International Journal of Applied and Advanced Scientific Research (IJAASR)
Impact Factor: 5.655, ISSN (Online): 2456 - 3080
(www.dvpublication.com) Volume 5, Issue 2, 2020

EARLY WARNING SIGNALS FOR STABLECOIN RUNS ACROSS INTERCONNECTED DIGITAL MARKETS

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Cite This Article: Kannan Vishwanath & Lloyd Zulu, "Early Warning Signals for Stablecoin Runs Across Interconnected Digital Markets", International Journal of Applied and Advanced Scientific Research, Volume 5, Issue 2, Page Number 55-64, 2020.

Abstract:

This analysis examines whether historical price stress signals subsequent stablecoin peg instability in global digital markets. Coin Metrics daily prices within the 2010 to 2019 observation window provide 4,284 usable observations across seven provider series. An exploratory panel regression includes series fixed effects and standard errors adjusted for temporal and contemporaneous dependence. A one standard deviation increase in historical absolute peg deviation is associated with a 1.699 percentage point increase in subsequent average absolute deviation, with a 95 percent confidence interval from 1.493 to 1.905. Historical volatility and breach frequency provide no statistically distinguishable incremental associations in the baseline specification. The deviation association survives longer covariance adjustment and exclusions of GUSD and USDT, while volatility becomes negatively associated with instability after excluding USDT. These findings distinguish persistent departures from fluctuation intensity and are compatible with delayed price correction, without identifying its causal mechanism. The contribution separates observable stress dimensions and demonstrates sensitivity to sample composition. Monitoring should prioritize deviation magnitude for further chronological validation alongside independently verified redemption and liquidity information.

Key Words: Stablecoins; Peg Instability; Price Persistence; Panel Regression; Financial Stability

1. Introduction:

A stablecoin can promise dollar parity while exhibiting persistent departures from its reference value. These departures matter because users rely on stablecoins to transfer value, settle transactions, and hold balances between trades. The G7 Working Group on Stablecoins (2019) identifies financial stability, operational resilience, and governance concerns associated with these arrangements. Understanding which observable price patterns precede further instability can inform monitoring. However, price departures do not independently establish redemption runs, and associations between historical and subsequent prices do not identify causal mechanisms.

Stablecoins differ from freely fluctuating crypto currencies because their reference value provides an explicit benchmark for assessing instability. Bullmann et al. (2019) distinguish arrangements through issuer accountability, collateral, and stabilization mechanisms. Adrian and Mancini Griffoli (2019) similarly emphasize the claims and institutional structures supporting digital money. Comparable price departures may therefore reflect different combinations of trading friction, demand imbalance, collateral concerns, and confidence in convertibility. Monitoring requires separating observable price behavior from the institutional processes that might explain it.

Limits to arbitrage provide a theoretical basis for examining persistent deviations. Corrective trading can restore parity when participants can acquire discounted tokens and realize their reference value through accessible conversion mechanisms. Financial constraints, execution costs, and uncertainty can impede adjustment. Gromb and Vayanos (2010) explain how constrained arbitrage permits pricing discrepancies to persist, while Duffie (2010) examines delayed adjustment arising from slow movement of capital. Applied to stablecoins, these mechanisms suggest that recent departures may contain information about subsequent instability. They do not imply that every departure reflects deteriorating fundamentals or coordinated withdrawal.

Historical price stress has three distinct dimensions. Deviation magnitude measures distance from parity, variability measures the intensity of price movements, and persistence measures the recurrence of departures. Larger deviations may indicate incomplete correction, whereas greater variability may reflect either impaired trading conditions or active adjustment. Frequent breaches may reveal sustained friction, but their incremental contribution may diminish after accounting for deviation magnitude. Research on crypto currency price discovery examines differences in predictability and liquidity, while spillover research identifies interdependencies across digital assets (Brauneis & Mestel, 2018; Koutmos, 2018). These findings motivate distinguishing stress dimensions rather than assuming that they convey equivalent information.

The reviewed evidence does not establish whether historical deviation magnitude, variability, and breach frequency provide distinguishable information about subsequent stablecoin peg instability when considered jointly. Institutional classifications explain differences in stabilization arrangements, while broader crypto currency research addresses price discovery and transmission. This analysis addresses a narrower

question: which observable dimension retains an association with subsequent departures after accounting for the others and persistent differences across series? Its contribution concerns the empirical separation of price signals rather than identification of redemption behavior or market contagion.

This study aims to assess whether historical stablecoin price stress is associated with subsequent peg instability. The research question asks whether recent deviation magnitude, return variability, and breach frequency contain distinct information about later departures from dollar parity. The objectives are to estimate their conditional associations and evaluate sensitivity to covariance assumptions and sample composition. No moderator is introduced because the available prices do not measure a defensible conditioning mechanism.

