fundamental or speculative factors, mapping them to the asymmetry factor and the bifurcation factor, respectively.

Tables 1 and 2 present the key control variables screened via LightGBM–SHAP and their descriptions. USDT and USDC, both fiat-backed, have largely overlapping variable sets. However, because FTSE100 and DAX30 are highly correlated, we assign FTSE100 to USDT and DAX30 to USDC in subsequent models to achieve more robust fit.

Table 1. Key Variable Descriptions

Variable	Definition and Construction	Data Source	Stablecoins
Volume (%)	Trading volume in log differences, capturing market activity and liquidity changes	CoinMarketCap	USDT, USDC, DAI, FRAX
Market Cap (%)	Market capitalization in log differences, reflecting expansion or contraction in stablecoins outstanding	CoinMarketCap	USDT, USDC, DAI, FRAX
Active Addresses Ratio	Daily active addresses divided by total addresses, measuring on-chain participation and trading activity $\frac{Daily\ Active\ Addresses}{Total\ Addresses}$	IntoTheBlock	USDT, USDC, FRAX
Historical concentration whales (Whales)	Holdings concentration, i.e., the share of balances held by large addresses, measuring capital concentration and large-trader influence	IntoTheBlock	USDT, USDC, DAI, FRAX
Break Even	Historical break-even price indicator, capturing the structure of addresses at break-even	IntoTheBlock	DAI
BTC Dominance	Bitcoin dominance (market share), measuring whether capital flows are concentrating in Bitcoin	AICoin	USDT, USDC, DAI, FRAX
BTC Active	BTC active addresses, in log differences or percentage changes, reflecting BTC on-chain activity and overall crypto market transaction state	Coinmetrics	USDT, USDC, DAI, FRAX
FGI	Crypto Fear and Greed Index, capturing market sentiment	Alternative.me	FRAX
Google Trend	Google search intensity for “Stablecoin”, weekly data converted to daily, reflecting changes in market attention	Google Trends	USDT, USDC, DAI
Gold	Gold spot price in log differences, controlling for safe-haven asset price changes	World Gold Council	USDT, USDC, DAI, FRAX
Brent	Brent crude oil spot price in log differences, controlling for energy market changes	U.S. Energy Information Administration	DAI

Variable	Definition and Construction	Data Source	Stablecoins
GSCI	S&P GSCI commodity index in log differences, reflecting broad commodity market changes	S&P Dow Jones Indices	USDT, USDC
SP500	S&P 500 index in log differences, controlling for U.S. equity market volatility	S&P Dow Jones Indices	USDT, USDC, FRAX
HS300	CSI 300 index in log differences, controlling for Chinese equity market volatility	Investing	USDT, USDC, DAI
DAX30	German DAX 30 index in log differences, controlling for European equity market volatility	Investing	USDC
FTSE100	FTSE 100 index in log differences, controlling for UK equity market volatility	Investing	USDT, DAI, FRAX
DGS10	10-year U.S. Treasury yield in log differences, reflecting the dollar interest-rate environment and long-term funding cost	Federal Reserve Economic Data	USDT, USDC, DAI, FRAX
VIX	VIX index in log differences, controlling for traditional financial market risk sentiment	Investing	FRAX
Inflation	Consumer price inflation rate, monthly data converted to daily, reflecting the macro inflation environment	OECD	DAI
Unemployment	Unemployment rate, monthly data converted to daily, reflecting macroeconomic conditions	OECD	DAI
EUR	Euro nominal effective exchange rate index in log differences, reflecting the euro exchange-rate environment	European Central Bank	USDT, USDC
Sterling	Sterling nominal effective exchange rate index in log differences, reflecting the pound exchange-rate environment	Bank of England	USDT, USDC, DAI, FRAX
SGDX	Singapore dollar nominal effective exchange rate index in log differences, reflecting the Asia-dollar substitution and regional FX environment	BIS	FRAX
USDX	U.S. dollar index in log differences, reflecting overall dollar strength	Board of Governors of the Federal Reserve System	FRAX

Table 2. Key Control Variables Selected Using LightGBM–SHAP across Stablecoin Mechanisms

USDT (fiat-backed)	USDC (fiat-backed)	DAI (crypto-collateralized)	FRAX (hybrid)
Active Addresses Ratio	Active Addresses Ratio	Market Cap	Market Cap
Historical concentration whales	Historical concentration whales	FTSE100	FGI
Volume	Volume	Historical concentration whales	DGS10
Market Cap	Market Cap	BTC Dominance	Historical concentration whales
EUR	EUR	Sterling	Active Addresses Ratio
DGS10	DGS10	Gold	BTC Active
HS300	HS300	Google Trend	FTSE100
BTC Active	BTC Active	DGS10	VIX
SP500	SP500	BTC Active	BTC Dominance
FTSE100[4]	DAX30	Inflation	Volume
Google Trend	Google Trend	HS300	SGDX
GSCI	GSCI	Unemployment	Gold
Sterling	Sterling	Volume	Sterling
BTC Dominance	BTC Dominance	Break Even	USDX
Gold	Gold	Brent	SP500

3.3 Variable Construction: Price Deviation and Log Return

Stablecoin depegging can occur in two ways: price declines gradually with fundamentals, or jumps discontinuously beneath an apparently stable surface. To distinguish between these two paths, we need a model that describes sudden state transitions, and we need to choose the right measure of price state. Following this logic, we use the gap between the price and \$1 as the primary state variable (hereafter, price deviation) to identify jumps relative to the peg. We also consider the stablecoin log return for comparison. Price deviation captures directional departures from the peg and is well-suited for detecting whether the pegging mechanism has been damaged under major shocks. Log return captures relative changes between consecutive trading days and is more sensitive to short-term trading and liquidity shocks.

Let $P_{i,t}$ denote the closing price of stablecoin i on day t. We define the price deviation variable as:

$$Dev_{i,t} = P_{i,t} - 1 \tag{1}$$

where $Dev_{i,t} > 0$ indicates that the stablecoin trades above the \$1 peg, and $Dev_{i,t} < 0$ indicates that it trades below the peg. This variable measures the direction and magnitude of

[4] Correlation tests show that FTSE100 and DAX30 are strongly correlated. We use FTSE100 in the USDT model and DAX30 in the USDC model to achieve better model performance.

deviations from the peg. In subsequent analysis, we also examine the absolute value of price deviation to measure the degree of deviation itself.

To capture short-term relative changes in stablecoin prices, we further construct a log return variable:

$$Ret_{i,t}=ln(P_{i,t})-ln(P_{i,t-1}) \tag{2}$$

3.4 Cusp Catastrophe Model Specification

To identify discontinuous adjustments and critical transitions in stablecoin prices near the peg, we follow Kukacka and Kristoufek (2023) and introduce a cusp catastrophe model to characterize structural jumps in the depegging process. This model describes situations in which a system exhibits jumps, hysteresis, and transitions between multiple stable states after the accumulation of continuous disturbances. It is suitable for identifying critical states in which a stablecoin shifts from small deviations to short-term depegging. Let $Y_{i,t}$ denote the observed state variable of stablecoin i on day t, either $Dev_{i,t}$ or $Ret_{i,t}$. Because the volatility scale differs across stablecoins and state variables, we estimate daily volatility using the Garman-Klass method and standardize the observed state variable accordingly:

$$\sigma_{GK,i,t}=\sqrt{\frac{1}{2}\left[\ln\left(\frac{H_{i,t}}{L_{i,t}}\right)\right]^2-(2\ln 2-1)\left[\ln\left(\frac{C_{i,t}}{O_{i,t}}\right)\right]^2} \tag{3}$$

$$y_{i,t}=c_0+c_1\frac{Y_{i,t}}{\sigma_{GK,i,t}} \tag{4}$$

where $H_{i,t}$, $L_{i,t}$, $O_{i,t}$, and $C_{i,t}$ denote the daily high, low, open, and close prices; $\sigma_{GK,i,t}$ is the Garman-Klass daily volatility; and $y_{i,t}$ is the standardized state variable. The parameters c_0 and c_1 adjust for baseline location and scale differences, respectively. We then assume that $y_{i,t}$ follows the stochastic process:

$$dy_{i,t}=-\frac{\partial V(y_{i,t};a_{i,t},b_{i,t})}{\partial y_t}dt+\sigma_y dW_t \tag{5}$$

where $V(\cdot)$ is the potential function, σ_y is a constant diffusion term, and W_t is a Wiener process. The cusp potential function is specified as:

$$V(y_{i,t};a_{i,t},b_{i,t})=\frac{1}{4}y_{i,t}^4-\frac{1}{2}b_{i,t}y_{i,t}^2-a_{i,t}y_{i,t} \tag{6}$$

The first-order condition of the potential function yields the system's equilibrium states:

$$y_{i,t}^3-b_{i,t}y_{i,t}-a_{i,t}=0 \tag{7}$$

where $a_{i,t}$ is the asymmetry factor, which captures the force pushing the variable toward a deviation from the peg in one direction. The parameter $b_{i,t}$ is the bifurcation factor, which

captures the possibility that the system transitions from a single state to multiple stable states. When $b_{i,t}$ is positive and jointly satisfies the multiple-equilibria condition with $a_{i,t}$, the system may exhibit jumps, hysteresis, or state transitions.

In economic terms, the asymmetry factor determines the direction in which the potential function tilts. When it is positive, price is more likely to be pushed above the peg; when it is negative, price is pushed below the peg. The bifurcation factor determines whether the system exhibits bistability. When it is positive and jointly satisfies the multiple-equilibria condition with the asymmetry factor, the system has two stable states and thus possesses the conditions for sudden jumps; otherwise, only a single stable state exists. Here, hysteresis refers to the feature that after the system is shocked into a new stable state, the system cannot immediately return to the original position even when the shock recedes, exhibiting path dependence.

