COMILLAS
UNIVERSIDAD PONTIFICIA

Facultad de Ciencias Económicas y Empresariales
ICADE

WHEN THE PEG BREAKS: CHARACTERIZING STABLECOIN CRISES

Author: Álvaro Moroño Moreno
Director: David Tercero Lucas

MADRID | June 2026

ABSTRACT

This thesis examines stablecoin de-pegging episodes through the lens of traditional currency crisis theory. Using daily price data from CryptoCompare for six major stablecoins (USDT, USDC, TUSD, BUSD, DAI, and USTC) over the period July 2017 – December 2025, the analysis identifies 85 crisis episodes under a 2% deviation threshold and characterizes them along three dimensions: frequency, duration, and severity. The results reveal a clear gradient across stablecoin design types. Fiat-backed stablecoins experience frequent but mild and quickly resolved episodes, consistent with first-generation crisis models where reserve credibility limits the depth of speculative pressure. Crypto-backed stablecoins exhibit fewer but longer and more severe episodes concentrated during periods of broad market stress, consistent with third-generation models emphasizing financial fragility and contagion. The single algorithmic stablecoin in the sample (USTC) suffered a catastrophic and irreversible collapse, consistent with second-generation models where the absence of reserves allows self-fulfilling expectations to drive peg failure. These findings suggest that stablecoin de-pegs, despite occurring in a novel institutional environment, appear to reflect monetary dynamics similar to those studied in the sovereign currency crisis literature. The thesis contributes a systematic, replicable framework for identifying and measuring stablecoin crises, and offers insights relevant to stablecoin design, risk assessment, and regulatory policy.

Keywords: stablecoins, de-pegging, currency crises, fixed exchange rates, financial stability, cryptocurrency

TABLE OF CONTENTS

INDEX OF TABLES AND FIGURES

Tables

Figures

1. INTRODUCTION

1.1. Why are stablecoin crises relevant?

Stablecoins have become one of the most consequential innovations in crypto markets, mediating trillions of dollars of annual transaction volume and serving as the main bridge between digital asset ecosystems and traditional finance. Yet their core promise, maintaining a stable peg to a reference asset, has repeatedly failed in practice. Although the literature has made important progress in documenting stablecoin instability (Briola et al., 2023; Duan & Urquhart, 2023; Hoang & Baur, 2024; Lee et al., 2025), it remains fragmented along methodological and conceptual lines. Existing studies typically focus on either aggregate price stability metrics, individual crisis events, contagion dynamics, or predictive modelling, but rarely integrate these perspectives into a unified analytical framework grounded in monetary theory (Ante et al., 2023). In particular, there is no systematic characterization of stablecoin crises comparable to the extensive empirical literature on sovereign currency crises (Eichengreen et al., 1995; Frankel & Rose, 1996; Kaminsky & Reinhart, 1999), a literature that provides standardized crisis dating, severity measurement, and theoretical interpretation across countries and time periods.

This thesis addresses three interrelated gaps. First, it provides a systematic identification of stablecoin crisis episodes using transparent and replicable criteria adapted from the currency crisis literature (Frankel & Rose, 1996; Girton & Roper, 1977). Rather than focusing on a single event or stablecoin, the analysis covers multiple major stablecoins (USDT, USDC, TUSD, BUSD, DAI and USTC, formerly known as UST) across different design types (fiat-backed, crypto-backed, algorithmic) and an extended time period, allowing for meaningful cross-sectional and temporal comparisons. We aim at identifying patterns that may be obscured in case-study-based research.

Second, the thesis introduces a multidimensional measurement of crisis severity, capturing not only the maximum deviation from the peg but also the cumulative deviation and the time required for recovery, consistent with the currency crisis literature. The separate measurement of these dimensions allows the thesis to complement studies based on binary crisis indicators or single severity measures, offering a more detailed characterization of crisis intensity.

Third, and most importantly from a conceptual standpoint, the thesis explicitly interprets stablecoin crises through the lens of established currency crisis models (Kaminsky & Reinhart, 1999; Krugman, 1979; Obstfeld, 1984). We map observed de-pegging events onto first-generation (fundamentals-driven), second-generation (expectations-driven), and third-generation (contagion and financial fragility) crisis mechanisms. Hence, the analysis situates stablecoin instability within a well-developed theoretical tradition spanning nearly five decades of research. This perspective allows stablecoin de-pegs to be understood not as isolated failures of digital technology, but as digital manifestations of familiar monetary dynamics: fixed exchange rate commitments vulnerable to reserve exhaustion, self-fulfilling expectations, and systemic contagion.

1.2. Research questions:

This thesis tries to provide insights about two core empirical questions:

1. How frequent are stablecoin crises, and how do their frequency, duration, and severity vary across stablecoin designs?
2. To what extent do stablecoin de-pegging episodes exhibit patterns consistent with traditional currency crisis models?

1.3. Contribution of the thesis

The contribution of the thesis is therefore primarily conceptual and empirical rather than predictive. Unlike studies focused on forecasting future de-pegs (Lee et al., 2025), this work seeks to characterize past crisis episodes systematically and interpret them through established theoretical frameworks. We adapt classical crisis-measurement tools (Eichengreen et al., 1995; Frankel & Rose, 1996; Girton & Roper, 1977) to stablecoin markets so as to bridge the gap between macroeconomic crisis theory and the emerging literature on digital currencies (Aldasoro et al., 2025; Ante et al., 2023). In doing so, the manuscript offers a structured framework for comparing stablecoin designs, evaluating their relative vulnerability to different crisis mechanisms, and provides insights relevant to researchers seeking to understand stablecoin instability, investors assessing risk exposure, and policymakers concerned with financial stability in digital asset markets (Aldasoro et al., 2025).

Ultimately, we demonstrate that stablecoin crises exhibit patterns consistent with traditional currency crises despite operating in radically different institutional environments, contributing to a deeper understanding of what makes fixed-value commitments credible or fragile, whether issued by central banks or algorithms. Figure 1 provides a visual overview of the main empirical findings.

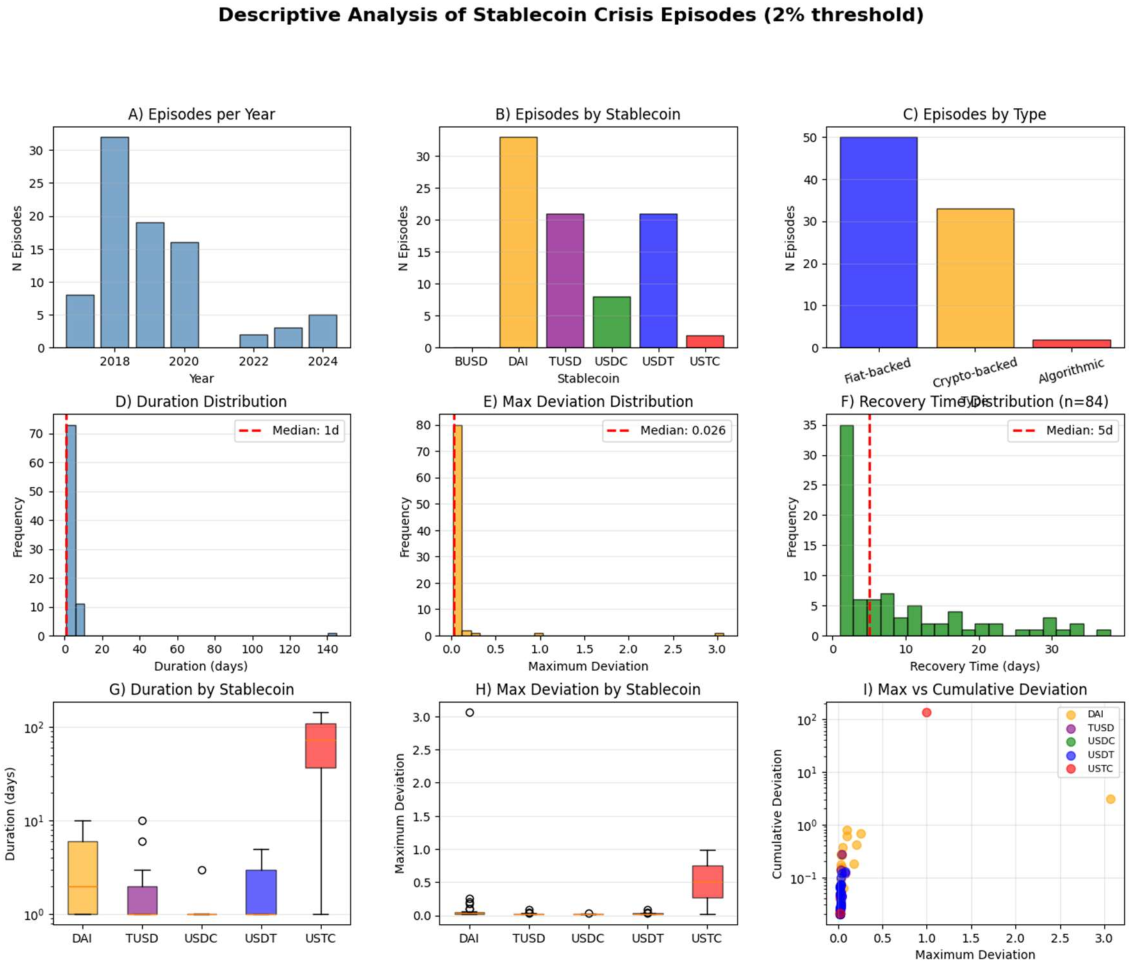


Figure 1: Summary of empirical findings

Source: own elaboration based on data from CryptoCompare (2017–2025).