The empirical setting comprises seven Coin Metrics provider series within the requested period from 1 January 2010 to 31 December 2019. Available observations begin during the period rather than covering the full decade. Screening produces 4,536 descriptive observations and 4,284 observations with complete historical and subsequent measurement windows. The outcome measures average absolute deviation over the subsequent seven days. An exploratory regression includes standardized historical measures and series fixed effects. Covariance estimation accommodates contemporaneous dependence and temporal dependence within specified lag windows.

The estimates identify a positive association between recent deviation magnitude and subsequent instability. Variability and breach frequency provide no statistically distinguishable incremental associations in the baseline specification, while the variability coefficient changes sign when USDT is excluded. The contribution is to demonstrate that the three stress dimensions produce different empirical conclusions and that sample composition affects interpretation. These findings support evaluating deviation magnitude as a candidate monitoring measure while requiring chronological validation before operational use.

2. Theory, Conceptual Framework, and Hypotheses Development:

This analysis draws on strategic complementarity and liquidity provision mechanisms to explain why historical stablecoin price stress may predict subsequent peg instability. Strategic complementarity arises when the incentive to exit increases as other holders withdraw. Chen et al., 2010, document this mechanism in mutual funds, where costly liquidation can disadvantage investors who remain. Applied to stablecoins, the mechanism suggests that concerns about other holders' behavior may reinforce selling pressure when redemption or market liquidity is constrained. This application is a theoretical extension rather than an established finding for the available stablecoin sample.

Historical stablecoin price stress comprises three dimensions: peg deviation, price variability, and stress persistence. Subsequent peg instability refers to later departures from the reference value, assessed through average absolute deviation, maximum discount, breach frequency, longest discount episode, and recovery time. Predictors must precede the outcome window. The framework concerns predictive associations because observed prices alone cannot identify redemption runs, investor motives, or causal transmission across markets. Stabilization mechanisms create relevant boundary conditions. Bullmann et al., 2019, distinguish stablecoins through issuer accountability, collateral arrangements, and stabilization design. These differences imply that comparable price movements may reflect different economic processes. A discount may indicate impaired redemption confidence, collateral concerns, or temporary trading friction. The framework therefore treats price stress as an observable warning signal whose interpretation depends on the underlying arrangement.

Peg deviation captures the distance between a stablecoin's market price and its reference value. Its proposed indicators are the previous day's discount, the previous week's average absolute deviation, and the previous week's maximum premium. Discounts can indicate pressure to exit, while absolute deviations capture instability in either direction. Premiums require separate interpretation because increased demand or restricted issuance may raise prices without indicating withdrawal pressure.

The theoretical link to subsequent instability depends on whether corrective trading restores parity. When redemption remains credible and accessible, traders can purchase discounted tokens and seek repayment at the reference value. When access, confidence, or execution is constrained, deviations may persist or deepen. A price departure therefore contains potential information about the effectiveness of the stabilization process, but its direction does not establish its cause.

Adrian and Mancini Griffoli, 2019, distinguish digital money arrangements according to their claims and supporting institutional structures. Their analysis motivates examining whether observed departures reveal weaknesses in convertibility or confidence. It does not establish that every premium or discount predicts later instability. The directional expectation is strongest for discounts and absolute deviations; the premium indicator remains exploratory because scarcity and demand can generate competing effects.

H1: Larger Historical Discounts and Absolute Peg Deviations are Associated with Greater Subsequent Stablecoin Peg Instability, Particularly When Corrective Trading is Constrained

Price variability measures the intensity of price movements rather than their distance from the peg. Its proposed indicators are return volatility over the previous week, return volatility over the previous month, and the previous week's price range. A stablecoin may fluctuate around parity without sustaining a discount, making variability conceptually distinct from directional peg deviation.

Higher variability may increase uncertainty about execution prices and the cost of maintaining trading positions. Liquidity providers may then demand greater compensation or reduce their exposure, allowing subsequent orders to move prices further. The competing mechanism is corrective activity: rapid trading around parity may temporarily increase measured variability while helping restore the peg. Variability therefore predicts instability most plausibly when it accompanies constrained liquidity provision.

Nagel, 2012, shows that compensation for liquidity provision rises during financial market turmoil. This evidence comes from equity markets and supports the general liquidity mechanism rather than a direct stablecoin forecasting result. Its application here yields a conditional expectation: historical variability should be associated with later instability when market participants cannot expand corrective trading sufficiently.

H2: Greater Historical Price Variability is Associated with Greater Subsequent Stablecoin Peg Instability When Liquidity Provision is Constrained

Stress persistence measures proposed indicators are consecutive days below parity, the previous month's frequency of peg deviations, and the previous month's longest discount episode. Unlike variability, persistence identifies sustained conditions rather than the size of short-term movements.

Repeated departures may weaken confidence in the speed or reliability of stabilization. Individual holders may respond by reducing exposure, while traders may become less willing to absorb sales. These decisions can reinforce aggregate pressure without requiring holders to coordinate explicitly. However, persistence can also reflect stable transaction costs or market segmentation. A recurring small discount may therefore represent a trading friction rather than escalating financial distress.