We further divide the control variables into fundamental and speculative factors, linking them to the asymmetry factor and the bifurcation factor, respectively:

$$a_{i,t} = a_0 + \sum_{k=1}^{K} \alpha_k F_{k,i,t} \tag{8}$$

$$b_{i,t} = b_0 + \sum_{m=1}^{M} \beta_m S_{m,i,t} \tag{9}$$

where $F_{k,i,t}$ represents fundamentals, mainly including market capitalization, on-chain activity, and external financial conditions; and $S_{m,i,t}$ represents speculative factors, mainly including market sentiment, large-holder behavior, trading volume, and structural changes in the crypto market.

4. Empirical Results

4.1 The Effect of Measurement Choice: Identification under Two State Variables

The model fit differs substantially between the two specifications. Relative to the linear and logistic benchmarks, the cusp model performs more favorably under the price-deviation specification than under the log-return specification (Tables 3 and 4). This suggests that the deviation measure better captures the nonlinear dynamics near the peg. However, the number of detected jumps tells a different story. The log-return specification identifies more cusp jumps. In contrast, the deviation specification exhibits weaker sensitivity to short-term volatility and produces a lower jump count. This divergence between fit quality and jump frequency reflects two distinct dimensions that we address separately below.

Table 3 reports the coefficient estimates and significance levels for the deviation model. The bifurcation factor b is statistically significant across all four stablecoins. The estimates

indicate that fundamentals and speculative factors are both associated with the deviation from and convergence toward the peg, with varying intensities across stablecoins.

Table 3. Coefficient Estimates and Significance Levels in the Deviation Model

Variable	USDT	USDC	DAI	FRAX
a	2.185***	-2.057***	-2.045***	1.821***
b	0.267***	0.891***	0.698***	0.889***
α_0	3.512***	-1.566***	-4.974***	2.306***
$\alpha_{\text{Active Addresses Ratio}}$	-0.246***	-0.870***		0.712***
$\alpha_{\text{Market Cap}}$	0.530***	-0.148***	0.068.	0.085***
α_{DGS10}		-0.029***		-0.079**
α_{HS300}	-0.146.	-0.089***		
α_{FTSE100}	-0.052***		0.127***	0.044**
α_{SP500}		0.080***		0.035.
α_{GSCI}	0.249***	-0.045***		
α_{Gold}	0.187*			0.043***
$\alpha_{\text{BTC Active}}$		0.024***		-0.085***
α_{Sterling}		-0.036***		0.076.
α_{EUR}	-0.234**	-0.079***		
$\alpha_{\text{Inflation}}$			-2.958***	
α_{SGDX}				-0.055***
β_0	3.934***	3.217***	1.398***	1.871***
β_{Whales}	0.116**	-0.724***	-0.104*	0.409***
$\beta_{\text{BTC Dominance}}$	-0.128***	-0.368***	0.550***	-0.370***
$\beta_{\text{Google Trend}}$	-0.252***	0.171***	-0.077.	
β_{DAX30}		0.010*		
$\beta_{\text{Break Even}}$			-0.172***	
β_{VIX}				0.069.
β_{FGI}				0.193***
Cusp model				
LL	-2340	-1818	-1364	-1293
AIC	4718	3674	2767	2623
BIC	4822	3778	2867	2718
Linear model				
LL	-2900	-1537	-1564	-852
AIC	5835	3107	3163	1737
BIC	5928	3200	3253	1822
Logistic model				
LL	-2856	-1789	-1516	-814
AIC	5749	3614	3068	1665
BIC	5848	3713	3163	1754

Notes: ***, **, *, and . denote significance at the 0.1%, 1%, 5%, and 10% levels, respectively. The same applies hereinafter.

Table 4 presents the coefficient estimates and significance levels for the log-return specification. The bifurcation factor b remains statistically significant across all four

stablecoins. Under the return specification, speculative factors play a more dominant role. BTC Dominance, Whales, and Market Cap remain significant, while the results show no strong association with traditional financial markets. The model primarily captures short-term discontinuous price movements.

Table 4. Coefficient Estimates and Significance Levels in the Log-Return Model

Variable	USDT	USDC	DAI	FRAX
a	-0.024	-0.072	0.030	-0.090.
b	0.665***	0.884***	0.810***	0.853***
α_0	-0.108		0.141	-0.471.
$\alpha_{\text{Market Cap}}$	-0.254***		-0.189***	-0.223**
α_{Sterling}	0.106.			
β_0	-4.999***	-4.999***	-4.998***	-4.998***
β_{Whales}	-0.998***	0.354.	1.457***	-0.993***
β_{Volume}	0.433**			
$\beta_{\text{BTC Dominance}}$	-1.681***	1.016***	1.590***	1.473***
$\beta_{\text{Google Trend}}$		0.822***		
β_{FGI}				-0.889**
Cusp model				
LL	-2564	-2574	-1999	-1512
AIC	5166	5185	4038	3064
BIC	5270	5290	4144	3164
Linear model				
LL	-1676	-1164	-1230	-756
AIC	3386	2362	2495	1548
BIC	3479	2455	2590	1637
Logistic model				
LL	-1670	-1159	-1230	-721
AIC	3376	2354	2498	1479
BIC	3475	2453	2598	1573

In terms of fit performance, the cusp model is consistently outperformed by both the linear and logistic models across all four cases under the log-return specification. Because stablecoins exhibit multiple equilibria around the $1 peg — alternating between pegging and depegging — using log returns as the state variable tends to smooth or dilute the critical-jump structure. Hence, the cusp model cannot fully leverage its ability to capture catastrophic transitions.[5] In contrast, using the deviation from $1 as the state variable better exposes the underlying jump structure, which is why the cusp model shows a fit advantage in the deviation specification.

[5] Due to considerations of model fit and space constraints, we do not present the cusp catastrophe analysis results from the event perspective for the log-return model.

The two state variables point to different risk dimensions. The deviation model yields a superior fit and identifies relatively sparse jumps, suggesting that in most periods arbitrage, redemption, and market-making mechanisms remain effective in constraining price deviations from the peg. This model is suited for assessing whether the pegging mechanism has experienced material impairment. The log-return model shows weaker fit performance than the deviation model but identifies more jumps during stress episodes such as the UST collapse and the FTX bankruptcy. This specification reflects the sensitivity of daily returns to inflows, outflows, trading congestion, and market sentiment shocks.

The jump counts further support this interpretation. When price deviation is the state variable, most event windows produce few cusp jumps. When log returns are used, the jump count increases markedly. Table 5 lists the number of jumps identified by the two models across different events and market regimes.

Table 5. Number of Cusp Jumps during the Sample Period

Events	USDT		USDC		DAI		FRAX	
	1	**2**	**1**	**2**	**1**	**2**	**1**	**2**
Black Swan (Event 1)	0	79	8	6	0	71	—	—
China Ban (Event 2)	0	62	2	0	0	56	0	6
UST Collapse (Event 3)	0	66	0	8	0	15	0	12
FTX Bankruptcy (Event 4)	0	62	0	0	0	8	0	6
SVB Failure (Event 5)	0	53	0	0	0	6	0	2
Expansion[6]	0	204	2	10	10	226	0	16
Downturn	0	139	0	8	0	44	0	20
Global Period	0	643	10	26	10	338	0	48

Notes: 1 = deviation model; 2 = log-return model.

When the deviation from $1 is used as the state variable, the number of cusp jumps is extremely low across most event windows. Some stablecoins (USDT, FRAX) exhibit no detectable jumps in any period. Only under extreme conditions (USDC during the Black Swan event, DAI during the expansion period) do a limited number of jumps appear. The reason is that under normal market conditions, most stablecoins trade very close to $1. The absolute deviation remains too small to trigger the cusp model's threshold unless a deep depegging event occurs.

When log returns are used as the state variable, the jump count rises markedly. This is because log returns amplify the impact of short-term price fluctuations. Even when the absolute price deviation is small, a relatively large gain or loss in the daily return can still

[6] We define the cryptocurrency market expansion period as 2020.3.13 – 2021.11.10 and the downturn period as 2021.11.10 – 2022.11.21. The choice of these periods involves a degree of subjectivity.

trigger a jump. A price move from 1.000 to 1.002, for instance, corresponds to a noticeable return and is therefore more likely to be flagged as a jump in the statistical sense.

Table 5 shows that USDT exhibits many jumps under the return specification, consistent with its role as an on-chain dollar and a high-frequency liquidity conduit. USDC displays fewer jumps overall, reflecting its institutionalized usage and redemption channels that help dampen short-term disturbances. The jumps in DAI and FRAX are more closely tied to the DeFi ecosystem, collateralization structure, and reserve nesting. DAI records 338 jumps under the log-return measure, second only to USDT, suggesting that its short-term trading structure is particularly sensitive to speculative capital flows and liquidity shocks.

The high jump frequency under the return measure reflects small but detectable nonlinear jumps embedded in daily volatility. The two models are not mutually exclusive. The deviation model better captures the impact of major events on the pegging mechanism and is suited for assessing long-run robustness. The log-return model is more responsive to daily volatility and speculative sentiment and is suited for monitoring high-frequency trading activity. Together, the two specifications characterize stablecoin price behavior from two complementary perspectives: the degree of deviation from the peg and the magnitude of short-term price changes.

4.2 Beyond the Mechanism Label: Cross-Coin Differences in Jump Risk

USDT, USDC, DAI, and FRAX represent centralized fiat-backed, institutionally oriented fiat-backed, overcollateralized crypto-backed, and hybrid algorithmic stablecoins, respectively. The empirical results show that mechanism labels provide only a preliminary classification and do not fully explain jump risk. Whether a stablecoin is more prone to price deviations depends on reserve structure, redemption channels, exchange embeddedness, DeFi use cases, liquidity depth, and market trust foundations. Table 6 summarizes the primary sensitive factors and risk explanations for the four stablecoins.

Table 6. Structural Sources of Jump Risk across Stablecoins

Stablecoin	Mechanism	Primary Sensitive Factors	Risk Explanation
USDT	High-liquidity fiat-backed	Market Cap, Whales, BTC Dominance, on-chain activity	Widest trading use, serving both as a safe haven and a risk-absorbing node.
USDC	Institutionally oriented fiat-backed	Market Cap, traditional finance variables, reserve trust	Scale expansion aids stability, but off-chain reserve risks transmit to on-chain prices.