1.4. Structure of the work

The remainder of this thesis is organized as follows. Section 2 reviews the relevant literature on stablecoin stability and currency crisis theory, establishing the three-generation analytical framework. Section 3 describes the data, including stablecoin selection criteria, variable definitions, and data quality filters. Section 4 presents the crisis identification methodology. Section 5 reports the descriptive results across four dimensions: frequency, duration, severity, and comparison across design types. Section 6 discusses the findings, interpreting them through the currency crisis framework and drawing comparisons with sovereign experience. Section 7 presents conclusions, limitations, and directions for future research. Supplementary materials, including the full episode catalog and robustness check results, are provided in the Appendices.

2. LITERATURE REVIEW

2.1. Stablecoins: definition and main types

Stablecoins are a class of crypto-assets designed to maintain a stable value relative to a reference asset, most commonly the US dollar (Ante et al., 2023). Unlike traditional cryptocurrencies such as Bitcoin or Ethereum, whose prices are highly volatile, stablecoins aim to function as a diversifier, a hedge, and a safe-haven within digital markets (Gubareva et al., 2023). Their stability objective has made them a critical component of the crypto ecosystem, facilitating trading, lending, payments, and acting as a bridge between traditional finance and decentralized finance (DeFi) (Wen et al., 2025).

At their core, stablecoins can be understood as private digital instruments that promise a fixed exchange rate, typically one-to-one with a fiat currency. This promise is operationalized through different mechanisms, which give rise to distinct categories of stablecoins. The literature generally distinguishes between three main types: fiat-backed stablecoins, crypto-backed stablecoins, and algorithmic stablecoins (Ante et al., 2023).

Fiat-backed stablecoins are the most widely used and intuitively structured. They are backed by reserves denominated in fiat currency or near-cash instruments, such as Treasury bills, bank deposits, or money market funds. In principle, each token in circulation is matched by an equivalent value of reserves, allowing holders to redeem the stablecoin at par. Prominent examples include USDT (Tether) and USDC (USD Coin). These stablecoins operate under a model where liabilities are fully backed by liquid assets (Aldasoro et al., 2025). Their stability therefore depends on the credibility, liquidity, and transparency of the reserve backing, as well as on users' confidence in the issuer's ability to honor redemptions. However, empirical evidence suggests that even well-established fiat-backed stablecoins experience episodes of de-pegging during periods of market stress (Hoang & Baur, 2024).

Crypto-backed stablecoins rely on reserves denominated in other cryptocurrencies rather than fiat assets. Because crypto-assets are volatile, these systems typically require overcollateralization and automatic liquidation mechanisms to absorb price fluctuations (Ante et al., 2023; Duan & Urquhart, 2023). DAI is the most prominent example of this category. Its peg is maintained through smart contracts that lock crypto collateral (such as ETH) and issue stablecoins against it, subject to collateralization ratios above 100%. While this design reduces reliance on traditional financial institutions, it introduces exposure to crypto market volatility and complex feedback loops during periods of stress. The instability inherent in crypto-collateralized systems becomes particularly acute during broad market downturns, when collateral values decline rapidly and liquidation cascades can emerge.

Algorithmic stablecoins aim to maintain their peg without explicit collateral backing, instead relying on supply-adjustment rules and market incentives. These systems expand or contract the supply of the stablecoin in response to deviations from the peg, often through a secondary token that absorbs volatility. The collapse of TerraUSD (UST) in

May 2022 illustrates the fragility of this design (Briola et al., 2023): when confidence in the stabilization mechanism eroded, the system entered a self-reinforcing spiral that led to a rapid and irreversible de-peg, wiping out approximately $40 billion in market value. Algorithmic stablecoins therefore resemble highly fragile fixed-rate systems with no effective reserves to defend parity.

This typology is central to the present study, as each stablecoin design embeds different sources of vulnerability. While fiat-backed stablecoins are primarily exposed to reserve adequacy and transparency issues, crypto-backed designs face collateral volatility and liquidation risks, and algorithmic stablecoins depend critically on expectations and confidence. These differences suggest that stablecoin crises may not be homogeneous, but instead reflect distinct failure mechanisms closely related to their underlying stabilization architecture. We will test the hypothesis empirically in the analysis of de-pegging episodes presented in Sections 4 and 5.

2.2. Peg mechanisms, analogy with fixed exchange rate regimes

The defining feature of stablecoins is their commitment to a fixed value relative to a reference asset, most commonly the US dollar. This commitment closely parallels the logic of traditional fixed exchange rate regimes, in which a monetary authority pledges to maintain a stable parity between the domestic currency and a foreign anchor currency. Although stablecoins are privately issued and operate in digital markets, the economic logic underlying their pegs is remarkably similar to that of conventional exchange rate arrangements.

In traditional fixed exchange rate systems, maintaining parity requires the ability to intervene in currency markets, typically by using foreign exchange reserves to absorb excess demand or supply (Krugman, 1979). When confidence in the peg weakens, speculative pressure may emerge, forcing the authority to spend reserves or raise interest rates to defend the exchange rate (Eichengreen et al., 1995). If reserves are insufficient or agents anticipate collapse, the peg collapses (Flood & Garber, 1984).

Stablecoins operate under an analogous framework. Instead of a central bank, the issuer or protocol commits to maintaining parity through redemption mechanisms, collateral backing, or algorithmic rules (Ante et al., 2023). If the stablecoin trades below its target value, arbitragers are expected to buy the token and redeem it at par, restoring the peg. Conversely, when it trades above parity, new issuance increases supply and pushes the price back down. In both cases, the credibility of the peg depends on the market's belief that the stabilizing mechanism will function as intended, a dynamic extensively documented in the currency crisis literature (Obstfeld, 1984).

Fiat-backed stablecoins most closely resemble currency boards or hard pegs. Their stability relies on the availability and liquidity of reserves, as well as on legal and operational guarantees of convertibility (Aldasoro et al., 2025). In this sense, concerns about reserve composition, custody, or transparency can generate dynamics similar to those observed in traditional balance-of-payments crises. Even if reserves are nominally sufficient, uncertainty about their quality or accessibility may trigger redemption waves, placing stress on the peg. The March 2023 USDC de-pegging episode, triggered by concerns over Silicon Valley Bank's exposure, exemplifies this mechanism: market participants lost confidence despite adequate aggregate reserves, leading to brief but significant price deviations.

Crypto-backed stablecoins can be compared to fixed exchange rate regimes supported by volatile reserves. Overcollateralization plays a role analogous to holding excess foreign reserves, but sharp declines in collateral value can quickly undermine confidence. During periods of market stress, forced liquidations may amplify downward pressure, resembling the interaction between currency crises and financial fragility highlighted in third-generation crisis models (Kaminsky & Reinhart, 1999; Krugman, 1999). Exactly the feedback mechanism described, where asset prices decline and force liquidations that further depress prices, creates acute vulnerability particularly during broad crypto market downturns.

Algorithmic stablecoins represent the most extreme case. With no effective reserves, their peg depends almost entirely on expectations and coordination among market participants (Briola et al., 2023). This structure closely mirrors second-generation currency crisis models, where self-fulfilling beliefs can trigger a collapse even in the absence of clear fundamental imbalances (Obstfeld, 1984). Once confidence erodes, stabilization mechanisms fail to operate, leading to rapid and irreversible de-pegging, as demonstrated catastrophically by the Terra-Luna collapse in May 2022 (Briola et al., 2023).

Despite important differences, such as the absence of a lender of last resort, 24/7 market operation, and the speed at which digital markets operate, the analogy between stablecoins and fixed exchange rate regimes provides a powerful conceptual framework for analysis. It allows stablecoin de-pegs to be interpreted not as idiosyncratic crypto failures, but as digital manifestations of well-known monetary phenomena. This perspective underpins the empirical analysis that follows, in which stablecoin crises are identified and measured using methodologies originally developed to study exchange rate crises (Frankel & Rose, 1996; Girton & Roper, 1977), adapted to the specific characteristics of the stablecoin market. The application of this framework is detailed in Section 4, where crisis identification criteria are defined.