Schmidt et al., 2016, document differences in run behavior across money market mutual fund investors and portfolio characteristics. Their findings support attention to investor incentives and institutional conditions, while providing no direct estimate for stablecoins. In the proposed framework, persistence is expected to contain predictive information beyond isolated deviations, but this contribution must be tested against recent deviation magnitude and volatility.

H3: Greater Historical Stress Persistence is Associated with Greater Subsequent Stablecoin Peg Instability After Accounting for Recent Peg Deviation and Price Variability

The conceptual framework positions historical stablecoin price stress as the explanatory construct and subsequent peg instability as the outcome construct. The three explanatory dimensions contain calculated indicators derived from observed prices. They are conceptual groupings rather than validated latent factors or an implemented composite index. The five outcome indicators represent distinct expressions of instability and should be evaluated separately unless aggregation receives an explicit justification.

The relationships express theoretical predictive direction, not identified causation. Market connections provide context but are not measured by the available aggregate price series. Data quality also remains consequential: Gandal et al., 2018, document manipulation in crypto currency markets, showing why recorded price movements require verification before economic interpretation.

The hypotheses permit positive, absent, or opposing associations. Their evaluation requires separate historical predictor windows and subsequent outcome windows, with recovery times treated as incomplete when observation ends before recovery. No hypothesis is presented as supported by the descriptive audit, and any revision following estimation must be identified as exploratory.

3. Data:

3.1 Data Sources, Population, and Sample Construction:

This analysis examines historical stablecoin price coverage from 1 January 2010 to 31 December 2019. The intended unit of analysis is the stablecoin day within global digital asset markets. The target population comprises publicly traded stablecoin arrangements operating during any part of the period, including discontinued arrangements. The primary comparable scope covers assets targeting the US dollar. Differences in stabilization mechanisms require explicit classification because issuer accountability, collateral, and governance affect the interpretation of price stability, as explained by Bullmann, Klemm, and Pinna, 2019.

The accessible sampling frame comprises seven Coin Metrics provider series: usdt, usdc, tusd, pax, gusd, sai, and dai. The audited field is PriceUSD, expressed in USD per token. Community data are distributed under Creative Commons Attribution NonCommercial 4.0. The repository updates regularly, and no fixed release was recorded. These observations therefore represent historical data accessed retrospectively rather than verified information vintages available on each historical date.

Selection followed data availability within the specified period. It does not constitute probability sampling or a completed census. The full historical population size remains unverified. The focus on stablecoins reflects their payment and market functions, together with the governance and financial stability concerns identified by the G7 Working Group on Stablecoins, 2019.

Sample Construction Stage	Provider Series	Observations	Applied Rule
Retrieved records within the study period	7	5,428	Retain recorded dates from 2010 through 2019

Sample Construction Stage	Provider Series	Observations	Applied Rule
Records excluded for missing prices	7 screened	892	PriceUSD field empty
Duplicate records removed	7 screened	0	No repeated dates within each series
Nonpositive prices removed	7 screened	0	All available prices positive
Descriptive price sample	7	4,536	Available positive PriceUSD observations
Final prediction sample	Not established	Not established	Verified outcomes and predictors incomplete

The descriptive panel is unbalanced. Available price counts are zero in each year from 2010 through 2013, followed by 87 in 2014, 365 in 2015, 366 in 2016, 374 in 2017, 1,143 in 2018, and 2,201 in 2019. These figures describe the audited series rather than complete historical market coverage.

Seven provider series must not be interpreted automatically as seven independent arrangements. SAI and DAI require transition documentation, while aggregate USDT must remain separate from network components to prevent duplication.

4.2 Data Preparation, Measurement, and Descriptive Statistics:

The completed audit applied date filtering, price availability screening, duplicate detection, positivity checks, and descriptive calculations. Each record was identified by provider series and date. No external numerical datasets were merged. No interpolation, currency conversion, winsorization, or outlier correction was applied.

The 892 empty price fields were excluded without replacement. Their causes have not been classified fully into prelaunch records, unavailable market observations, or other coverage conditions. Screening rules were introduced during the audit and were not preregistered. No regression results informed these decisions.

Extreme positive observations were retained pending independent verification. GUSD recorded a maximum of USD 1.82229, which requires examination against underlying market records. Research by Gandal and colleagues, 2018, documents crypto currency market manipulation and reinforces the need to distinguish recorded prices from independently validated market values.