Stablecoin	Mechanism	Primary Sensitive Factors	Risk Explanation
DAI	Overcollateralized crypto-backed	BTC Dominance, collateral volatility, DeFi liquidation	Risk manifests through collateral value, oracles, liquidation efficiency, and on-chain liquidity.
FRAX	Hybrid algorithmic	Active Addresses Ratio, Whales, USDC reserve dependence	Mechanism hybridization and reserve nesting make it more sensitive to on-chain activity and large-holder flows.

USDT exhibits a dual characteristic of high liquidity and high disturbance. Its positive and significant market capitalization coefficient indicates that while market capitalization expansion improves liquidity, it is also associated with short-term deviations, potentially through asynchronous issuance distribution, arbitrage-channel frictions, and localized supply-demand mismatches. Active Addresses Ratio is negatively associated with USDT, suggesting that higher on-chain activity facilitates arbitrage correction. Whales is positively associated with USDT, indicating that large-holder concentration amplifies short-term depegging risk when local liquidity is insufficient.

USDC's risk structure differs from USDT. USDC's negative market capitalization coefficient suggests that scale expansion is more likely associated with price stability, which relates to its institutional use cases, direct redemption arrangements, and higher reserve transparency. However, USDC is not immune to all risks. Its price deviations are more closely associated with traditional finance variables, regional market indicators, and reserve-information shocks. The SVB event illustrates how off-chain reserve risks can rapidly transmit to on-chain prices.

DAI's jump risk is primarily embedded in DeFi collateralization and on-chain liquidation systems. As an overcollateralized crypto-backed stablecoin, DAI depends on collateral value coverage, oracle pricing, liquidation efficiency, and on-chain liquidity. When market risk appetite contracts, collateral asset prices fall, or DeFi leverage passively unwinds, DAI couples indirectly with external risks through collateral assets and liquidation mechanisms. FRAX reflects the complexity introduced by hybrid algorithmic mechanisms and reserve nesting. It is more sensitive to on-chain activity and large-holder behavior and may experience cross-coin resonance due to reliance on external stablecoins such as USDC in its reserves.

Hence, the static judgment that "fiat-backed stablecoins are more stable while decentralized or algorithmic ones are more fragile" is insufficient. USDT and USDC both belong to the fiat-backed category, but the former more strongly reflects exchange liquidity and high-frequency trading shocks, while the latter more strongly reflects institutional

redemption, reserve transparency, and traditional finance linkages. DAI and FRAX both operate within the DeFi ecosystem, but the former depends more on over-collateralization and liquidation efficiency, while the latter is simultaneously influenced by hybrid algorithmic mechanisms, USDC reserve dependence, and liquidity concentration. Stablecoin risk identification should shift from static mechanism classification to dynamic structural analysis.

This point is especially evident in jump frequency. Although USDT and USDC both belong to the fiat-backed category and employ similar collateral structures, their cusp jump frequencies during the sample period differ markedly. Even when mechanism classifications are similar, a stablecoin's risk level still depends on its liquidity characteristics, trading inertia, and market trust structure, not on market share. FRAX nominally belongs to the decentralized category, but its reserve structure is highly dependent on USDC; in terms of jump frequency, it is closer to USDC than to DAI. However, the directions of specific factors differ between the two: large-holder concentration and on-chain activity are positively related to FRAX but negatively related to USDC. This reflects that FRAX's smaller scale and thinner liquidity are associated with concentrated capital inflows more directly moving prices away from the peg. This indicates that mechanism classification does not fully explain risk heterogeneity across stablecoins: reserve nesting is associated with risk levels but not with convergence in risk structures.

4.3 From External Shocks to Endogenous Volatility: Market Structure Evolution in Event Windows

For the event-window analysis, we estimate the deviation model, which provides the better fit, to examine the price deviation and reversion patterns of each stablecoin under different market shocks and to characterize the core factors associated with price jumps.

The event-window results further indicate that stablecoin risk structures evolve with market stages. Table 7 reports the estimates for the March 2020 "Black Swan" event. At that time, the stablecoin market was still in its early development stage, with exchanges holding a dominant position and the on-chain financial ecosystem not yet mature. Traditional financial variables—stock indices, commodities, and exchange rates—are significantly associated with price deviation in some stablecoins, indicating that the early stablecoin market remained tightly coupled with global liquidity conditions.

Table 7. Coefficient Estimates and Significance Levels for the Black Swan Event

Variable	USDT	USDC	DAI
a	-2.383***	-1.927***	-0.197
b	0.989***	0.808***	0.723***
α_0	-4.757	-1.808***	-0.550
α_{DGS10}		0.225*	
α_{HS300}		-0.265***	
α_{GSCI}	-0.495.	-0.070**	
α_{EUR}	-0.844**	-0.499***	
β_0	5.443.	2.098*	6.653
β_{Whales}		1.378***	-1.311*
β_{Volume}		-0.028*	-1.722***
$\beta_{\text{BTC Dominance}}$	-2.878**		-7.736*
$\beta_{\text{Google Trend}}$		1.406.	
$\beta_{\text{Break Even}}$			-0.818.

Table 8 reports the estimates for China's September 2021 regulatory ban, which highlights the importance of on-chain capital flows under a regulatory shock. The coefficients on Active Addresses Ratio are large for USDT (10.364) and USDC (13.359), suggesting that changes in active on-chain addresses are associated with more pronounced short-term price responses in centralized stablecoins. At the same time, some regional financial indices remain associated with USDT and USDC, reflecting that these stablecoins serve cross-border liquidity, transaction intermediation, and store-of-value functions in specific markets.

Table 8. Coefficient Estimates and Significance Levels for China's Regulatory Ban Event

Variable	USDT	USDC	DAI	FRAX
a	-1.443***	-1.883***	-1.022***	-1.692***
b	0.890***	0.767***	1.414***	1.432***
α_0	-0.260	1.110	-0.372**	-3.346
$\alpha_{\text{Active Addresses Ratio}}$	10.364***	13.359***		
$\alpha_{\text{Market Cap}}$	0.535***			
α_{DGS10}	-0.437**	-0.319***		
α_{HS300}		0.480.	-0.274.	
α_{FTSE100}		0.286**		
α_{SP500}	0.765**			
α_{Gold}		-0.152***		
$\alpha_{\text{BTC Active}}$	-0.225***			
α_{Sterling}	-0.762***	-0.709*		
$\alpha_{\text{Unemployment}}$			7.165*	
$\alpha_{\text{Inflation}}$			5.372.	
β_0	-1.510***	0.727	-4.664*	0.331
β_{Whales}	4.136***	-1.882*	3.661*	0.817*
$\beta_{\text{BTC Dominance}}$	1.145.			-1.109.
$\beta_{\text{Google Trend}}$	1.149***	-0.211***		
β_{DAX30}		0.534***		

The 2022 UST collapse was a typical endogenous crisis in the cryptocurrency market. Traditional financial variables had relatively limited explanatory power for stablecoin price deviations, whereas USDT's on-chain activity and transaction demand increased significantly. This indicates that when the failure of an algorithmic stablecoin triggers a reversal of market confidence, capital flows preferentially to the stablecoin with the highest liquidity and the broadest range of transaction use cases, treating it as an on-chain dollar and a channel for exiting risk.

Table 9. Coefficient Estimates and Significance Levels for the UST Collapse Event

Variable	USDT	USDC	DAI	FRAX
a	1.130***	1.902	-0.599*	0.258.
b	0.233***	1.216***	1.140***	1.167***
α_0	19.210***	-0.224	-6.724.	0.033
$\alpha_{\text{Active Addresses Ratio}}$	28.617***			
$\alpha_{\text{Market Cap}}$	0.802*	-2.110***		
α_{DGS10}			-0.482.	
α_{Gold}	0.489*			
α_{USDX}				0.308.
β_0	-17.035***	3.781	-12.331*	-4.819
β_{Whales}	-11.725***	4.861***		
β_{Volume}			-0.727*	
$\beta_{\text{BTC Dominance}}$	-15.166***	2.425**	-9.055*	

Table 10 reports the estimates for the November 2022 FTX bankruptcy, which further reshapes the risk transmission structure. The exchange credit crisis prompts capital to exit platforms and reallocate among stablecoins, on-chain protocols, and fiat currencies. USDT exhibits a strong "exit channel" function. The associations between DAI and FRAX and traditional financial variables increase. This pattern is consistent with the FTX event inducing DeFi liquidity withdrawals, collateral asset volatility, and broader shifts in risk appetite, which indirectly couple on-chain stablecoins with external financial conditions through collateralization and liquidation structures.

Table 10. Coefficient Estimates and Significance Levels for the FTX Bankruptcy Event

Variable	USDT	USDC	DAI	FRAX
a	-0.204***	-0.542**	-0.990***	0.982***
b	0.296***	1.583***	1.933***	0.967***
α_0	0.671	-3.196*	-17.344.	3.521***
$\alpha_{\text{Market Cap}}$		-2.239***		
α_{DGS10}			-0.559*	-0.502***
α_{HS300}			-0.341*	
$\alpha_{\text{BTC Active}}$				-0.550*
α_{Sterling}				-0.044***
$\alpha_{\text{Unemployment}}$			-21.165*	
$\alpha_{\text{Inflation}}$			2.977*	
α_{SGDX}				-0.286***
β_0	-38.850***	7.917	-16.464***	1.587
β_{Whales}	-3.371.	5.819*	-1.431***	2.469***
β_{Volume}	-0.674*			0.197.
$\beta_{\text{BTC Dominance}}$	-27.072***	8.943*	-10.936***	5.458***
$\beta_{\text{Google Trend}}$	-7.663***	-2.837***	2.336***	

Table 11 reports the estimates for the March 2023 SVB failure, which illustrates the transmission of off-chain reserve risk to on-chain stablecoins. This episode indicates that a stablecoin's response to a shock does not simply mirror the entity directly affected in the news. Instead, the response depends on reserve linkages, market expectations, the speed of arbitrage restoration, and secondary market liquidity. In particular, when stablecoins are connected through reserve nesting or liquidity pools, off-chain banking risk can transmit through the reserve chain to stablecoins with other pegging mechanisms.