2.3. Currency Crisis Models and Their Relevance to Stablecoins

Literature on currency crises has traditionally been organized around three generations of theoretical models, each emphasizing different mechanisms through which fixed exchange rate regimes can collapse. Although these models were originally developed to explain sovereign currency crises, their core insights provide a useful framework for interpreting stablecoin de-pegs. Despite important institutional differences between public monetary systems and privately issued digital tokens, the mechanisms of reserve adequacy, expectations, and contagion are highly relevant in both contexts.

This section reviews the three main generations of currency crisis models and explains how their logic can be applied to the analysis of stablecoin instability.

2.3.1. First-generation models: fundamentals-driven crises

First-generation currency crisis models, pioneered by Krugman (1979) and Flood & Garber (1984), explain crises as the inevitable outcome of unsustainable economic fundamentals. In these models, governments attempt to maintain a fixed exchange rate while pursuing policies, such as persistent fiscal deficits or excessive monetary expansion, that are incompatible with the peg. As foreign reserves are gradually depleted to defend the parity, rational investors anticipate the eventual collapse and launch a speculative attack, forcing a devaluation before reserves are fully exhausted (Krugman, 1979).

Speculative attacks in first-generation frameworks are not merely mechanical accelerations of an inevitable collapse, but rather endogenous, rational responses by investors who anticipate reserve exhaustion based on observable policy inconsistencies (Flood & Garber, 1984). If a government monetizes fiscal deficits while maintaining a fixed peg, rational agents forecast the eventual depletion of reserves and act preemptively, launching coordinated attacks that force the abandonment of the peg before reserves reach zero (Flood et al., 1996; Flood & Marion, 2000). The attack itself is thus an integral part of the crisis mechanism, triggered by deteriorating fundamentals rather than exogenous panic.

This logic applies to fiat-backed stablecoins experiencing documented reserve inadequacy. Tether (USDT) provides a clear example: during 2016-2018, the CFTC found that USDT maintained full fiat backing for only 27.6% of the time, with reserves regularly diverted to cover related-entity obligations (CFTC, 2021). Once the evidence of systematic under-collateralization emerged publicly in 2018-2019, rational market participants sold USDT, causing de-pegs to $0.88-$0.95. This mirrors first-generation dynamics: fundamental reserve inadequacy made collapse inevitable if redemptions accelerated, and speculative selling represented a rational response to revealed policy inconsistency between promised full backing and actual fractional reserves (Krugman, 1979).

2.3.2. Second-generation models: expectations and self-fulfilling crises

Second-generation models, most notably developed by Obstfeld (1984), challenge the determinism of first-generation frameworks. These models emphasize the role of expectations and multiple equilibria, showing that a currency peg can collapse even when economic fundamentals appear sound. The key insight is that maintaining a fixed exchange rate imposes costs on policymakers, such as high interest rates or unemployment, and if market participants believe these costs will become politically intolerable, their collective actions can make abandonment of the peg the optimal policy response (Obstfeld, 1984).

In this framework, crises are self-fulfilling: expectations of collapse generate behaviors, such as capital flight or speculative selling, that cause the collapse itself (Eichengreen et al., 1995). Because multiple equilibria exist, a “good” equilibrium where the peg holds and a “bad” equilibrium where it collapses can both be rational outcomes depending on coordination among market participants. Credibility and confidence therefore play a central role, and small shocks, rumors, or shifts in sentiment can trigger large market reactions that push the system from one equilibrium to another (Obstfeld, 1984).

Second-generation models are particularly relevant for fiat-backed stablecoins because even when reserves are nominally sufficient, uncertainty regarding their composition, liquidity, or accessibility may undermine confidence (Obstfeld, 1984). Episodes of heightened scrutiny or negative information, such as concerns about the quality of backing assets or the issuer's transparency, can lead to redemption waves, placing pressure on the peg. Importantly, these dynamics do not require actual insolvency; perceived fragility is sufficient to trigger a crisis (Obstfeld, 1984). The March 2023 USDC de-pegging episode appears consistent with this mechanism: concerns over Circle’s exposure to Silicon Valley Bank, despite adequate overall reserves, triggered redemption pressure that pushed the price to approximately $0.92. Such an episode exhibits characteristics of a crisis rooted in confidence rather than fundamental under-collateralization.

Crypto-backed stablecoins may exhibit similar vulnerabilities. DAI’s “Black Thursday” episode on March 12, 2020 (CoinDesk, 2020), illustrates how second-generation dynamics operate in overcollateralized systems. A 43% ETH price crash coincided with extreme Ethereum network congestion, causing gas prices to spike twentyfold and preventing MakerDAO's oracles from updating prices and liquidation auctions from functioning normally. When prices finally updated, thousands of positions were liquidated simultaneously, many at zero bids due to lack of competing liquidators. The system was fundamentally solvent (collateral existed), yet extreme conditions created a coordination failure where users lost 100% of collateral rather than the advertised 13% penalty. As with second-generation currency crises, these stablecoin de-pegs appear to reflect coordination failures and shifts in market expectations triggered by external shocks, rather than fundamental insolvency.

2.3.3. Third-generation models: financial fragility and contagion

Third-generation crisis models, developed in response to the Asian Financial Crisis of 1997-98, extend the analysis by incorporating interactions between currency markets and financial systems (Kaminsky & Reinhart, 1999). Contributions by Kaminsky & Reinhart (1999) on twin crises and Krugman (1999) on balance-sheet effects highlight how currency depreciation, leverage, and interconnected financial institutions can amplify shocks and transmit crises across markets. These models emphasize corporate and financial sector balance sheets, particularly the dangers posed by currency mismatches, short-term foreign debt, and fire-sale dynamics during liquidity crises (Krugman, 1999).

In these models, currency crises are not isolated events but part of broader episodes of financial instability. The collapse of a peg can weaken balance sheets (especially when liabilities are denominated in foreign currency), trigger liquidity shortages, force asset liquidations at depressed prices, and propagate stress through domestic and international financial networks (Kaminsky & Reinhart, 1999). Contagion effects, where crises in one country or market spread to others through trade linkages, common creditors, or shifts in investor sentiment, are also central to third-generation frameworks.

There is a case to be made that stablecoin markets also exhibit similar amplification mechanisms (Gregory et al., 2024). Many stablecoins are deeply embedded in decentralized finance (DeFi) platforms, trading venues, and collateral chains. A de-peg in one major stablecoin can disrupt liquidity provision across multiple protocols, force automated liquidations of leveraged positions, and affect the pricing and stability of other digital assets. Moreover, when stablecoin reserves are held within the traditional financial system, such as bank deposits or money market instruments, stress can transmit across institutional boundaries, as demonstrated when Silicon Valley Bank's failure affected USDC. These dynamics resemble third-generation crisis mechanisms, where fragility, leverage, and interconnectedness magnify the impact of shocks and enable contagion across seemingly distinct market segments (Gregory et al., 2024).

Other historical episodes illustrate these dynamics concretely. The Iron Finance collapse of June 2021 demonstrates classic bank-run mechanics in decentralized systems: when whales withdrew liquidity from IRON-USDC pools, the resulting TITAN price decline triggered redemption cascades, with newly minted TITAN flooding the market during redemptions and accelerating the death spiral until both tokens reached effective zero within hours. The event destroyed approximately $2 billion in value and propagated stress across the Polygon DeFi ecosystem through shared liquidity pools and interconnected protocols. Similarly, when TerraUSD collapsed in May 2022, contagion spread to Magic Internet Money (MIM), an unrelated stablecoin, which de-pegged to $0.91 as Abracadabra Money absorbed $12 million in bad debt from Terra-linked positions and faced rapid liquidity withdrawals. These episodes display features commonly associated with third-generation crisis features: leverage amplification (high-yield farming positions liquidated en masse), fire-sale dynamics (cascading price collapses), and cross-market contagion where stress in one protocol or token transmitted rapidly through interconnected DeFi infrastructure.

2.3.4. Implications for this thesis

The three generations of currency crisis models provide a structured lens through which stablecoin crises can be interpreted. Rather than estimating or formally testing these models econometrically, this thesis uses them as a conceptual classification framework to organize and interpret empirical patterns. Stablecoin de-pegging episodes are identified and analyzed in terms of their frequency, duration, and severity (Sections 4 and 5), and then interpreted through the lens of fundamentals-driven collapse (first-generation), expectation-driven instability (second-generation), or contagion-based stress (third-generation).

This approach allows stablecoin crises to be understood not as isolated failures of novel technology, but as digital manifestations of well-established monetary phenomena. We ground the empirical analysis in canonical crisis theory, so the thesis connects the emerging literature on stablecoins (Ante et al., 2023; Briola et al., 2023; Hoang & Baur, 2024) with decades of research on exchange rate instability. This theoretical scaffolding informs both the crisis identification methodology presented in Section 4 and the comparative analysis with traditional currency crises developed in Section 6.