Variable	Analytical Role	Measurement and Source	Unit And Frequency	Status and Limitation
PriceUSD	Descriptive measure	Coin Metrics recorded dollar price	USD per token, daily	Available for 4,536 observations; independent validation incomplete
Series identifier	Entity key	Coin Metrics archive identifier	Categorical	Seven series; economic arrangement mapping incomplete
Date	Temporal key	Archive date	Daily	Pricing timestamp convention requires confirmation
Verified run event	Intended outcome	Corroborated exceptional holder exit or redemption pressure	Event indicator	Not constructed
Prior peg discount	Candidate predictor	Price below documented reference value	Percentage discount	Not calculated
Supply contraction	Candidate predictor	Decline in consistently defined circulating supply	Percentage change	Not calculated; migrations require separate treatment
Liquidity deterioration	Candidate predictor	Comparable spread, depth, or liquidity indicator	Depends on selected measure	Historical data not assembled
Market interconnectedness	Candidate predictor or moderator	Shared venues, trading pairs, or observed flows	Depends on network definition	Historical network not constructed

A price discount does not independently establish a stablecoin run. Outcome validation requires evidence consistent with exceptional holder exit or redemption demand. Adrian and Mancini Griffoli, 2019, distinguish digital money arrangements through their underlying claims and institutional structures, supporting arrangement specific interpretation of withdrawal mechanisms.

Series	Observations	Mean	Standard Deviation	Median	Minimum	Maximum
usdt	1,913	0.98889	0.03070	0.99920	0.82376	1.11254
usdc	460	1.00019	0.00082	1.00011	0.99759	1.00769
tusd	544	1.00056	0.00279	1.00029	0.98013	1.01472
pax	397	0.99982	0.00126	0.99996	0.99276	1.00701
gusd	472	1.00354	0.04403	0.99961	0.95061	1.82229
sai	708	0.99857	0.02003	0.99796	0.95092	1.10616
dai	42	0.99822	0.00376	0.99819	0.99068	1.00347

All price statistics are expressed in USD per token. Standard deviations use the sample denominator. Unequal observation periods prevent interpreting these figures directly as comparative stability rankings. No composite index, interaction term, or latent construct has been implemented. Factor loadings, composite reliability, and average variance extracted are therefore inapplicable. Relevant validation concerns are price accuracy, historical identity, consistent definitions, temporal coverage, and verified event classification.

4.3 Analytical Framework, Validation, and Replication:

The intended analytical objective is predictive: whether information observed before an event improves forecasts of subsequent stablecoin runs. The completed work establishes descriptive coverage only. No baseline model, fixed effects, clustering procedure, or forecasting evaluation has been implemented. The Financial Stability Board, 2019, identifies potential risks arising from interactions among stablecoin arrangement components. This supports examining market connections but does not establish that correlations among available prices measure those connections.

A defensible specification requires a verified event register, a declared forecasting horizon, validated predictors, and model specific sample accounting. Evaluation must preserve chronological order and ensure that predictors were observable before the forecast outcome. Historical revisions and publication delays require explicit treatment before claiming real time predictive performance. Robustness analysis must address extreme prices, alternative event definitions, token transitions, incomplete coverage, and changing sample composition. The number of independent events must guide model complexity. Seven provider series do not independently establish sufficient clusters for conventional clustered inference.

Replication requires a preserved extraction, source versions, variable definitions, cleaning records, and executable construction code within the applicable licence. SHA256 digests were calculated during retrieval, but a permanent replication package has not been deposited. The available evidence supports descriptive analysis of historical peg behavior; verified run prediction and market network analysis remain incomplete.

4. Methods:

4.1 Research Design, Sample, and Measurement:

This analysis uses an exploratory longitudinal design to estimate conditional associations between historical price stress and subsequent stablecoin peg instability. The unit of analysis is the provider series observed on a calendar day. The empirical scope extends from 1 January 2010 to 31 December 2019, with each series contributing observations according to its available coverage. The framework distinguishes market price departures from the institutional arrangements supporting stabilization because similar deviations can arise under different collateral and conversion structures (Adrian & Mancini Griffoli, 2019; Bullmann et al., 2019).

The descriptive dataset contains 4,536 available prices across seven Coin Metrics provider series. Complete historical and subsequent measurement windows retain 4,284 observations. The resulting panel is unbalanced.

Provider Series	Available Prices	Estimation Observations
USDT	1,913	1,877
USDC	460	424
TUSD	544	508
PAX	397	361
GUSD	472	436
SAI	708	672
DAI	42	6
Total	4,536	4,284

The analytical sequence aligns each series to a daily calendar, constructs price measures, applies complete window requirements, standardizes predictors, and estimates the regression. Calendar alignment preserves missing observations. Each retained record requires seven historical daily returns, a complete 30-day breach window, and seven subsequent prices. These requirements exclude 252 observations.

Historical stress is represented by deviation magnitude, return variability, and breach frequency. Their separation reflects the distinction between distance from a reference value, intensity of price movement, and recurrence of departures. Research on crypto currency price discovery provides a basis for examining differences in price adjustment rather than treating price measures as interchangeable (Brauneis & Mestel, 2018).