Table 11. Coefficient Estimates and Significance Levels for the SVB Failure Event

Variable	USDT	USDC	DAI	FRAX
a	-0.426***	-0.777*	2.373***	0.815***
b	0.502***	1.516***	1.413***	1.158***
α_0	1.002	-5.64.	13.014	7.758***
$\alpha_{\text{Active Addresses Ratio}}$				7.322***
$\alpha_{\text{Market Cap}}$	1.377*			
β_0	-18.562***	6.994.	0.036	0.059
β_{Whales}				5.703***
β_{Volume}				
$\beta_{\text{BTC Dominance}}$	-14.938***	9.196*		3.332**
$\beta_{\text{Google Trend}}$	-5.698***	1.951.		
$\beta_{\text{Break Even}}$			-0.489.	
β_{FGI}				-1.875.

Table 12 summarizes the evolution of stablecoin market structure and restoration capacity across the five events. The stablecoin market has transitioned from being dominated by external shocks to being dominated by endogenous volatility. In the early stage, stablecoin prices were more susceptible to traditional financial markets and global liquidity conditions. As the DeFi ecosystem and on-chain trading deepened, endogenous market liquidity, exchange credit, on-chain collateral, and speculative sentiment gradually became the primary drivers. By the SVB event, stablecoins had formed a risk network intertwining on-chain and off-chain financial systems. Market restoration capacity strengthened, but cross-mechanism transmission pathways also became more complex.

Table 12. Evolution of Stablecoin Market Structure and Adaptability

Event	Stablecoin Market Stage	Linkage with Traditional Financial Markets	Transaction Structure	Market Restoration Capacity
Black Swan (2020.3)	Early development; stablecoin market capitalization still expanding	Highly susceptible to traditional financial markets; large cross-market capital flows	Exchange-dominated; on-chain trading ecosystem not yet mature	Relatively weak restoration; more volatile

Event	Stablecoin Market Stage	Linkage with Traditional Financial Markets	Transaction Structure	Market Restoration Capacity
China Ban (2021.9)	Structural optimization; stablecoins gradually expanding across exchanges and on-chain applications	On-chain capital flows exert greater price impact; traditional financial market linkages present but not dominant	Exchanges remain central; DeFi ecosystem begins to form	Partial shock; adjustment capacity somewhat improved
UST collapse (2022.05)	Application deepening; USDT/USDC become mainstream transaction media	Traditional financial market influence small	DeFi ecosystem influence strengthening; exchange and on-chain liquidity interact	Larger shock, but restoration capacity somewhat improved
FTX bankruptcy (2022.11)	Market maturity rising; institutional capital share increasing	Exchange bankruptcy triggers trust crisis; capital flight creates linkages with traditional financial markets	Exchange liquidity drops sharply; some capital migrates to on-chain DeFi	Market resilience strengthened; greater capacity to adapt to shocks
SVB failure (2023.03)	Market adaptability further reinforced	Traditional financial system influence weakened	On-chain and off-chain financial systems increasingly interconnected; some stablecoins experience short-term depegging	Only short-term volatility; market adjusts rapidly

5. From Structural Identification to Early Warning

The cusp catastrophe model has identified the nonlinear risk characteristics of stablecoin depegging. We now test whether common risk factors possess systematic explanatory power, whether their impact varies across coins, and whether these factors can serve as early-warning signals for depegging risk.

The common risk factors examined in this section are drawn from the identification results in Section 4. Bitcoin dominance reflects shifts in crypto market funding structure and risk appetite. Google Trend and the FGI capture investor attention to stablecoin safety, reserve disclosures, and market events. Trading volume, market capitalization, the active address ratio, and large-holder concentration correspond to each stablecoin's own liquidity, scale changes, on-chain participation, and large-holder capital behavior. These variables exhibit commonality because all four stablecoins are embedded in the same crypto market funding cycle. However, the direction and strength of their effects differ across coins — heterogeneity in mechanisms is at work here.

5.1 Impact of Common Risk Factors on Price Depegging

We employ three types of dependent variables.

The first is a continuous measure:

$$AbsDev_{i,t} = |P_{i,t} - 1| \times 100 \tag{10}$$

The second is a volatility-adjusted price deviation measure.[7] To maintain consistency with the volatility-scaling approach in the cusp catastrophe model, we construct absolute deviation adjusted by Garman-Klass daily volatility:

$$AbsDevSD_{i,t} = \frac{|P_{i,t} - 1|}{\sigma_{GK,i,t}} \tag{11}$$

For estimation, we winsorize AbsDevSD within each coin at the 1st and 99th percentiles, denoting the resulting measure by $\text{AbsDevSD}^{\text{w}}$. The third dependent variable is a depegging indicator:

$$\text{Depeg}_{i,t}^{\tau} = 1\left(|P_{i,t} - 1| \geq \tau\right) \tag{12}$$

where τ is the depegging threshold. Given that stablecoin prices exhibit small fluctuations around the \$1 peg most of the time, we set $\tau = 0.5\%$.

The explanatory variables are the common risk factors identified in Section 4: BTC Dominance, Google Trend, large-holder concentration (Whales), Active Addresses Ratio, Volume, and Market Cap. The baseline specification is:

$$AbsDev_{i,t} = \alpha + \beta^{\top} X_{i,t} + \mu_i + \lambda_m + \varepsilon_{i,t} \tag{13}$$

$$AbsDevSD_{i,t}^{\text{w}} = \alpha + \beta^{\top} X_{i,t} + \mu_i + \lambda_m + \varepsilon_{i,t} \tag{14}$$

Here, X is the vector of six contemporaneous risk factors, entered jointly and standardized to zero mean and unit variance over the pooled estimation sample. Active Addresses Ratio, Volume, and Market Cap are transformed using log(1+x) before standardization. The models include coin and calendar-month fixed effects and use HC3 robust standard errors. Daily fixed effects are excluded because they would absorb market-wide factors such as BTC Dominance and Google Trend.

For the depegging indicator, we further employ a linear probability model (LPM):

$$\text{Depeg}_{i,t}^{\tau} = \alpha + \beta^{\top} X_{i,t} + \mu_i + \lambda_m + \varepsilon_{i,t} \tag{15}$$

[7] The deviation model in the main text uses directional price deviations scaled by Garman-Klass volatility as the state variable. This section focuses on depegging risk intensity and thus uses absolute deviations.

Table 13. Common Risk Factors and Stablecoin Price Depegging

Variable	Depegging Risk (LPM)	Volatility-Adjusted Deviation	Absolute Deviation
BTC Dominance	-0.0488*	-0.0115	-0.0595*
Google Trend	0.0095*	-0.0644***	0.0031
Whales	0.0291**	0.3682***	0.0181
Active Addresses Ratio (log)	0.0656***	-0.3526***	0.0099
Volume (log)	-0.0472*	-0.2520***	-0.0013
Market Cap (log)	-0.1802***	-0.2294***	-0.2563***

Notes: The dependent variables are the indicator for an absolute price deviation of at least 0.5%, volatility-adjusted absolute deviation winsorized within each coin at the 1st and 99th percentiles, and absolute price deviation in percent. The first column is a linear probability model; the other columns are estimated by OLS. All six contemporaneous risk factors enter jointly and are standardized over the pooled estimation sample. Active Addresses Ratio, Volume, and Market Cap are transformed using log(1+x) before standardization. All columns include coin and calendar-month fixed effects and use HC3 robust standard errors. ****, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

Table 13 shows that stablecoin price depegging is jointly associated with market scale, on-chain activity, and holder structure, exhibiting structural characteristics. Three core findings emerge. First, market capitalization is related to a stablecoin's capacity to absorb shocks. The coefficient on market capitalization is significantly negative across all depegging measures. This pattern is consistent with larger stablecoins relying on deeper liquidity and more efficient arbitrage mechanisms to correct price deviations, which lowers both the probability and the magnitude of depegging. Market capitalization reflects not only issuance scale but also market depth and price-correction capacity.

Second, on-chain activity and holder concentration characterize the risk-release process. Active Addresses Ratio is significantly positive in the depegging-risk model, suggesting that concentrated surges in on-chain transaction activity often accompany capital migration and risk release, and that the probability of a stablecoin entering a depegged state rises accordingly. Large-holder concentration is likewise significantly and positively associated with depegging risk and volatility-adjusted deviation. The more concentrated holdings are among a few actors, the more easily large rebalancing or redemptions amplify price shocks. Active Addresses Ratio captures risk shifts from the transaction-activity perspective, while Whales explains the source of price pressure from the holder-structure perspective.

Third, market conditions and liquidity are related to both the occurrence and the correction of depegging. Google Trend and BTC Dominance reflect market attention and funding-structure shifts, respectively. Higher Google Trend is associated with a higher contemporaneous depegging probability, whereas higher BTC Dominance is associated with smaller price deviations. Volume is negatively associated with depegging in most models,

indicating that when liquidity is ample, active trading is consistent with prices converging back toward the peg.

5.2 Coin-Level Heterogeneity in Risk Factor Responses

This section examines whether the same risk factor exerts differential impacts across stablecoins. Stablecoin depegging risk cannot be explained solely by static labels such as fiat-backed, crypto-collateralized, or algorithmic. Instead, it is jointly determined by pegging mechanisms, reserve structure, liquidity distribution, on-chain use cases, and market trust.

Given the limited number of stablecoin types in our sample and the existence of overlapping classifications, we employ coin-level interaction terms rather than type-level interactions. USDT and USDC, though both fiat-backed, differ in transaction scenarios, redemption mechanisms, institutional attributes, and market-trust structures. DAI is more deeply embedded in DeFi collateral and liquidation systems. FRAX, though featuring hybrid algorithmic attributes, exhibited reliance on USDC in its reserve structure during the sample period. Hence, coin-level interactions are better suited to reveal structural differences beyond mechanism labels.