2.4. Measurement of Currency Crises in Literature

A central challenge in the empirical study of currency crises is defining precisely when a crisis occurs and how its severity should be measured. Because crises are not directly observable events but rather episodes of abnormal pressure on an exchange rate regime, the literature has developed several operational approaches to identify and date them (Eichengreen et al., 1995). Two broad methodologies dominate empirical work: exchange market pressure indices and threshold-based approaches. These methods provide the foundation for the identification of crisis episodes in this thesis and are adapted to the specific characteristics of stablecoin markets.

2.4.1. Exchange Market Pressure (EMP) indices

One of the earliest and most influential approaches to measuring currency crises is the Exchange Market Pressure (EMP) index, introduced by Girton & Roper (1977) and later refined by Eichengreen et al. (1995). EMP indices aim to capture speculative pressure on a currency by combining movements in the exchange rate with changes in foreign exchange reserves and, in some formulations, interest rates.

The intuition behind the EMP framework is that pressure on a fixed exchange rate may manifest in different ways depending on the policy response (Girton & Roper, 1977). If the peg is successfully defended, pressure appears through reserve losses or interest rate increases. If the defense fails, pressure is observed through sharp exchange rate depreciation. EMP aggregates these components into a single index, measuring the intensity of speculative stress regardless of the policy response, effectively capturing both observed devaluations and successful but costly defenses (Eichengreen et al., 1995).

EMP-based approaches have been widely used in empirical studies of currency crises and form the basis of influential crisis databases, such as those developed by the International Monetary Fund. However, their application requires detailed macroeconomic data, particularly on reserves and interest rates, which are often unavailable or ill-defined outside sovereign monetary systems.

2.4.2. Threshold-based approaches

An alternative and more widely used methodology relies on threshold rules applied directly to exchange rate movements. In this framework, a currency crisis is defined as an episode in which the exchange rate depreciates beyond a specified threshold relative to its recent history or trend (Frankel & Rose, 1996). Prominent contributions by Frankel

& Rose (1996) and Kaminsky & Reinhart (1999) adopt this approach, typically defining crises as large and abrupt devaluations, commonly 25% or more within a 12-month period, though specific thresholds vary across studies.

Threshold-based methods offer several advantages. They are transparent, easy to replicate, and less dependent on auxiliary macroeconomic variables that may be measured with error or unavailable for certain countries (Frankel & Rose, 1996). While the choice of threshold is inherently somewhat arbitrary, the literature has converged on ranges that balance sensitivity (capturing genuine crises) and specificity (avoiding false positives). Moreover, robustness checks using alternative thresholds are commonly employed to ensure that results are not driven by a particular parameter choice (Kaminsky & Reinhart, 1999).

Importantly, threshold approaches emphasize observable outcomes (actual exchange rate movements) rather than policy intentions or unobservable fundamentals, making them particularly suitable for environments where institutional information is limited or heterogeneous (Frankel & Rose, 1996). For this reason, they have become the dominant tool in empirical crisis dating exercises, particularly in cross-country comparative studies.

2.4.3. Adapting crisis measurement to stablecoins

Stablecoins differ fundamentally from sovereign currencies in that they lack central banks, monetary policy instruments, and official reserve disclosures in many cases (Aldasoro et al., 2025). As a result, EMP-style indices are not directly applicable: there are no interest rate adjustments or transparent reserve data to incorporate. However, the core insight of threshold-based approaches can be readily adapted to stablecoin markets (Lee et al., 2025).

In the context of stablecoins, the exchange rate is replaced by the market price of the stablecoin relative to its target value, typically one US dollar. A stablecoin crisis can therefore be defined as an episode in which the price deviates from parity beyond a specified threshold for a minimum duration (Frankel & Rose, 1996). This approach has been increasingly adopted in recent empirical studies on stablecoin instability (Duan & Urquhart, 2023; Lee et al., 2025).

Following the logic of the currency crisis literature, this thesis defines crisis episodes based on three key dimensions:

<u>Deviation threshold</u>: A crisis is identified when the stablecoin price deviates from its peg by more than a predefined percentage (e.g., 2% or 5%). This captures economically meaningful departures from parity while filtering out minor price fluctuations attributable to normal market microstructure or temporary liquidity imbalances. The choice of threshold reflects a trade-off between capturing all significant stress episodes (lower threshold) and focusing on severe disruptions (higher threshold).

<u>Persistence criterion</u>: To avoid classifying short-lived market noise as crises, the deviation must persist for a minimum time window, for example, at least 24 hours or several consecutive daily observations. This requirement ensures that identified episodes reflect

sustained stress rather than transient liquidity effects or momentary arbitrage opportunities that are quickly corrected.

Event-based dating: Crisis episodes are dated from the first day the threshold is breached until the price returns within a narrow band around the peg (e.g., within 1% of parity). This allows each crisis to be treated as a distinct event with a clear beginning and end, facilitating duration analysis and severity measurement.

2.4.4. Measuring crisis severity

Beyond identifying the occurrence of crises, the literature emphasizes the importance of measuring their severity (Kaminsky & Reinhart, 1999). Currency crises vary substantially in magnitude and duration, and simple binary indicators, which treat all crises as equivalent, fail to capture this heterogeneity. To address this limitation, empirical studies commonly rely on continuous measures of crisis intensity.

In line with this tradition, the severity of stablecoin crises in this thesis is captured using three complementary metrics:

Maximum deviation from the peg: This measures the largest observed price departure during the crisis episode, capturing the peak intensity of stress. For example, during the TerraUSD collapse, the maximum deviation approached 100% as the stablecoin became effectively worthless (Briola et al., 2023).

Cumulative deviation: Defined as the sum or integral of deviations from parity over the duration of the crisis, this metric captures both magnitude and persistence. A crisis with moderate deviations sustained over many days may exhibit higher cumulative stress than a sharp but brief spike.

Time to recovery: Measured as the number of days (or hours, depending on data frequency) required for the stablecoin to return to a narrow band around its target value. Longer recovery times indicate deeper disruptions to market confidence and arbitrage mechanisms.

Together, these indicators provide a multidimensional view of crisis severity and allow meaningful comparisons across stablecoins, crisis episodes, and stablecoin design types. They also enable comparison with traditional currency crises, where similar severity metrics have been employed (Frankel & Rose, 1996).

2.4.5. Relevance for empirical analysis

The measurement framework outlined above provides a transparent and replicable method for identifying stablecoin crises. Our approach adapts well-established tools from the currency crisis literature (Eichengreen et al., 1995; Frankel & Rose, 1996; Girton & Roper, 1977) to the specific features of digital asset markets, ensuring conceptual consistency while remaining empirically feasible given available data. The resulting crisis episodes form the basis for the descriptive analysis conducted in Section 5, where the frequency, duration, and severity of stablecoin crises are systematically examined and compared across different stablecoin designs. This methodology also enables the comparative analysis with traditional currency crises presented in Section 6.

2.5. Existing Studies on Stablecoin De-pegs

A growing body of empirical literature has examined the stability of stablecoins and the occurrence of de-pegging events. Early studies primarily focused on assessing whether stablecoins succeed in maintaining price stability relative to their reference asset, while more recent contributions have explored specific crisis episodes and, in some cases, attempted to predict de-pegging risk (Ante et al., 2023).

Recent empirical work documents that stablecoins are significantly more stable than unbacked cryptocurrencies but nonetheless experience non-trivial deviations from their pegs (Hoang & Baur, 2024). Empirical analyses show that these deviations vary widely across stablecoin designs, with fiat-backed stablecoins generally exhibiting greater stability than crypto-backed or algorithmic alternatives, yet even well-established coins occasionally revert slowly to parity or experience prolonged instability (Duan & Urquhart, 2023). This strand of the literature establishes that de-pegs are not rare anomalies but recurring features of stablecoin markets, particularly during periods of broader crypto market stress or uncertainty about backing assets (Hoang & Baur, 2024).

A second group of studies adopts a case-based approach, focusing on major crisis events. The collapse of TerraUSD (UST) in May 2022 has received particular attention, often analyzed as a catastrophic failure of algorithmic stabilization mechanisms and market confidence (Briola et al., 2023). Briola et al. (2023) provide a detailed forensic analysis of the Terra-Luna ecosystem collapse, documenting the self-reinforcing dynamics that led to the destruction of over $40 billion in value within days. These studies provide valuable insights into the mechanisms underlying individual crises, such as death spirals in algorithmic designs or contagion from traditional finance, but are inherently event-specific, limiting their ability to draw broader conclusions about stablecoin instability as a general phenomenon.