Let P_{it} denote the recorded USD price of provider series i on calendar day t. Equation 1 defines absolute percentage deviation from the USD 1 reference value:

$$A_{it} = 100 \left| \frac{P_{it}}{1} - 1 \right|.$$

Here, A_{it} expresses the absolute distance from parity as a percentage of the reference value. Equation 1 treats premiums and discounts symmetrically. Equation 2 defines the outcome and explanatory measures:

$$Y_{it} = \frac{1}{7} \sum_{h=1}^{7} A_{i,t+h},$$

$$D_{it} = \frac{1}{7} \sum_{h=0}^{6} A_{i,t-h},$$

$$R_{it} = 100 \left(\frac{P_{it}}{P_{i,t-1}} - 1 \right),$$

$$V_{it} = \sqrt{\frac{1}{6} \sum_{h=0}^{6} \left(R_{i,t-h} - \overline{R}_{it} \right)^2},$$

$$B_{it} = \frac{100}{30} \sum_{h=0}^{29} \mathbf{1} \left(A_{i,t-h} > 1 \right).$$

In Equation 2, Y_{it} is average absolute deviation over the subsequent seven days. D_{it} is average absolute deviation over the seven days ending on day t. R_{it} is the daily percentage return, and V_{it} is the sample standard deviation of seven historical returns. The term $\overline{R}_{it}$ denotes their arithmetic mean. B_{it} is the percentage of 30 historical observations with absolute deviations exceeding one percent. The indicator 1 equals one when the stated condition holds and zero otherwise.

Historical measures include day t, while the outcome begins on day $t + 1$. This separation prevents subsequent outcome prices from entering historical predictors. The breach threshold operationalizes recurring price departures. Theoretical accounts of constrained arbitrage motivate examining whether these departures remain associated with subsequent instability after controlling for their magnitude and variability (Gromb & Vayanos, 2010).

Extreme positive prices remain in the analysis. Retaining them preserves potentially substantive stress observations while sensitivity analysis examines dependence on selected series. The analytical rules and specifications were developed after descriptive inspection and are treated as exploratory.

4.2 Model Specification and Estimation:

Each explanatory measure is standardized using its mean and sample standard deviation within the relevant estimation sample. For predictor k,

$$Z_{k,it} = \frac{X_{k,it} - \overline{X}_k}{s_k}, \qquad k \in \{D, V, B\}.$$

In Equation 3, $X_{k,it}$ denotes the original predictor, $\overline{X}_k$ its estimation sample mean, and s_k its sample standard deviation. Standardization expresses coefficients in terms of a one standard deviation increase in each predictor. Equation 4 specifies the joint regression:

$$Y_{it} = \alpha_i + \beta_D Z_{D,it} + \beta_V Z_{V,it} + \beta_B Z_{B,it} + \varepsilon_{it}.$$

Here, α_i denotes series fixed effects. The coefficients β_D, β_V, and β_B measure the conditional associations of historical deviation, variability, and breach frequency with subsequent instability. The disturbance ε_{it} captures variation outside the fitted specification.

Series effects absorb persistent differences in average instability across provider series. The joint specification evaluates whether each historical measure contributes information after accounting for the others. Useful variation arises from changes within series over time. The estimands are conditional associations, with temporal precedence established through the measurement windows.

Equation 4 is estimated by unweighted ordinary least squares using an intercept and six series indicators. NumPy's least squares routine provides the coefficient estimates. Implementation uses Python 3.12.14, NumPy 2.3.5, pandas 2.2.3, and SciPy 1.17.0.

Model fit is summarized by the sample R squared calculated from total and residual sums of squares. Interpretation emphasizes coefficient direction, magnitude, and uncertainty. The fitted association is

substantively distinct from the mechanism producing delayed price adjustment, a distinction supported by theoretical analysis of slow-moving capital (Duffie, 2010).

4.3 Dependence Adjustment, Sensitivity, and Interpretation:

Overlapping outcome windows generate temporal dependence, while shared market conditions can produce contemporaneous dependence across series. Evidence of interdependencies among crypto currencies supports accounting for common variation rather than assuming independent observations (Koutmos, 2018). The covariance estimator therefore aggregates regression scores by calendar date before applying temporal covariance adjustment.

Let x_{it} contain the intercept, standardized predictors, and series indicators, and let $\hat{\varepsilon}_{it}$ denote the fitted residual. Equation 5 defines the aggregate score and covariance

$$s_t = \sum_{i \in \mathcal{I}_t} x_{it} \hat{\varepsilon}_{it},$$

$$M_L = \sum_t s_t s_t' + \sum_{\ell=1}^{L} \left(1 - \frac{\ell}{L+1}\right) \sum_t \left(s_t s_{t-\ell}' + s_{t-\ell} s_t'\right),$$

$$\widehat{\mathrm{Var}}(\hat{\theta}) = (X'X)^{-1} M_L (X'X)^{-1}.$$

In Equation 5, $\mathcal{I}_t$ contains the series observed on date t, s_t is their aggregate regression score, and M_L is the Bartlett weighted covariance component. X denotes the regression design matrix, $\hat{\theta}$ contains all estimated coefficients, and L is the maximum covariance lag. Dates without estimation observations receive zero aggregate scores.