The specification is:

$$\begin{aligned} AbsDev_{i,t} = \alpha + \beta^{\top} X_{i,t} + \gamma_1^{\top}\left(X_{i,t} \times USDC_i\right) \\ + \gamma_2^{\top}\left(X_{i,t} \times DAI_i\right) + \gamma_3^{\top}\left(X_{i,t} \times FRAX_i\right) + \mu_i + \lambda_m + \varepsilon_{i,t} \end{aligned} \tag{16}$$

where USDT is the reference category and X is the same vector of six contemporaneous standardized risk factors used in Section 5.1. All six factors and their coin interactions enter jointly. Each interaction coefficient measures the difference from USDT in the association between a one-standard-deviation increase in the factor and absolute price deviation, measured in percentage points.

Table 14. Coin-Interaction Regression Results

Variable	DAI	FRAX	USDC
BTC Dominance	-0.1838***	-0.1526***	-0.1151***
Google Trend	-0.0258***	0.0145	-0.0049
Whales	0.8645**	-0.0494	-0.0666*
Active Addresses Ratio (log)	-1.8493***	0.0249	-0.2005***
Volume (log)	0.2167	-0.2704***	0.2557**
Market Cap (log)	-1.0016***	-0.7244***	-0.6148***

Notes: The dependent variable is absolute price deviation from the $1 peg, expressed in percent. The model is estimated by OLS with coin and calendar-month fixed effects and HC3 robust standard errors. USDT is the reference category. All six contemporaneous risk factors are included jointly and standardized; Active Addresses Ratio, Volume, and Market Cap are transformed using log(1+x) before standardization. The table reports interaction coefficients relative to USDT. A coin-specific slope combines the interaction coefficient with the USDT main effect from this same regression. ****, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.*

Table 14 reports the coin-interaction results. Overall, the same risk factor is associated with DAI, FRAX, and USDC differently from USDT, in both direction and strength. The interaction terms for BTC Dominance and market capitalization are significantly negative for all three coins, indicating that relative to USDT, their responsiveness to crypto-market funding-structure shifts and scale changes is weaker. USDT is more deeply embedded in trading systems, and its price stability is more tightly linked to exchange liquidity and capital flows. DAI, FRAX, and USDC are more constrained by collateral structures, reserve arrangements, and redemption mechanisms. The stabilizing effect of market capitalization depends not only on scale itself but also on the liquidity sources and use cases behind that scale.

Divergence is even more pronounced for on-chain behavioral variables. The interaction term for Whales is significantly positive for DAI, consistent with its embedding in on-chain collateralization, liquidation, and protocol treasuries — large holders in DAI often correspond to collateral positions and liquidation accounts rather than simple concentration. The Active Addresses Ratio interaction is significantly negative for DAI and USDC: while on-chain activity reflects exchange capital migration for USDT, it corresponds to collateral adjustments and liquidation execution for DAI, and institutional fund transfers for USDC.

Interaction terms for Volume and Google Trend also diverge. Google Trend is significantly negative for DAI and insignificant for FRAX and USDC; the Volume interaction is negative for FRAX and positive for USDC. This indicates that trading activity and market attention carry different risk meanings across stablecoins and cannot be used as uniform risk indicators. In sum, the coin-interaction results are consistent with the finding in Section 4.2: the direction of risk-factor effects depends on a stablecoin's market embeddedness and on-chain functionality, not on its type classification.

5.3 High-Risk State Identification and Early-Warning Signal Testing

Building on the explanation of stablecoin depegging risk, this section examines whether the identified risk factors can detect high-risk states in advance. A high-risk state is defined by price deviation exceeding a fixed threshold:

$$\mathrm{HighRisk}_{i,t}=1\left(|P_{i,t}-1|>0.5\%\right) \tag{17}$$

We further construct a linear probability early-warning model:

$$\Pr\left(\mathrm{HighRisk}_{i,t}=1\right)=F\left(\alpha+\beta X_{i,t-\mathrm{h}}^{lag}+\mu_i+\lambda_m\right),\mathrm{h}=1,3,7 \tag{18}$$

where $X_{i,t}^{lag}$ represents the set of lagged risk factors formed after prior data processing, with lags that can be set to 1, 3, or 7 days. By setting lagged terms of different lengths, we can test whether the relevant risk factors can identify depegging risk in advance and avoid having the results reflect only contemporaneous correlations.

Table 15. Out-of-Sample Early-Warning Results

Target Type	Prediction Target	Horizon (days)	Best Model (AP)	Test-Set Event Rate	ROC-AUC	Average Precision	AP/Event Rate	Brier Score
Price threshold	Baseline 0.5%	1	LPM 1d	0.0303	0.8538	0.1242	4.096	0.0356
Price threshold	Baseline 0.5%	3	LPM 3d	0.0578	0.8291	0.1553	2.685	0.0636
Price threshold	Baseline 0.5%	7	LPM 7d	0.0915	0.8090	0.2235	2.443	0.0887
Price threshold	Severe 1%	1	LPM 1d	0.0047	0.7152	0.0102	2.191	0.0105
Price threshold	Severe 1%	3	LPM 3d	0.0126	0.7298	0.0282	2.235	0.0246
Price threshold	Severe 1%	7	LPM 7d	0.0258	0.7931	0.1355	5.253	0.0412

Notes: The sample is split chronologically into training and test sets; all metrics reported here are computed on the test set (out-of-sample). Predictor variables are lagged by 1, 3, and 7 days. AP/Event Rate is the ratio of Average Precision to the test-set event rate, reflecting the model's improvement multiple over random prediction; a lower Brier score indicates better probability-forecast calibration.

To distinguish early-warning patterns for moderate versus severe depegging, we set two thresholds: 0.5% and 1%. A deviation of 0.5% represents the transition from routine small fluctuations to an observable deviation zone, classified as moderate depegging. A 1% deviation represents a low-frequency but more damaging extreme state, classified as severe depegging. Table 15 reports out-of-sample test results for both thresholds across warning horizons of 1, 3, and 7 days.

Table 15 shows that the risk factors deliver good out-of-sample early-warning performance for price-threshold depegging. For the baseline 0.5% threshold, the area under the receiver operating characteristic curve (ROC-AUC) exceeds 0.80 at all three horizons, and Average Precision is higher than the corresponding test-set event rate. This indicates that the model assigns higher risk rankings to observations that are more likely to depeg. Lagged risk factors thus signal depegging before prices formally cross the threshold.

For the 1% severe-depegging threshold, the model also retains discriminatory power. This state occurs rarely in the sample; test-set event rates are below 3% at all three horizons. Yet the 7-day horizon achieves a ROC-AUC near 0.80, and Average Precision reaches 5.25 times the test-set event rate, substantially higher than at the 1-day horizon. Early-warning

performance for the baseline threshold declines as the horizon lengthens. Moderate deviations are more often triggered by short-term liquidity shocks and are better monitored at shorter horizons. For severe depegging, the 7-day horizon performs best, consistent with its formation mechanism: it builds up over several days through the accumulation of funding-structure shifts, on-chain activity, and market attention.

6. Conclusions and Policy Discussion

We study USDT, USDC, DAI, and FRAX and apply a cusp catastrophe model to identify the nonlinear features of stablecoin depegging. We measure the price state in two ways, the deviation from the $1 peg and the log return, and examine jump behavior in the full sample, in major event windows, and across different market cycles. We reach the following conclusions.

First, we clarify how jump identification differs across state variables and what those differences mean economically. Comparing the two measures, jumps identified under price deviation are relatively sparse, whereas jumps identified under log returns are more frequent. The two measures capture different objects: the degree of deviation from the peg and short-term price movements, respectively. Return-based jumps correspond to ordinary trading volatility, whereas only deviation-based jumps point to impairment of the pegging mechanism. Assessments of stablecoin stability should therefore distinguish between these two dimensions.

Second, jump characteristics differ systematically across stablecoins, and what determines this difference is market embeddedness and the supply-and-demand adjustment mechanism rather than the type label. Traditional financial variables, including stock indices, exchange rates, and commodities, are most broadly associated with price deviations of USDT and USDC, while these associations are weakest for DAI. USDT and USDC have entered a broader funding ecosystem and are used by institutions for liquidity management and portfolio allocation. DAI and FRAX remain active mainly within DeFi, where price deviations arise more from on-chain trading and collateral fluctuations. Although USDT and USDC are both fiat-backed with similar collateral structures, market capitalization expansion works in opposite directions for the two. Newly issued USDT may not yet be fully distributed across exchanges, which can create local supply-and-demand imbalances. In addition, non-dollar markets rely on matched-order pricing, and arbitrage is constrained by trading depth and redemption policies. As a result, market capitalization growth is instead associated with longer deviation episodes. USDC issuance flows directly into the accounts of regulated

institutions and its redemption path is shorter, so market capitalization growth is associated with greater price stability. What determines the level of risk is liquidity characteristics and redemption arrangements rather than market share. The role of large-holder concentration also varies with the nature of holders: it is positive for USDT and FRAX but negative for USDC and DAI, whose large holdings come more from institutional long-term positions and protocol treasuries. When Bitcoin dominance rises, trading demand for USDT, USDC, and FRAX declines in step, whereas DAI exhibits local premiums because of active on-chain contract and leveraged trading. The role a stablecoin plays in the risk-appetite cycle depends on the setting in which it is embedded.

These differences are present along the time dimension as well. The event-window results show that short-term depegging behavior has gradually shifted from a passive response to co-movement with the traditional financial system toward a more endogenous market mechanism. During the March 2020 “Black Swan” event, the stablecoin market was still in its early stage, and traditional financial market variables and global liquidity conditions were strongly associated with price deviations. After the 2021 Chinese cryptocurrency regulatory shock, on-chain capital flows and regional trading demand gained importance. The 2022 UST collapse and FTX bankruptcy show that algorithmic mechanism failure, exchange credit crises, DeFi liquidity withdrawal, and on-chain leverage liquidations had become important sources of stablecoin jumps. By the 2023 SVB failure, the stablecoin market had formed a risk network in which on-chain and off-chain financial systems are intertwined. Off-chain bank reserve risk could affect other stablecoins through reserve linkages, liquidity pools, and market expectations. As the market has matured, the ability of stablecoin prices to recover has strengthened, but cross-mechanism transmission paths have also become more complex.