A third strand explores interconnections and contagion among stablecoins. Gregory et al. (2024) analyze co-instability patterns, demonstrating that stress in one major stablecoin can transmit to others through shared liquidity pools, common collateral assets, or shifts in investor sentiment. This work resonates with third-generation currency crisis models emphasizing financial fragility and contagion (Kaminsky & Reinhart, 1999), though it stops short of systematically cataloging crisis episodes across time and stablecoin types.

More recently, some authors have explored predictive frameworks for stablecoin de-pegs, incorporating variables such as trading volume, volatility, liquidity measures, blockchain network activity, and market sentiment into econometric or machine-learning models (Lee et al., 2025). Lee et al. (2025), for instance, develop early-warning indicators for de-pegging risk using high-frequency on-chain data and demonstrate predictive performance for several major stablecoins. These contributions suggest that de-pegging risk may be anticipated using observable market indicators and represent important advances in real-time risk monitoring. However, their focus is typically forward-looking and model-driven, rather than descriptive and comparative, and they often rely on high-frequency data or complex methodologies that are difficult to generalize across all stablecoins and time periods.

Despite these contributions, the existing literature exhibits several common limitations. First, most studies either analyze stability at a high level, comparing aggregate volatility statistics across stablecoin types, or focus on a small number of prominent episodes, rather than providing a systematic inventory of crisis events across multiple stablecoins and an extended time period (Ante et al., 2023). Second, the severity of de-pegs is often measured using a single metric (such as maximum deviation) or binary crisis indicators, obscuring meaningful differences in magnitude, persistence, and recovery dynamics (Hoang & Baur, 2024). Third, while parallels with traditional financial crises are sometimes mentioned in passing, few studies explicitly anchor stablecoin instability within the established theoretical framework of currency crisis models (Kaminsky & Reinhart, 1999; Krugman, 1979; Obstfeld, 1984), missing the opportunity to leverage decades of theoretical and empirical insights.

As a result, the literature lacks a unified approach that combines systematic episode identification, multidimensional severity measurement, and explicit theoretical interpretation through the lens of currency crisis theory. This gap motivates the present thesis, which seeks to move beyond isolated case studies and fragmented analyses toward a coherent characterization of stablecoin crises grounded in canonical monetary economics.

3. DATA

3.1. Stablecoins included in the sample

The empirical analysis focuses on six major stablecoins representing distinct stabilization mechanisms: USDT (Tether), USDC (USD Coin), TUSD (TrueUSD), BUSD (Binance USD), DAI, and USTC (TerraUSD Classic, formerly UST). These stablecoins were selected to capture variation across the three main design categories identified in Section 2, while ensuring sufficient historical data, market relevance, and data availability from the chosen source (CryptoCompare).

USDT and USDC are fiat-backed stablecoins, meaning they are purportedly backed by reserves held in traditional currency or near-cash instruments. USDT, launched in 2014, is the oldest and most widely used stablecoin by market capitalization, making it a natural benchmark for stability analysis. USDC, introduced in 2018, represents a more transparent alternative within the fiat-backed category, with regular third-party attestations of reserve holdings and strong institutional adoption. The inclusion of both allows for comparisons within the fiat-backed design, particularly regarding the role of transparency and credibility in maintaining peg stability.

TUSD (TrueUSD), launched in 2018, is a fiat-backed stablecoin that provides an additional data point within the collateralized category. It experienced multiple documented de-peg episodes, including a significant deviation in June 2023 linked to the Prime Trust crisis and subsequent reserve attestation controversies. Its inclusion enriches the fiat-backed subsample by introducing variation in governance quality and regulatory oversight within the same design category.

BUSD (Binance USD), launched in 2019 and issued by Paxos under the supervision of the New York Department of Financial Services (NYDFS), represents a regulated fiat-backed stablecoin that maintained exceptional peg stability throughout its active life. In February 2023, NYDFS directed Paxos to cease minting new BUSD tokens, and Binance ended support for BUSD in December 2023, effectively terminating the stablecoin. BUSD's inclusion serves a dual analytical purpose: it acts as a stability benchmark within the sample (having experienced zero crisis episodes under the methodology adopted in this thesis), and its regulatory-driven termination provides a qualitatively distinct case of stablecoin failure that differs fundamentally from market-driven de-pegs

DAI, launched in 2017, is a crypto-backed stablecoin issued by MakerDAO. Unlike fiat-backed alternatives, DAI is collateralized by other cryptocurrencies, primarily Ethereum, and maintains its peg through overcollateralization and automated liquidation mechanisms enforced by smart contracts. Its decentralized structure and reliance on volatile crypto-assets as backing distinguish it fundamentally from USDT and USDC, providing a test case for the stability of crypto-collateralized designs under market stress.

USTC (TerraUSD Classic) is an algorithmic stablecoin that attempted to maintain its peg without explicit reserve backing, instead relying on a dual-token system with the LUNA token to stabilize price through supply adjustments and arbitrage incentives. Originally launched as UST in 2020, it experienced a catastrophic collapse in May 2022, losing its peg irreversibly and destroying approximately $40 billion in market value. Following the collapse, the original chain was renamed Terra Classic and the stablecoin became USTC. Its inclusion is essential for analyzing the extreme case of algorithmic stablecoin failure and provides a natural experiment in the fragility of expectation-dependent stabilization mechanisms.

Together, these six stablecoins provide a representative cross-section of the stablecoin ecosystem, covering the spectrum from regulated fiat-backed designs (BUSD, USDC) to offshore fiat-backed issuers (USDT, TUSD), decentralized crypto-collateralized systems (DAI), and algorithmic mechanisms with no effective collateral (USTC). This selection enables meaningful comparisons across design types while focusing analytical resources on coins with sufficient market depth, liquidity, and historical significance to yield robust empirical results.

However, it is worth keeping under consideration that the selected stablecoins differ substantially in market size. As shown by Figure 2, USDT and USDC dominate the sample, with market capitalizations of approximately $175 billion and $73 billion respectively at the end of 2025. In turn, DAI, TUSD, BUSD, and USTC are several orders of magnitude smaller.

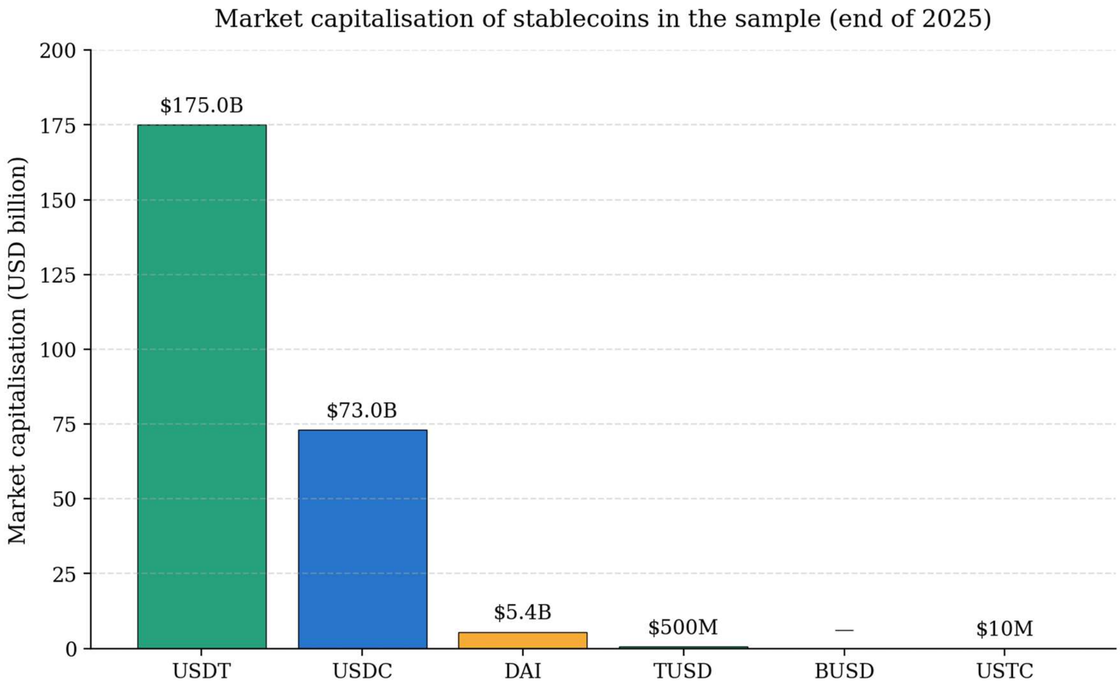


Figure 2: Market capitalisation of stablecoins in the sample (end of 2025)

Source: own elaboration based on data from CoinGecko, CoinMarketCap, and DefiLlama.

3.2. Variables

For each stablecoin, daily observations of two core variables are collected: closing price in US dollars, and trading volume in US dollars. These variables are standard in cryptocurrency market analysis and provide the necessary information to identify and characterize de-pegging episodes.