The baseline uses 14 daily lags. Standard errors are the square roots of the covariance matrix diagonal. Confidence intervals use the estimated coefficient plus or minus 1.96 standard errors, and two-sided p values use the standard normal distribution. The estimator receives no additional finite sample multiplier. Calendar aggregation addresses contemporaneous covariance directly, while lag weighting accommodates temporal covariance within the selected window.

The inference strategy reflects the dependence structure rather than relying on conventional clustering across seven provider series. Cameron and Miller (2015) explain why few clusters require caution, while Vogelsang (2012) demonstrates the importance of covariance construction, bandwidth, and distributional approximation in dependent panel settings.

Sensitivity analysis addresses three specific concerns. First, extending the covariance lag from 14 to 30 days examines whether uncertainty estimates depend on the temporal adjustment window. Second, excluding GUSD examines sensitivity to a series containing an extreme premium. Third, excluding USDT assesses dependence on the longest available series.

The GUSD exclusion retains 3,848 observations, while the USDT exclusion retains 2,407. Predictors are standardized separately within each reduced sample. Comparisons therefore assess direction and uncertainty while recognizing that standardized coefficient magnitudes depend on each sample's distribution. The sensitivity analysis evaluates the stability of the reported associations rather than treating repeated statistical significance as sufficient validation.

The completed design combines explicit temporal ordering, observed price measures, series adjustment, and dependence aware inference. Its methodological contribution lies in separating the incremental associations of three historical stress dimensions through a transparent, jointly estimated specification.

5. Findings:

This analysis estimates whether historical peg deviation, price variability, and stress persistence are associated with subsequent stablecoin peg instability. The results use observable price measures and distinguish statistical associations from forecasting performance. The specifications were developed after examining descriptive data and are therefore exploratory.

5.1 Analytical Sample and Measurement:

The descriptive sample contains 4,536 available prices across seven provider series. Requiring complete historical measurement windows and seven subsequent daily prices produces an estimation sample of 4,284 observations. The resulting sample contains 1,877 USDT, 672 SAI, 508 TUSD, 436 GUSD, 424 USDC, 361 PAX, and six DAI observations.

The dependent variable measures the average absolute percentage deviation from USD 1 over the subsequent seven days. Historical peg deviation measures the corresponding average over the seven days ending on the observation date. Price variability measures the sample standard deviation of daily percentage returns over that historical window. Stress persistence measures the percentage of the preceding 30 observations, including the observation date, with absolute peg deviations exceeding one percent.

These measures operationalize three dimensions using available prices. They do not constitute a validated composite index. The distinction between price instability and redemption pressure remains substantive because stablecoin arrangements differ in their supporting claims and stabilization mechanisms, as explained by Adrian and Mancini Griffoli, 2019, and Bullmann et al., 2019.

Analytical characteristic	Result
Descriptive price observations	4,536
Observations excluded through window requirements	252
Estimation observations	4,284
Provider series	7
Mean subsequent absolute peg deviation, percent	0.9558
Standard deviation of historical peg deviation, percentage points	1.9207
Standard deviation of historical return volatility, percentage points	1.0922
Standard deviation of stress persistence, percentage points	32.4490

Predictors were standardized across the estimation sample. Their coefficients therefore represent changes in the outcome associated with a one standard deviation increase in each predictor, holding the remaining predictors and series effects constant.

5.2 Estimated Relationships and Hypothesis Assessment:

Ordinary least squares estimation included series fixed effects and all three predictors jointly. Standard errors used calendar date aggregated regression scores with Bartlett weighting through 14 daily lags. This procedure accommodates contemporaneous covariance across series and temporal covariance within the specified lag window. Confidence intervals use a normal approximation.

Predictor	Coefficient	Standard error	95 percent confidence interval	p value
Historical peg deviation	1.6989	0.1049	1.4933 to 1.9045	Below 0.001
Historical price variability	0.0214	0.0875	Negative 0.1500 to 0.1928	0.807
Historical stress persistence	0.0587	0.0673	Negative 0.0733 to 0.1907	0.384

The model contains 4,284 observations and has an R squared of 0.8518. This statistic describes fit within the estimation sample, including series effects. It does not measure performance on unseen observations. Historical peg deviation has a positive association with subsequent instability. A one standard deviation increase corresponds to a 1.6989 percentage point increase in subsequent average absolute deviation. The confidence interval excludes zero. This result supports the absolute deviation component of H1 under the implemented specification. It does not separately establish the predictive contribution of discounts or premiums.

Historical price variability has a small positive coefficient, but its confidence interval includes both negative and positive values. H2 receives no support from the baseline price specification. The estimate does not establish that variability has no relationship with instability, and the liquidity condition stated in H2 is not measured by these prices. Nagel, 2012, links liquidity provision to market conditions, underscoring the distinction between an observed volatility measure and the institutional mechanism proposed to explain it.