Third, depegging risk can be observed before a pronounced price deviation appears. Tests of common risk factors show that stablecoin depegging is significantly related to market size, on-chain activity, holdings structure, and market attention. The coin interaction terms further show that the direction and strength of the same risk factor’s association differ systematically across stablecoins. The out-of-sample early-warning results show that structural indicators such as on-chain capital flows, holdings concentration, and market size emit warning signals before the price formally crosses the depegging threshold. Moderate deviations are more often triggered by short-term liquidity shocks and are suited to monitoring over shorter horizons. Severe depegging builds up over several days through the funding structure and on-chain behavior, and a 7-day horizon identifies it best. This implies

that stablecoin risk identification can extend from ex post observation of price deviations to ex ante monitoring of changes in market structure, on-chain behavior, and capital concentration.

Based on these findings, we offer the following recommendations.

First, risk monitoring should jointly track peg deviations and short-term return fluctuations, which capture different dimensions of price behavior (Table 5). The out-of-sample results for lagged structural indicators (Table 15) support considering shorter monitoring horizons for moderate deviations and a 7-day horizon for severe depegging. Return volatility, trading volume, market capitalization, and on-chain capital flows should therefore be monitored alongside price deviations.

Second, differentiated supervision and information transparency could be advanced. The differing market-capitalization and large-holder-concentration coefficients for USDT and USDC (Tables 3 and 14) indicate that a common protocol label can mask important differences in risk structure. Supervisors may wish to tailor regulation to each stablecoin's reserve structure and operating mechanism, and to raise the transparency of reserve disclosure and redemption mechanisms, thereby reducing the shock from a sudden reversal of market confidence.

Third, on-chain behavior monitoring and risk-response mechanisms could be strengthened. Table 13 associates greater large-holder concentration and higher active-address intensity with an increased probability of depegging. Supervisors and market institutions may wish to focus on large capital migrations, changes in liquidity pools, and cross-mechanism risk transmission. During major events, timely disclosure of reserve and redemption information, together with liquidity support measures where necessary, may help limit the spread of risk.

Overall, stablecoin stability is maintained jointly by multiple mechanisms, while the risk is latent and nonlinear. Beyond price deviations, risk monitoring should also track changes in on-chain funding structure and holding behavior. Risk assessment should be made with reference to how a stablecoin is embedded in the market and the stage of the market it operates in.

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Appendix A. Event Selection

After reviewing events reported by major cryptocurrency information platforms and news websites during the sample period for dollar-pegged stablecoins, we identify five major shocks to the cryptocurrency market. We partition the sample timeline around these five events based on return break points, allowing us to observe dynamic correlations during the event windows.

Table A1 presents the specific content of these extreme events. Following the exposition of the event-study method (ESM) in Sorescu et al. (2017), we confirm the identified event nodes by testing for return break points in mainstream cryptocurrencies. For the market index return (R_{mt}) required by the event-study method, we select the log return of the S&P Cryptocurrency Broad Digital Market Index, which is designed to reflect the overall trend of broad digital assets.[8]

Table A1. Sample Subperiod Partition Nodes

Event Date	Event Content
March 12, 2020	Event 1: Cryptocurrency market crash, BTC declined 50% in one day
September 24, 2021	Event 2: People's Bank of China reaffirmed crackdown on cryptocurrency
May 9, 2022	Event 3: Stablecoin UST collapse
November 12, 2022	Event 4: FTX exchange bankruptcy
March 10, 2023	Event 5: SVB failure

For the event study, we use the actual event occurrence date in the cryptocurrency market as the event day. To ensure a reasonable event-window design and minimize interference from other external factors, we follow prior studies (Tu and Zhao, 2021; El Ghoul et al., 2023) and select log return data for five trading days before and after each event date for empirical analysis. That is, with the event occurrence date as the base, we define an event window of $[-5,+5]$, covering 11 trading days in total. The trading day immediately before the first day of the event window is set as the end date of the estimation window. We then select the 120 trading days before this date as the estimation period $[-125,-6]$, totaling 120 days. For Event 1, due to sample period constraints, the estimation window is appropriately adjusted to $[-110,-6]$. We use the return data in the estimation period to construct a model that estimates the normal return the cryptocurrency would have had in the absence of the

[8] This index follows the convention of equity markets (five trading days per week), which differs from the 7×24 conti nuous trading of cryptocurrency markets. Missing values occur mainly on weekends, so we take the 7×24 continuous t rading calendar as the benchmark and fill each missing observation with the prior trading day's value.

extreme event, and we calculate abnormal returns through time-series analysis. For this purpose, we adopt the market model as the estimation tool for normal returns:

$$R_{i,t}/R_{i,t}^{'}=\alpha_i+\beta_i R_{mt}+\mu_{i,t} \quad \text{(A-1)}$$

where $R_{i,t}$ is the actual return, $R_{i,t}^{'}$ is the "normal" return, and R_{mt} is the market index return.

Both normal and abnormal returns need to be estimated and measured in order to assess whether the impact of the extreme event on the relevant currency's return is significant. Abnormal return is defined as the difference between the actual return during the event window and the "normal" return that would have occurred in the absence of the event. The abnormal return is expressed as:

$$AR_{i,t}=R_{i,t}-R_{i,t}^{'} \quad \text{(A-2)}$$

We sum the abnormal returns over the event window to obtain the cumulative abnormal return:

$$CAR_{i,t}=\sum_{t=-5}^{5} AR_{i,t} \quad \text{(A-3)}$$

We then propose the null hypothesis H_0: within the event window, the cumulative abnormal return $CAR_{i,t}$ for the tested cryptocurrency equals zero. If we cannot reject the null hypothesis, the extreme event has no significant impact on the cryptocurrency; if we reject the null hypothesis, the event affected the cryptocurrency's return, with the direction of impact determined by the sign of $CAR_{i,t}$. The test results are shown in Table A2.

Table A2. CAR Test Results within Event Windows

	Event 1	Event 2	Event 3	Event 4	Event 5
BTC	-4.72***	-10.54***	-4.09***	-1.47	1.47
ETH	-5.28***	-8.25***	-2.45**	1.81*	1.95*
BNB	-6.51***	-3.30***	-3.42***	-2.996**	3.72***
DOGE	-5.04***	-8.09	-2.67**	-7.92***	0.27
MATIC	-4.27***	-4.02***	-2.07*	2.71**	0.99

In Event 1, all mainstream cryptocurrencies in the sample show t-values significant at the 1% level within the event window covering five trading days before and after the event. Hence, we reject the null hypothesis: the cryptocurrency market crash had a significant negative impact on all five mainstream cryptocurrencies. Events 2 and 3 likewise had varying degrees of negative impact on the five mainstream cryptocurrencies, though DOGE, due to its meme attributes and contrarian market characteristics, was not significantly affected by Event 2. In Event 4, BNB, DOGE, and MATIC were most affected, while BTC and ETH, which

dominate the market, were less affected; ETH even experienced a positive impact on returns. In Event 5, apart from BNB, which experienced significant positive impact, and ETH, which was affected at the 10% significance level, the other three mainstream cryptocurrencies were not significantly affected.

Because the event window design averages performance over the entire window, we use Figure A1 to more intuitively illustrate the impact of the SVB failure, a global financial event.

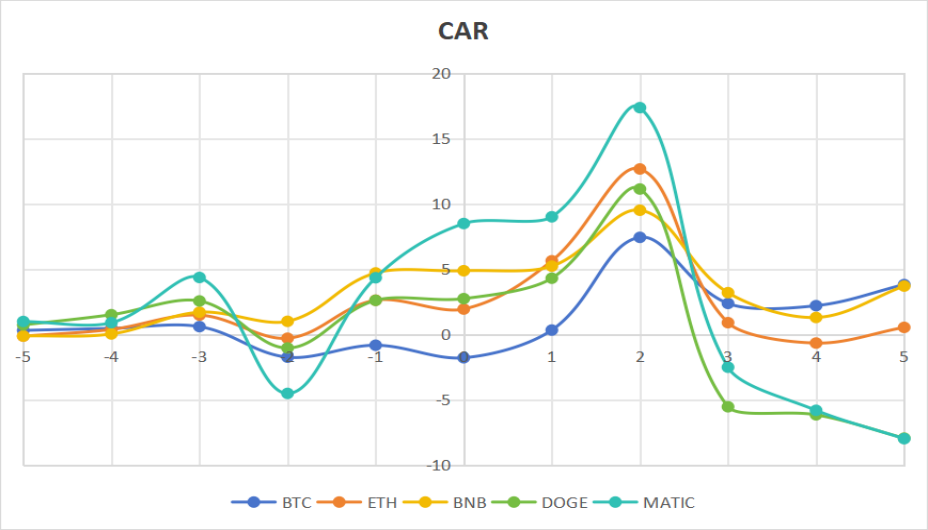


Figure A1. Cumulative abnormal returns of five mainstream cryptocurrencies during the SVB failure event window.

According to the figure, on the day SVB failed, the returns of the five mainstream cryptocurrencies did not show significant volatility. As the event unfolded further, positive return movements began to appear in subsequent trading days. This indicates that although the market's initial reaction to this financial event was muted, over time investors may have begun to view cryptocurrencies as safe-haven assets. Hence, capital began flowing into the cryptocurrency market, and panic sentiment showed signs of spreading. However, this situation began to improve on the fourth and fifth trading days after Event 5. Overall, although this event had an impact on cryptocurrencies, the effect was not persistent.