The closing price serves as the primary variable for measuring deviation from the peg. Since all stablecoins in the sample target a 1:1 parity with the US dollar, deviations can be calculated directly as the absolute difference between the observed price and the $1 target. Daily closing prices capture end-of-day market consensus and smooth out intraday volatility that may reflect temporary liquidity imbalances rather than genuine stress on the peg.

Trading volume, measured in US dollars, reflects market activity and liquidity. High volumes during de-pegging episodes may indicate panic selling or arbitrage activity, while low volumes can signal illiquidity or market fragmentation. Volume data is collected but treated as supplementary, given that it is not required for the threshold-based crisis identification approach adopted in Section 4.

3.3. Frequency and time coverage

All data is collected at daily frequency. Daily observations represent a natural compromise between the need for sufficient temporal granularity to capture crisis dynamics and the practical constraints of data availability and reliability across the full sample period. Higher-frequency data (hourly or minute-level) are available for some stablecoins during recent periods but suffer from inconsistencies, exchange-specific variations, and limited historical coverage, particularly for earlier years. Daily data provides a consistent and comparable foundation across all stablecoins and time periods.

The sample period begins in the second half of 2017, within this window, the time coverage varies by stablecoin, reflecting their different launch dates and, in two cases, data quality constraints that required further trimming. For USDT, data begins in July 2017. DAI data begin in December 2017, shortly after its launch. TUSD data begin in April 2018, and USDC in October 2018. BUSD data are retained from October 2019 through December 15, 2023: the first four months following its May 2019 launch were excluded due to thin-market artifacts (prices of $1.20–$9.31 on daily volumes below $10,000), and observations after December 15, 2023 were excluded because Binance ceased BUSD support on that date, after which CryptoCompare reports a frozen price with zero trading volume. USTC data are retained from October 2020 through September 30, 2022: the post-collapse period was excluded because, from October 2022 onward, USTC traded at approximately $0.01–$0.04 with declining volume, reflecting speculative activity on a defunct stablecoin rather than peg-relevant market behavior. Additionally, USTC has a data gap from November 2020 through August 2021, likely corresponding to limited exchange listings prior to broader adoption. Table 1 summarizes the final sample coverage for each stablecoin.

Table 1: Summary of final sample coverage per stablecoin

Stablecoin	Type	Sample Period	Observations
USDT	Fiat-backed	Jul 2017 – Dec 2025	3,106
DAI	Crypto-backed	Dec 2017 – Dec 2025	2,934
TUSD	Fiat-backed	Apr 2018 – Dec 2025	2,815
USDC	Fiat-backed	Oct 2018 – Dec 2025	2,639
BUSD	Fiat-backed	Oct 2019 – Dec 2023	1,537
USTC	Algorithmic	Oct 2020 – Sep 2022	379
Total			**13,410**

Source: own elaboration based on data from CryptoCompare (2017–2025).

The extended sample coverage spans periods of relative market stability, broad crypto downturns, idiosyncratic stablecoin-specific shocks, and contagion events. Such breadth provides sufficient variation to identify and characterize crisis episodes across diverse market conditions.

3.4. Sources and data treatment

Price and volume data are sourced from CryptoCompare, a widely used cryptocurrency data aggregator that compiles information from multiple exchanges and applies proprietary weighting methodologies to produce representative market-wide figures. CryptoCompare is accessed via its public API, which provides historical daily data in a structured and programmatically accessible format. This data source has been employed in recent academic and institutional research on stablecoin markets, including studies by the Federal Reserve and the Bank for International Settlements (Ahmed et al., 2025; Du et al., 2025; Watsky et al., 2024). While CryptoCompare is a reputable and commonly cited data source in academic and industry research, its use introduces several limitations that merit acknowledgment. These are discussed alongside the broader methodological limitations of the analysis in Section 7.2.

A separate data-quality concern affects DAI's earliest weeks. DAI launched on December 18, 2017, and initially traded on a handful of decentralized exchanges with very thin order books. One observation from this period is a reported close of $4.07 on February 8, 2018, which is best treated as a data artefact: a deviation of that size would imply a complete breakdown of MakerDAO's collateral and arbitrage mechanisms, but no such event appears to have taken place. The print is retained in the catalog for transparency and flagged again in Section 5.3, where it inflates DAI's mean maximum deviation. Medians and the ordinal comparison across stablecoin types are unaffected.

We also identified several data quality issues during preliminary inspection which required targeted filtering. BUSD exhibited erratic prices ($1.20–$9.31) on negligible daily volumes (below $10,000) during its first months after launch in mid-2019, reflecting thin-market artifacts rather than genuine peg deviations; observations prior to October 2019 were therefore excluded. Similarly, following Binance's cessation of BUSD support on December 15, 2023, CryptoCompare continued to report a frozen closing price of $0.9772 with zero trading volume; these post-wind-down observations were removed as they reflect no real market activity. For USTC, post-collapse observations from October 2022 onward were excluded: after its irreversible de-peg in May 2022, USTC traded at approximately $0.01-$0.04 with declining speculative volume, representing residual activity on a defunct stablecoin rather than peg-relevant behavior. USTC also has a data gap from November 2020 through August 2021, likely corresponding to limited exchange listings prior to broader adoption; this gap is acknowledged but does not affect the analysis, as the relevant crisis episode occurs in May 2022. All data filters are documented in the accompanying code and summarized in Table 1.

Despite these limitations, the data is adequate for the purposes of this analysis. The stablecoins selected are sufficiently large and liquid that aggregated price data are likely to be representative of broader market conditions. The daily frequency, while coarser than intraday data, is consistent with the methodological tradition in the currency crisis literature, where daily or lower-frequency data are standard (Eichengreen et al., 1995; Frankel & Rose, 1996).

4. IDENTIFICATION OF EPISODES

4.1. Definition of crisis: deviation thresholds

A stablecoin crisis is defined as an episode in which the market price deviates significantly and persistently from its target peg of $1. Following the threshold-based approach standard in the currency crisis literature (Frankel & Rose, 1996), a crisis is identified when the absolute deviation from parity exceeds a predefined percentage threshold for a minimum duration.

Two threshold levels are employed. The primary threshold is set at 2%, meaning a crisis is flagged whenever the stablecoin price falls below $0.98 or rises above $1.02. This relatively tight threshold is chosen to capture economically meaningful departures from the peg while filtering out minor price fluctuations attributable to normal market microstructure, temporary liquidity imbalances, or rounding artifacts in exchange rate reporting. A 2% deviation represents a non-trivial loss of parity that would be visible to market participants and could trigger redemption behavior, particularly for large institutional holders.

A secondary threshold of 5% is used as a robustness check and to identify episodes of severe stress. A deviation of 5% or more (price below $0.95 or above $1.05) signals a substantial breakdown in peg credibility. We apply both thresholds to distinguish between moderate peg instability and acute crises, providing a richer characterization of stablecoin fragility. While classic currency crisis studies measure depreciation thresholds over annual windows (Kaminsky & Reinhart, 1999), our analysis employs daily thresholds, better reflecting stablecoins' continuous markets and explicit commitment to maintaining tight peg stability at all times. Stablecoin's core value proposition is an explicit and continuous promise of $1 parity at every point in time, not merely over the medium term. A 2% daily deviation therefore constitutes a material breach of the issued commitment (one that would be immediately observable by market participants and could trigger redemption behavior in a way that a 2% annual depreciation would not for a sovereign currency). This difference in commitment horizon is reinforced by two structural features of crypto markets. First, stablecoin markets operate continuously, 24 hours a day, seven days a week, without the trading halts, circuit breakers, or policy deliberation intervals that can absorb stress in traditional currency markets. Second, automated arbitrage and redemption mechanisms can respond within a single trading cycle, meaning that a persistent daily deviation genuinely reflects a failure of stabilization, not a lag in the adjustment process. Applying long-horizon EMP-style thresholds to stablecoins would therefore systematically understate the frequency and significance of de-pegging episodes, and would misrepresent the nature of the commitment being tested.

The choice of these thresholds reflects a balance between sensitivity and specificity. Lower thresholds would capture more episodes but risk including transient noise, while higher thresholds would focus only on the most extreme events, potentially missing economically significant but moderate de-pegs. The 2% and 5% levels align with emerging practices in the stablecoin literature (Lee et al., 2025) and provide consistency with the broader crisis identification tradition.

4.2. Criteria for persistence

To ensure that identified episodes reflect sustained stress rather than momentary price spikes, a persistence criterion is applied. In the primary analysis, a crisis is recorded when the deviation threshold is breached for at least one day. Given the 24/7 nature of cryptocurrency markets and the speed of digital arbitrage, a single daily close outside the threshold band already represents a meaningful failure of stabilization mechanisms to restore parity within a full trading cycle.