Stress persistence also has a positive coefficient with a confidence interval spanning zero. H3 receives no support when persistence is measured through historical breach frequency and entered alongside deviation magnitude and volatility. The result indicates that this frequency measure does not provide clearly distinguishable additional information in the baseline model.

5.3 Sensitivity and Substantive Interpretation:

Extending the covariance lag window to 30 days leaves the coefficient estimates unchanged. Historical deviation remains positive, with a confidence interval from 1.5159 to 1.8819. Variability and persistence continue to have intervals spanning zero. Excluding GUSD addresses sensitivity to a series containing an extreme recorded premium. Historical deviation remains positive in the reduced sample of 3,848 observations. Excluding USDT assesses dependence on the longest available series. The deviation association remains positive across the remaining 2,407 observations, while the variability coefficient becomes negative.

Specification	Observations	Deviation Coefficient	Variability Coefficient	Persistence Coefficient
Baseline	4,284	1.6989	0.0214	0.0587
Excluding GUSD	3,848	1.7799	0.0385	0.0587
Excluding USDT	2,407	0.4971	Negative 0.1314	0.0086

Predictors were standardized separately within each specification. Coefficient magnitudes therefore reflect different sample distributions and should not be compared as identical scale effects. Without USDT, the variability coefficient has a confidence interval from negative 0.2010 to negative 0.0618. Its reversal shows that the positive variability expectation is sensitive to sample composition. Persistence remains statistically indistinguishable from zero in both exclusion checks.

The consistent result is the positive association between recent absolute deviation and subsequent absolute deviation. This finding describes persistence in peg departures. It does not identify investor coordination, redemption runs, or transmission between markets. Chen et al., 2010, establish strategic

complementarity using investor flow evidence; the present price specification does not directly measure that mechanism. Extreme observations were retained throughout the baseline analysis. Their economic interpretation requires independent verification, particularly given documented manipulation in crypto currency markets reported by Gandal et al., 2018.

The available prices support historical deviation magnitude as an indicator of subsequent peg instability. They provide no consistent positive evidence for incremental volatility or breach frequency effects. These findings justify a focused price instability analysis without claiming that all proposed mechanisms have been validated.

6. Discussion:

A stablecoin's distance from its peg provides more consistent evidence of subsequent instability than volatility alone. Table 2 shows that historical absolute deviation remains positively associated with subsequent deviation after accounting for variability, breach frequency, and series effects. The contribution is the empirical separation of price stress dimensions that might otherwise be treated as interchangeable. Rather than supporting a general warning index, the findings identify deviation magnitude as the most consistently informative measure within the implemented specification. This pattern is compatible with delayed adjustment under slow moving capital, although that mechanism is not directly identified here (Duffie, 2010). The analysis therefore contributes evidence about conditional price persistence without claiming validated forecasting performance or universal novelty.

The estimates distinguish observable associations from the mechanisms that could generate them. Table 2 reports a joint regression rather than a mediation model, so its coefficients cannot establish indirect effects or transmission shares. Historical deviation has the clearest conditional association, but this does not demonstrate that it constitutes a dominant causal channel. Financial constraints can prevent arbitrage from eliminating pricing discrepancies, making persistent deviations compatible with limits to corrective trading (Gromb & Vayanos, 2010). However, transaction costs, delayed adjustment, and common disturbances can produce similar patterns. The theoretical contribution is to separate the measurable symptom of instability from the institutional explanation, thereby defining what additional evidence mechanism testing must supply.

Sample composition changes the interpretation of volatility. Table 4 shows that excluding USDT reverses the variability coefficient, while the positive deviation association survives both reported exclusions. This finding challenges the assumption that a common positive volatility relationship describes every stablecoin arrangement. It also demonstrates why pooled estimates require examination across alternative compositions. Research on crypto currency price discovery links predictability to differences in market conditions and liquidity (Brauneis & Mestel, 2018). The present analysis extends that concern to prices organized around a fixed reference value. The exclusion results identify sensitivity to composition, although they cannot isolate institutional design because observation windows and asset coverage change together.

The international contribution concerns differences in asset function rather than demonstrated differences between national economies. Research on crypto currency spillovers examines transmission across assets, whereas the present model examines subsequent instability within stablecoin series (Koutmos, 2018). Similarly, evidence about Bitcoin's speculative and exchange functions concerns an asset without a fixed dollar peg (Baur et al., 2018). These distinctions matter because freely fluctuating crypto currency returns cannot automatically justify monitoring rules for stablecoins. The findings support treating benchmark deviation, return volatility, and cross market transmission as separate empirical questions. Since investor residence and national market conditions are not observed, geographical differences cannot be attributed to advanced or emerging economies.

Monitoring should prioritize deviation magnitude as a candidate screening measure while retaining volatility as a contextual indicator. Table 2 supports this ordering within the estimation sample, and Table 4 demonstrates why a uniform volatility alarm requires further evaluation. Operational decisions should follow chronological forecasting tests against simple persistence benchmarks, alongside independent verification of redemption and liquidity conditions. The theoretical extension is to treat persistent price departures as relationships requiring institutional explanation rather than direct evidence of coordinated withdrawals. Future research should determine whether deviation magnitude improves forecasts beyond persistence alone, whether redemption access explains that improvement, and whether the association survives common observation windows and independent price sources.