The impact Event 5 had on the cryptocurrency market differs from the previous four events. In terms of event nature, the first four events were directly linked to the cryptocurrency market and its internal factors, such as market crashes, regulatory pressure, stablecoin failure, and exchange bankruptcy. Event 5, however, was a traditional financial system event whose occurrence did not originate directly from the cryptocurrency market itself. In terms of market reaction differences, Event 5 did not have a direct and significant impact on the cryptocurrency market in its initial stage. This contrasts with the immediate

and significant negative reactions in the cryptocurrency market following the first four events. From the perspective of impact persistence and direction, the market reaction following Event 5 differed from the first four events, manifesting as positive changes over time rather than an immediate negative shock. This may indicate that the market gradually formed a response to events with non-direct impacts, rather than experiencing a one-time severe fluctuation. This event was essentially a major global financial event,[9] and its failure triggered widespread financial market chain reactions, including volatility impacts on the cryptocurrency market. Compared to the mechanism-specific shocks stablecoins faced in the first four events, Event 5 had more "exogenous" characteristics, with its impact pathway primarily operating through market sentiment transmission, fiat liquidity changes, and other indirect mechanisms affecting the crypto-asset market.

[9] SVB was a major financial institution serving innovative and technology firms, and its collapse had ripple effects acr oss financial markets, including cryptocurrency markets.

Appendix B. Candidate Variables and the LightGBM–SHAP Screening Procedure

Feature Selection

To predict stablecoin returns, we select a rich set of candidate features spanning financial assets, macroeconomic indicators, on-chain data, and market sentiment, in addition to stablecoin-specific characteristics. The selection builds on the extensive literature documenting cryptocurrency return drivers and aims to comprehensively capture potential factors affecting stablecoin prices.

Prior research on cryptocurrencies as an alternative medium of exchange or as analogues to traditional currencies provides the foundation for our approach (Glaser et al., 2014; Baur et al., 2018). Schilling and Uhlig (2019) further demonstrate a close link between Bitcoin's evolution and the dollar, particularly in endowment economies. As a circulating medium within the cryptocurrency market, stablecoins are designed to maintain value stability and thereby enhance usability and predictability in daily transactions. Following the view in Dag et al. (2023) that sovereign-currency returns can help predict stablecoin returns, we include the dollar, euro, renminbi, and Singapore dollar[10] in the feature set.

However, relying solely on major currencies proves insufficient. Cryptocurrency price formation and volatility reflect multiple economic, technical, psychological, and market-structure forces. Network effects, market sentiment, and trading activity are all shown to significantly affect cryptocurrency value fluctuations (Zhou et al., 2023). Interactions between fundamental information and speculation-driven factors also play a key role in price dynamics (Kukacka and Kristoufek, 2023). Moreover, stock market indices, precious metal prices, and crypto-market information such as Bitcoin-related Google search trends and the fear index are confirmed to significantly influence Bitcoin prices (Dag et al., 2023). These findings support the feasibility of selecting a broader variable set. We particularly focus on country-specific stock indices rather than global composites, as the relationship between national equity markets and cryptocurrencies warrants deeper investigation.

Given the unique characteristics of the cryptocurrency market, we also introduce market-specific dynamics such as Bitcoin dominance (BTC Dominance) and the FGI. These variables help illuminate market participants' behavioral patterns and their potential impact

[10] According to Google Trends city-level search intensity data, the top five cities are Shanghai, Washington, Singapor e, San Francisco, and Cambridge (accessed on December 15, 2023). We therefore include the Singapore Dollar Index in the feature set.

on stablecoin returns (Yi et al., 2018).[11] Changes in BTC Dominance not only reflect shifts in risk appetite in the crypto market. They also reveal how the prices of different stablecoin types diverge when mainstream assets attract capital and during market bubbles, and thus constitute a systematic factor for identifying irrational price behavior. In addition, investor activity and market dynamics can be captured through on-chain data, which effectively traces market evolution and reflects investor confidence in and acceptance of specific stablecoins (Liu and Tsyvinski, 2021). We therefore incorporate on-chain metrics such as the active address ratio (Active Addresses Ratio), historical holdings concentration (Historical concentration whales, or Whales),[12] and the break-even price (Break Even). Because stablecoins involve no mining costs, we exclude factors such as mining difficulty and mining cost.

Macroeconomic factors also warrant consideration when analyzing cryptocurrency markets. Global economic fluctuations (Cheng and Yen, 2019), monetary policy shifts (Ma et al., 2022), and the international trade environment (Chen et al., 2019) can all influence cryptocurrency market dynamics. Zhu et al. (2017) find that macroeconomic factors such as the consumer price index (CPI), the dollar index, the Dow Jones Industrial Average (DJIA), and the federal funds rate significantly affect Bitcoin prices over the long term. Furthermore, inflation and interest rates affect cryptocurrency prices by shaping investors' risk attitudes and investment strategies. Li and Huang (2020) show that interest-rate movements indirectly affect cryptocurrency market investment activity by altering borrowing costs. Nakagawa and Sakemoto (2021) further confirm the direct impact of macroeconomic indicator changes on the cryptocurrency market, underscoring the importance of considering macroeconomic conditions when analyzing and forecasting stablecoins. Drawing on Baker et al. (2016), we also introduce financial uncertainty indicators as important macroeconomic variables. Table B1 lists the abbreviation, description, frequency, and data source for each selected feature variable.

Table B1. Description of Candidate Feature Variables

Variable	Description	Frequency	Source
Stablecoin-related features			
Return(%)	Stablecoin log return	Daily	CoinMarketCap

[11] Yi, S., Xu, Z., & Wang, G.-J. (2018). Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? International Review of Financial Analysis, 60, 98–114. https://doi.org/10.1016/j.irfa.2018.08.012

[12] Measures whether stablecoin holdings have been excessively concentrated in a small number of large addresses (wh ales) over a given period.

Variable	Description	Frequency	Source
Volume*(%)	Stablecoin trading volume	Daily	CoinMarketCap
P1DR[13]	Previous One Day Return: the stablecoin's return on the preceding day	Daily	Authors' calculation
Market Cap*(%)	Stablecoin market capitalization	Daily	CoinMarketCap
Google Trend	Google search intensity for "Stablecoin"	Weekly	Google Trends
BTC Dominance(%)	Bitcoin dominance (Bitcoin's share of total crypto market cap)	Daily	AICoin
FGI	Crypto Fear and Greed Index: crypto-market fear gauge	Daily	Alternative.me
BTC Active*(%)	Bitcoin active addresses	Daily	Coinmetrics
Stablecoin on-chain indicators (Ethereum chain)			
Active Addresses Ratio(%)	$\frac{Daily\ Active\ Addresses}{Total\ Addresses}$ Stablecoin active address ratio	Daily	IntoTheBlock
Historical concentration whales(%)	Historical holdings concentration (share held by whale addresses)	Daily	IntoTheBlock
Break Even(%)	Historical Break Even Price: tracks the number of addresses that have realized break-even	Daily	IntoTheBlock
Macroeconomic indicators			
DFF(%)[14]	Federal Funds Effective Rate	Daily	Board of Governors of the Federal Reserve System (US)
Unemployment (%)	Unemployment Rate	Monthly	OECD[15]
Industrial Production (%)	Industrial Production Growth (month-over-month)	Monthly	OECD
Inflation(%)	Inflation measured by consumer price index (total)	Monthly	OECD
CCI(%)	Consumer Confidence Index (amplitude adjusted, month-over-month)	Monthly	OECD
GEPU_PPP(%)	Global Economic Uncertainty (PPP-adjusted GDP measure, month-over-month)	Monthly	Economic Policy Uncertainty
VIX(%)	VIX volatility (fear) index	Daily	Investing
Related financial assets			
Gold*(%)	Gold spot prices	Daily	World Gold Council
Brent*(%)	Crude Oil Prices: Brent — Europe	Daily	U.S. Energy Information Administration
GSCI*(%)	S&P GSCI Commodity Index	Daily	S&P Dow Jones Indices
SP500*(%)	S&P 500 Index	Daily	S&P Dow Jones Indices
HS300*(%)	CSI 300 Index	Daily	Investing

[13] Liu et al. (2023) confirms the role of prior-day return.
[14] Its code in the federal funds effective rate database is DFF.
[15] OECD indicators primarily reflect macroeconomic trends in developed economies and do not represent the aggregat e performance of all global economies.

Variable	Description	Frequency	Source
DAX30*(%)	DAX 30 Index	Daily	Investing
FTSE100*(%)	FTSE 100 Index	Daily	Investing
DGS10*(%)	Market Yield on U.S. Treasury Securities at 10-Year Constant Maturity (not adjusted for inflation)	Daily	Federal Reserve Economic Data
Sovereign currencies			
USDX*(%)	U.S. Dollar Index — Nominal Broad U.S. Dollar Index	Daily	Board of Governors of the Federal Reserve System (US)
CNYX*(%)	Renminbi Index	Daily	CNINDEX (Shenzhen Securities Information Co.)
EUR*(%)	Euro Index — Nominal effective exchange rate of the Euro	Daily	European Central Bank
SGDX*(%)	Singapore Dollar Index — S$ Nominal Broad Effective Exchange Rate Index	Daily	BIS
Sterling*(%)	Pound Sterling Index — New Sterling Nominal Broad Exchange Rate Index	Daily	The Bank of England

Notes: Return is the prediction target; all other variables are candidate features. * denotes a feature that has been log-differenced.

Stablecoin markets operate continuously 24/7 with no trading interruptions on weekends or holidays, whereas equity, foreign exchange, commodity, futures, and bond markets trade only on business days and are subject to holiday closures. Accordingly, we use the trading dates of stablecoins as the reference timeline when processing data. For financial market data that are reported daily but not continuously traded, we use the closing value from the most recent trading day prior to the prediction point. When weekends or holidays intervene, we forward-fill with the most recently available value. For weekly or monthly variables, we forward-fill the observation to subsequent daily samples only after the most recent complete reporting period or latest data release becomes available. For price or scale variables, we apply log differences or percentage changes to mitigate the effects of scale differences and nonstationarity. For ratio-type and index-type variables, we preserve the ratio or index form according to their original meaning.