The minimum threshold ensures that identified crises correspond to observable market events while maintaining maximum sensitivity to economically relevant episodes. Notably, increasing the persistence requirement to two consecutive days would exclude certain well-documented de-pegging events. For instance, the USDC de-peg of March 2023, triggered by exposure to Silicon Valley Bank, breached the 2% threshold on a single day (March 11, 2023) before arbitrage and issuer communication restored the peg. A two-day requirement would fail to capture this episode despite its clear economic significance and widespread coverage.

As a robustness check, the analysis is also conducted using a stricter two-consecutive-day persistence filter. The results, reported in Appendix C, are reassuring: the stricter criterion reduces the episode count from 85 to 38, dropping all 47 single-day events. Critically, the dropped episodes include some of the most widely cited stablecoin stress events in the literature: the USDC de-peg of March 2023 triggered by the Silicon Valley Bank failure (max deviation 3.21%), and DAI's Black Thursday episode of March 2020 (max deviation 6.2%). Yet the qualitative ranking of stablecoin types by frequency, severity, and duration is preserved in its entirety under the stricter criterion. The fact that the central findings survive this demanding test, which excludes economically significant and well-documented episodes, strengthens confidence that the cross-sectional gradient reflects genuine structural differences across design types rather than a sensitivity to the precise identification methodology.

4.3. Measurement of severity

Crisis episodes vary not only in occurrence but also in their intensity, duration, and speed of resolution. To capture this heterogeneity, three complementary severity metrics are calculated for each identified crisis.

Maximum deviation from the peg measures the peak intensity of the crisis. For each episode, the maximum absolute deviation is recorded as the largest distance between the observed price and the $1 target during the crisis window. This metric captures how far the stablecoin price moved from parity at its worst point. For example, during the TerraUSD collapse in May 2022, the maximum deviation approached 100% as the price fell to near zero (Briola et al., 2023), whereas the March 2023 USDC de-peg reached a maximum deviation of approximately 8% before recovering. Maximum deviation provides a single-number summary of crisis magnitude and is easily interpretable.

Cumulative deviation captures both the magnitude and persistence of the crisis. It is calculated as the sum of daily absolute deviations from the peg over the entire duration of the episode. Formally, for a crisis lasting from day $t_1$to day t_2, cumulative deviation is:

$$\text{Cumulative Deviation} = \sum_{t=t_1}^{t_2} | P_t - 1 |$$

where $P_t$is the closing price on day t. This metric reflects the total "area under the curve" of the deviation path and accounts for the fact that a moderate deviation sustained over many days may be as economically significant as a sharp but brief spike. Cumulative deviation is particularly useful for comparing crises of different durations and for assessing the overall market stress imposed by prolonged instability.

Recovery time measures the number of days required for the stablecoin to return to a narrow band around its peg after the crisis begins. Recovery is defined as the point at which the price re-enters and remains within a 1% deviation band (i.e., between $0.99 and $1.01) for at least one full day. This metric captures the speed of stabilization and the effectiveness of corrective mechanisms. Longer recovery times suggest deeper disruptions to market confidence, slower arbitrage, or structural impediments to restoring parity. In the extreme case of USTC, recovery never occurred, and the recovery time is effectively infinite, reflecting permanent peg loss.

Together, these three metrics provide a multidimensional characterization of crisis severity. Maximum deviation emphasizes peak stress, cumulative deviation emphasizes persistence, and recovery time emphasizes resilience. By examining all three, the analysis can distinguish between crises that are sharp but quickly resolved, those that are moderate but prolonged, and those that are both severe and persistent.

Alternative severity measures, such as the variance of deviations during the crisis or the rate of depreciation, could also be considered. However, the three chosen metrics align closely with the conceptual framework developed in Section 2, where currency crises are understood in terms of magnitude (how large the depreciation), duration (how long reserves must be defended or parity lost), and resolution (how quickly the peg is restored). These dimensions map directly onto the three severity metrics employed here.

4.4. Step-by-step procedure for identifying episodes

Crisis episodes are identified algorithmically using the following procedure:

1. Calculate daily deviations: For each stablecoin and each day in the sample, compute the absolute deviation from the 1 peg as $|P_t - 1|, where $P_t$is the closing price on day t.

2. Flag threshold breaches: Identify all days on which the deviation exceeds the chosen threshold (2% for the primary analysis, 5% for the robustness check).
3. Apply persistence filter: In the primary analysis, all flagged days are retained (minimum persistence of one day). As a robustness check, an alternative filter requiring at least two consecutive days is also applied.
4. Define crisis windows: Each continuous sequence of flagged days that meets the persistence criterion constitutes a distinct crisis episode. The crisis begins on the first day of the sequence and ends on the last day before the deviation returns below the threshold.
5. Calculate severity metrics: For each identified crisis, compute the maximum deviation (the largest $| P_t - 1 |$ during the episode), the cumulative deviation (the sum of daily deviations), and the recovery time (the number of days until $| P_t - 1 | < 0.01$ and remains there).
6. Catalog episodes: Record each crisis with its start date, end date, stablecoin identifier, and severity metrics, creating a comprehensive database of de-pegging events.

This procedure is applied separately to each stablecoin and to both threshold levels, generating multiple crisis catalogs that can be compared to assess robustness and to explore how crisis frequency and severity depend on the definition employed.

4.5. Illustration with key events

To illustrate the application of the crisis identification methodology, two prominent historical episodes are examined: the TerraUSD (USTC) collapse of May 2022 and the USDC de-peg of March 2023.

TerraUSD collapse (May 2022): On May 9, 2022, UST began losing its peg, with the price falling below \$0.98. Over the following days, selling pressure intensified, and the price entered a cascading decline. By May 11, UST had fallen below \$0.30, breaching even the 5% threshold by an order of magnitude. The collapse was driven by a self-reinforcing dynamic in which loss of confidence triggered redemptions, depleting the reserves of the stabilizing token (LUNA), which in turn further undermined confidence (Briola et al., 2023). Within a week, UST was trading below \$0.10, and the peg was never restored. This episode would be identified as a crisis under both the 2% and 5% thresholds, with a maximum deviation approaching 100%, an extremely high cumulative deviation due to prolonged mispricing, and an infinite recovery time reflecting permanent peg loss. The severity metrics unambiguously classify this as a catastrophic event, consistent with its characterization as one of the largest failures in cryptocurrency history.

USDC de-peg (March 2023): On March 10, 2023, concerns emerged regarding Circle's reserve exposure to Silicon Valley Bank, which had been placed under FDIC receivership. Despite aggregate reserves being sufficient, uncertainty about the liquidity and accessibility of USDC's backing triggered redemption pressure. The USDC price fell to approximately \$0.92 on major exchanges, breaching both the 2% and 5% thresholds. Unlike TerraUSD, however, USDC's de-peg was brief. Circle issued public statements clarifying its reserve position and the limited extent of SVB exposure, and as confidence stabilized, arbitrageurs restored the peg. By March 13, USDC had returned to within 1% of parity. This episode would be identified as a crisis under the 2% threshold with a maximum deviation of roughly 3%, a modest cumulative deviation due to its short duration, and a recovery time of approximately 1 day. The severity metrics reflect a significant but ultimately contained event, illustrating the role of issuer credibility and reserve transparency in limiting crisis intensity.

These two cases highlight the range of crisis dynamics captured by the methodology. TerraUSD represents an extreme, irreversible collapse driven by fundamental design fragility, while USDC exemplifies a sharp but transient stress episode resolved through credible communication and functioning arbitrage. The identification procedure, applied uniformly across all stablecoins and time periods, enables systematic comparison of such events and supports the descriptive analysis presented in Section 5.

5. DESCRIPTIVE ANALYSIS OF EPISODES

5.1. Frequency of crises by year and by stablecoin.

The methodology identifies 85 crisis episodes across six stablecoins over the period July 2017 – December 2025, using the primary 2% deviation threshold with a one-day minimum persistence criterion applied to closing prices. Crisis frequency exhibits substantial variation over time, with episodes concentrated in the 2017–2019 period. The most active year was 2018, with 32 episodes, followed by 2019 (19 episodes) and 2020 (16 episodes). Activity remained low in 2022–2024, with 2 episodes in 2022 (including the Terra/USTC collapse), 3 in 2023 (including the USDC/SVB episode), and 5 in 2024 (all TUSD).

Two years, 2021 and 2025, stand out for the absence of episodes. Both coincide with peaks of successive crypto bull markets: 2021 saw Bitcoin reach approximately $69,000 in November, while 2025 saw it surpass $120,000. These were periods of high market confidence and limited stress events. The pattern suggests that crisis frequency could be influenced by the broader crypto market cycle, with episodes concentrating during bear markets, perhaps prompted by a generalized lack of confidence in the crypto ecosystem.