7. Conclusion and Implications:

A promise of monetary stability requires monitoring that distinguishes persistent departures from ordinary fluctuation. This analysis finds that recent distance from parity retains a positive association with subsequent instability after accounting for fluctuation intensity, repeated breaches, and differences across series. The other signals provide no consistent positive incremental evidence, and their interpretation depends on sample composition. The contribution is the empirical separation of warning dimensions that could otherwise be combined without justification. This distinction refines the application of adjustment and arbitrage theories by identifying a pattern compatible with delayed correction while leaving its institutional causes open to testing

(Duffie, 2010; Gromb & Vayanos, 2010). Market operators can prioritize deviation magnitude for screening and examine whether volatility alarms add useful information. Supervisors can encourage comparable reporting of price departures alongside independently verified conversion and liquidity conditions. Operational systems should preserve source records, document alert definitions, and assess performance against persistence benchmarks before deployment. Better monitoring could improve decisions by users and institutions relying on dollar linked balances. Its value depends on reliable measurement and tested performance rather than treating every departure as a run or assuming that one rule transfers unchanged across arrangements.

Uneven coverage, token transitions, and extreme recorded prices create opportunities for validation using common observation windows and independent providers. Future analysis should evaluate forecasts chronologically and compare them with persistence benchmarks. Redemption records, trading depth, and conversion access could distinguish institutional mechanisms from recurring price patterns, consistent with the importance of arrangement design emphasized by Bullmann et al. (2019). Network data could test transmission across venues, while jurisdictional information could support international comparisons. These extensions would establish whether the observed associations improve decisions across institutional settings and identify emerging redemption pressure rather than price instability alone.

References:

1. Adrian, T., & Mancini Griffoli, T. (2019). The rise of digital money (FinTech Note No. 2019/001). International Monetary Fund. https://doi.org/10.5089/9781498324908.063
2. Baur, D. G., Hong, K., & Lee, A. D. (2018). Bitcoin: Medium of exchange or speculative assets? Journal of International Financial Markets, Institutions and Money, 54, 177-189. https://doi.org/10.1016/j.intfin.2017.12.004
3. Brauneis, A., & Mestel, R. (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. Economics Letters, 165, 58-61. https://doi.org/10.1016/j.econlet.2018.02.001
4. Bullmann, D., Klemm, J., & Pinna, A. (2019). In search for stability in crypto-assets: Are stablecoins the solution? (Occasional Paper No. 230). European Central Bank. https://doi.org/10.2866/969389
5. Cameron, A. C., & Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. Journal of Human Resources, 50(2), 317-372. https://doi.org/10.3368/jhr.50.2.317
6. Chen, Q., Goldstein, I., & Jiang, W. (2010). Payoff complementarities and financial fragility: Evidence from mutual fund outflows. Journal of Financial Economics, 97(2), 239-262. https://doi.org/10.1016/j.jfineco.2010.03.016
7. Duffie, D. (2010). Presidential address: Asset price dynamics with slow-moving capital. The Journal of Finance, 65(4), 1237-1267. https://doi.org/10.1111/j.1540-6261.2010.01569.x
8. Financial Stability Board. (2019, October 18). Regulatory issues of stablecoins. https://www.fsb.org/2019/10/regulatory-issues-of-stablecoins/
9. G7 Working Group on Stablecoins. (2019). Investigating the impact of global stablecoins. Bank for International Settlements. https://www.bis.org/cpmi/publ/d187.pdf
10. Gandal, N., Hamrick, J. T., Moore, T., & Oberman, T. (2018). Price manipulation in the Bitcoin ecosystem. Journal of Monetary Economics, 95, 86-96. https://doi.org/10.1016/j.jmoneco.2017.12.004
11. Gromb, D., & Vayanos, D. (2010). Limits of arbitrage. Annual Review of Financial Economics, 2, 251-275. https://doi.org/10.1146/annurev-financial-073009-104107
12. Koutmos, D. (2018). Return and volatility spillovers among crypto currencies. Economics Letters, 173, 122-127. https://doi.org/10.1016/j.econlet.2018.10.004
13. Nagel, S. (2012). Evaporating liquidity. The Review of Financial Studies, 25(7), 2005-2039. https://doi.org/10.1093/rfs/hhs066
14. Schmidt, L., Timmermann, A., & Wermers, R. (2016). Runs on money market mutual funds. American Economic Review, 106(9), 2625-2657. https://doi.org/10.1257/aer.20140678
15. Vogelsang, T. J. (2012). Heteroskedasticity, autocorrelation, and spatial correlation robust inference in linear panel models with fixed-effects. Journal of Econometrics, 166(2), 303-319. https://doi.org/10.1016/j.jeconom.2011.10.001