Considering the effects of different time zones on cryptocurrency market volatility and the inconsistency in data update times, we adjust the number of lag days for different features. For example, for USDT on day t, if these variables are unavailable on day $t-1$, data from day $t-2$ are used. We use a rolling-window model for prediction, with the prediction step uniformly set to 7 days, and all input features are standardized using Z-scores.

Table B2. Summary Statistics for USDT Feature Variables

Variable	N	Mean	Median	Minimum	Maximum	Standard Deviation
Volume(%)	1792	0.115	-0.579	-138.019	133.964	23.562
P1DR(%)	1792	-0.001	0.000	-5.261	5.341	0.312
Market Cap(%)	1792	0.214	0.035	-5.257	32.297	1.382
Historical concentration whales(%)	1792	30.935	25.158	3.343	88.756	20.766
Active Addresses Ratio(%)	1792	6.667	3.031	0.783	67.745	9.574
Break Even(%)	1792	47.484	50.266	1.572	81.031	20.297
BTC Dominance(%)	1792	51.660	48.770	36.800	72.320	9.823
FGI	1792	46.160	45.000	5.000	95.000	21.688
BTC Active(%)	1792	0.026	-1.026	-45.209	41.508	11.833
Gold(%)	1792	0.030	0.018	-5.265	5.133	0.874
HS300(%)	1792	0.004	0.021	-8.209	5.778	1.248
DAX30(%)	1792	0.035	0.105	-13.055	10.414	1.251
FTSE100(%)	1792	0.019	0.084	-11.512	8.667	1.049
EUR(%)	1792	0.008	0.000	-1.124	1.308	0.244
Sterling(%)	1792	0.003	0.006	-2.615	3.016	0.428
CNYX(%)	1792	0.005	0.009	-1.245	1.254	0.231
SGDX(%)	1792	0.006	0.007	-0.736	0.757	0.112
Google Trend	1792	8.145	6.000	1.000	100.000	8.382
DFF(%)	1792	1.800	1.550	0.040	5.330	1.860
VIX(%)	1792	0.063	-0.637	-26.623	48.021	7.039
Brent(%)	1792	0.032	0.228	-64.370	41.202	3.515
SP500(%)	1792	0.049	0.108	-12.765	8.968	1.245
GSCI(%)	1792	0.027	0.136	-12.523	7.683	1.513
DGS10(%)	1792	0.060	0.000	-31.508	34.175	3.620
USDX(%)	1792	0.005	-0.007	-1.909	1.874	0.303
CCI(%)	1792	-0.046	0.010	-1.140	0.416	0.303
GEPU_PPP(%)	1792	1.408	-3.087	-24.619	66.395	17.571
Industrial Production(%)	1792	0.039	0.000	-14.321	7.150	2.431
Inflation(%)	1792	4.711	4.051	0.705	10.688	3.227
Unemployment(%)	1792	5.730	5.360	4.764	8.828	1.045

Notes: The time periods for feature variables differ across stablecoins, so we report only the statistics for the USDT-specific feature set.

Table B2 presents summary statistics for variables associated with the USDT market. Trading volume (Volume) exhibits substantial volatility, with a standard deviation of 23.562%, consistent with the high volatility characteristic of cryptocurrency markets. The fluctuation in USDT's trading volume reflects the level of market participant activity and indicates that even during periods of pronounced price movements, trading volume remains elevated, suggesting strong liquidity and market depth.

The active address ratio provides an alternative measure of market activity. Its high mean and standard deviation suggest that the number of active addresses fluctuates considerably

across time. This pattern indicates that even when market prices experience sharp movements, a large number of participants continue to trade, sustaining market vitality and dynamic equilibrium. The historical concentration of large holders (whales) ranges from 3.343% to 88.756%, revealing significant variation in market concentration. Large holders' influence on the market varies over time and is associated with different trading behaviors and price movements. The break-even price indicator also displays high volatility, with a standard deviation of 20.297%. Its mean below 50% suggests that during the observation period, market participants face considerable uncertainty regarding the break-even threshold, implying that at certain times, some participants may trade near their break-even point, thereby increasing market uncertainty and risk.

Moreover, the FGI, a cryptocurrency market sentiment indicator, exhibits a volatility of 21.69%, reflecting frequent shifts in market sentiment. In contrast, equity and foreign exchange markets maintain relatively lower volatility, indicating greater stability. Bitcoin dominance (BTC Dominance) averages 51.660%, showing that Bitcoin continues to dominate the cryptocurrency market. Combined with the analysis of the VIX and the Global Economic Policy Uncertainty Index, the data reveal right-skewed distributions in these external environment variables, indicating pervasive uncertainty and risk in the market.

Overall, these summary statistics reveal the high-volatility characteristics of the USDT market and reflect the behavioral patterns of market participants under uncertain conditions. Through deeper analysis of these variables, we can better understand USDT's performance in the cryptocurrency market and the extent to which it is influenced by external factors.

Feature Importance Ranking from the LightGBM–SHAP Model

We apply the LightGBM model to each stablecoin category and compute SHAP values to identify which features matter most for predicting stablecoin returns. For each feature, we calculate the mean absolute SHAP value (Mean(|SHAP|)) across the test dataset, then average the rankings by stablecoin mechanism type to obtain the final feature ranking for each category. These rankings reflect the extent to which each feature influences the model's predictive ability. A higher rank indicates a stronger impact on stablecoin price volatility.

Table B3 reports the feature importance rankings by stablecoin mechanism. Across all three categories, prior-day return (P1DR) ranks first, indicating that it is the most predictive variable for stablecoin returns. This finding is consistent with momentum or reversal effects, whereby stablecoin prices exhibit short-term trending behavior. Holdings concentration (Whales) ranks in the top five for all three categories, suggesting that the trading behavior of

large holders is strongly associated with price volatility and confirming the dominant role of on-chain capital structure in market pricing. Market capitalization ranks second in both crypto-collateralized and hybrid stablecoins, consistent with market scale supporting price stability. Notably, the FGI ranks third in hybrid stablecoins, ahead of Bitcoin dominance and the VIX, indicating that sentiment plays a pivotal role in this category.

The features at the bottom of the ranking are mostly macroeconomic variables (e.g., industrial production, inflation, unemployment), suggesting that while macroeconomic fundamentals matter, their direct impact on short-term stablecoin returns is limited in the high-frequency crypto market. This finding is consistent with He et al. (2024), who argue that economic policy uncertainty (EPU) has little short-term effect on cryptocurrency markets. It also echoes the expectation raised in the Introduction. Prior research has shown that macroeconomic variables exert important influences on cryptocurrency markets (Corbet et al., 2020; Tzeng and Su, 2024; Sakariyahu et al., 2024). In stablecoin markets, however, and particularly for short-term return prediction, their explanatory power is far weaker than that of on-chain behavior and market structure features. This pattern reveals a high degree of endogeneity in stablecoin return volatility, in sharp contrast to the price-stability expectations implied by the dollar peg, and suggests that the pegging mechanism still harbors high-frequency risk transmission channels.

Table B3. Feature Importance Rankings by Stablecoin Mechanism

Fiat-Backed: Feature	Mean(| SHAP|)	Rank	Crypto-Collateralized: Feature	Mean(| SHAP|)	Rank	Hybrid: Feature	Mean(| SHAP|)	Rank
P1DR	0.0429	1	P1DR	0.0854	1	P1DR	0.1519	1
Active Addresses Ratio	0.0128	2	Market Cap	0.0359	2	Market Cap	0.0432	2
Historical concentration whales	0.0100	3	FTSE100	0.0236	3	FGI	0.0426	3
Volume	0.0084	4	Historical concentration whales	0.0208	4	DGS10	0.0303	4
Market Cap	0.0074	5	BTC Dominance	0.0174	5	Historical concentration whales	0.0301	5
EUR	0.0074	6	Sterling	0.0165	6	Active Addresses Ratio	0.0273	6
DGS10	0.0073	7	Gold	0.0152	7	BTC Active	0.0232	7
HS300	0.0070	8	Google Trend	0.0135	8	DAX30	0.0218	8
BTC Active	0.0070	9	DGS10	0.0133	9	FTSE100	0.0207	9
SP500	0.0070	10	BTC Active	0.0131	10	VIX	0.0199	10
FTSE100	0.0069	11	Inflation	0.0126	11	BTC Dominance	0.0192	11
Google Trend	0.0065	12	HS300	0.0123	12	Volume	0.0180	12
GSCI	0.0065	13	Unemployment	0.0119	13	SGDX	0.0178	13
Sterling	0.0064	14	Volume	0.0117	14	Gold	0.0168	14
BTC Dominance	0.0061	15	Break Even	0.0113	15	Sterling	0.0167	15
Gold	0.0058	16	Brent	0.0112	16	USDX	0.0159	16
DAX30	0.0058	17	VIX	0.0108	17	SP500	0.0159	17
VIX	0.0058	18	Industrial production	0.0099	18	Industrial production	0.0156	18
Break Even	0.0054	19	CNYX	0.0097	19	Break Even	0.0128	19
Brent	0.0049	20	FGI	0.0086	20	CNYX	0.0120	20
SGDX	0.0049	21	EUR	0.0082	21	Brent	0.0110	21
USDX	0.0044	22	USDX	0.0081	22	EUR	0.0104	22
CNYX	0.0043	23	DAX30	0.0075	23	Google Trend	0.0100	23
GEPU_PPP	0.0038	24	CCI	0.0061	24	GSCI	0.0091	24
FGI	0.0037	25	GSCI	0.0053	25	HS300	0.0087	25
Inflation	0.0028	26	DFF	0.0051	26	Inflation	0.0084	26
Industrial production	0.0027	27	SGDX	0.0050	27	DFF	0.0058	27
CCI	0.0023	28	GEPU_PPP	0.0046	28	CCI	0.0057	28
Unemployment	0.0019	29	SP500	0.0041	29	Unemployment	0.0030	29
DFF	0.0013	30	Active Addresses Ratio	0.0000	30	GEPU_PPP	0.0029	30