The distribution of episodes across stablecoins reveals meaningful differences. DAI accounts for the largest share with 33 episodes, followed by TUSD and USDT with 21 episodes each. USDC experienced 8 episodes, concentrated in its early period (2018–2019) and the March 2023 SVB event. USTC accounts for 2 episodes, including its catastrophic collapse. BUSD, despite being included in the sample from October 2019 through December 2023, registered zero episodes under the 2% threshold, serving as a stability benchmark. BUSD's stability is best understood as the result of the regulatory and operational regime under which it operated: issuance was handled by Paxos under direct supervision of the New York Department of Financial Services (NYDFS), with monthly reserve attestations and strict reserve composition rules.

The cross-tabulation (Table 2) reveals temporal clustering patterns. The 2018 concentration reflects broad market stress across multiple stablecoin types: DAI, TUSD, USDC, and USDT all experienced episodes that year. In 2020, DAI dominates with 14 of 16 episodes, consistent with the crypto market turmoil surrounding "Black Thursday" (March 12, 2020). The 2023 episodes in DAI, TUSD, and USDC reflect the SVB contagion.

Table 2: Year × Stablecoin cross-tabulation

	BUSD	DAI	TUSD	USDC	USDT	USTC	Total
2017	-	1	-	-	7	-	8
2018	-	9	9	5	9	-	32

	BUSD	DAI	TUSD	USDC	USDT	USTC	Total
2019	0	8	5	2	4	-	19
2020	0	14	0	0	1	1	16
2022	0	0	1	0	0	1	2
2023	0	1	1	1	0	-	3
2024	-	0	5	0	0	-	5
Total	0	33	21	8	21	2	85

Source: own elaboration based on data from CryptoCompare (2017–2025).

Note: "-" indicates that the stablecoin was outside the sample window for that year. (See Table 1 for sample coverage by stablecoin).

Figure 3 visualizes the temporal distribution of episodes by stablecoin. The concentration in 2017–2019 accounts for 69% of all episodes (59 of 85), while the 2020–2024 period accounts for the remaining 31%.

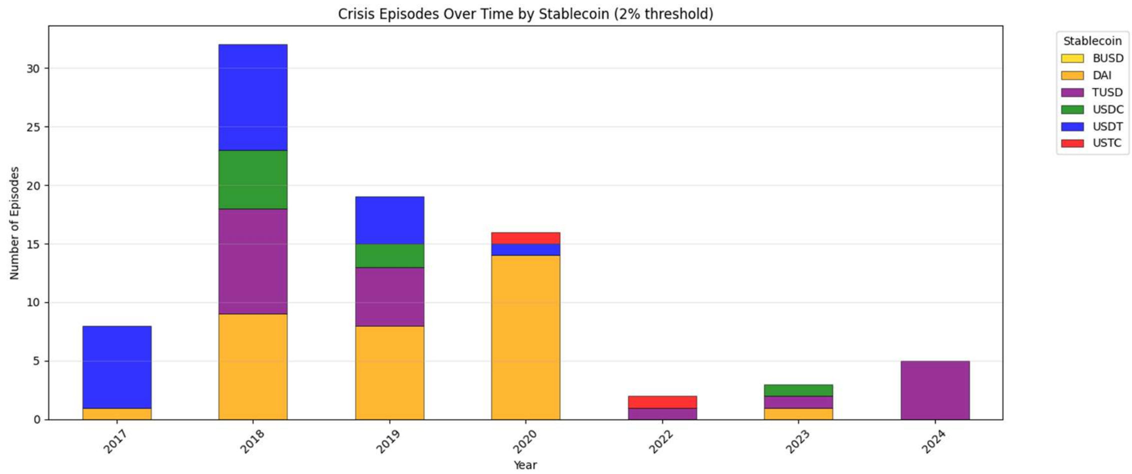


Figure 3: Crisis episodes over time

Source: own elaboration based on data from CryptoCompare (2017–2025).

5.2. Duration statistics

Crisis episodes vary substantially in duration. The median duration across all 85 episodes is 1 day, while the mean is 4.1 days. This discrepancy reflects the distribution's strong right skew: 93% of episodes (79 of 85) resolve within one week, and only one episode exceeds 90 days. The interquartile range spans 1 to 3 days, confirming that the vast majority of de-pegging events are short-lived.

Tables 3 and 4 present duration statistics disaggregated by stablecoin and duration category respectively. Note that the number of episodes per stablecoin should be read in light of the sample periods reported in Table 1, which vary across stablecoins. USTC exhibits the longest episode at 145 days (the May–September 2022 collapse, truncated at the end of the analysis window). Among the remaining stablecoins, DAI shows the highest mean duration (3.4 days, median 2 days), followed by TUSD (2.1 days, median 1 day) and USDT (2.0 days, median 1 day). USDC episodes are the shortest, with a mean of 1.3 days and a maximum of 3 days.

Table 3: Duration by stablecoin

Stablecoin	N Episodes	Mean (days)	Median (days)	Std	Min	Max
USTC	2	73.00	73.0	101.82	1	145
DAI	33	3.36	2.0	2.91	1	10
TUSD	21	2.05	1.0	2.18	1	10
USDT	21	2.00	1.0	1.22	1	5
USDC	8	1.25	1.0	0.71	1	3

Source: own elaboration based on data from CryptoCompare (2017–2025).

Table 4 shows that 79 episodes (92.9%) last one week or less, 5 episodes (5.9%) last between one and four weeks, and one episode (USTC) exceeds one month in duration.

Table 4: Episodes by duration category

Duration	N Episodes	Percentage
≤ 1 week	79	92.9%
1 – 4 weeks	5	5.9%
> 1 month	1	1.2%

Source: own elaboration based on data from CryptoCompare (2017–2025).

The overwhelming concentration of short-duration episodes is a notable finding, although it should be read in light of the sample composition: these are some of the largest and most liquid stablecoins in the market, and duration dynamics could plausibly differ for smaller or less liquid issuers not covered here.

5.3. Severity statistics

Severity is measured using three complementary metrics: maximum deviation (peak intensity), cumulative deviation (total stress), and recovery time (speed of stabilization). Table 5 presents summary statistics for each metric across all 85 episodes. The median maximum deviation is 2.6%, indicating that a typical crisis involves a peak price displacement of less than three percentage points from parity. The mean maximum deviation is 8.4%, substantially higher due to the extreme USTC and early DAI observations. Cumulative deviation shows a similar pattern, with a median of 0.04 and a mean of 1.73, reflecting the disproportionate contribution of the USTC collapse. Among the 84 episodes that recovered, the median recovery time is 5 days.

Table 5: Summary statistics of severity metrics

Metric	Mean	Median	Std Dev	Min	Max
Maximum deviation	0.084	0.026	0.346	0.020	3.068
Cumulative deviation	1.735	0.040	14.847	0.020	136.972
Recovery time (days)*	8.8	5.0	9.7	1.0	38.0

Source: own elaboration based on data from CryptoCompare (2017–2025).

**Note: Recovery time is computed only on the 84 episodes that returned to parity; the unrecovered USTC episode of May 2022 is excluded.*

Table 6 disaggregates severity by stablecoin. USTC exhibits the highest maximum deviation (0.993) and cumulative deviation (136.97), reflecting the irreversible nature of its collapse. Among collateralized stablecoins, DAI shows the highest mean maximum deviation (0.142), but this figure is dominated by the suspect $4.07 print of February 8, 2018 discussed in Section 3.4, which contributes a deviation of 3.068 on its own. Excluding that observation lowers DAI's mean to roughly 0.05, much closer to (though still above) the fiat-backed range. The median (0.030) is unaffected and is the more reliable summary. Fiat-backed stablecoins (USDT, USDC, TUSD) cluster between 2.3% and 3.0%. A noteworthy observation within this group is that USDT, the largest stablecoin by market capitalization and trading volume, ranks third in stability, behind both USDC (0.023) and TUSD (0.028). Market dominance does not appear to translate into superior peg performance. Recovery rates are 100% for all stablecoins except USTC (50%, reflecting one recovered and one unrecovered episode).

Table 6: Combined severity by stablecoin

Stablecoin	N Ep.	Mean Max Dev	Median Max Dev	Mean Cum Dev	Median Recovery (days)	Recovery Rate
DAI	33	0.142	0.030	0.243	7.0	100%

Stablecoin	N Ep.	Mean Max Dev	Median Max Dev	Mean Cum Dev	Median Recovery (days)	Recovery Rate
TUSD	21	0.028	0.025	0.052	2.0	100%
USDT	21	0.030	0.027	0.052	4.0	100%
USDC	8	0.023	0.022	0.029	9.0	100%
USTC	2	0.507	0.507	68.496	1.0	50%

Source: own elaboration based on data from CryptoCompare (2017–2025).

Figure 4 displays the distribution of the three severity metrics across all 85 episodes. The histograms confirm the heavily right-skewed nature of all three measures, with the majority of episodes clustered at low severity levels and a small number of extreme observations (principally the USTC collapse and early DAI episodes) extending the right tail.

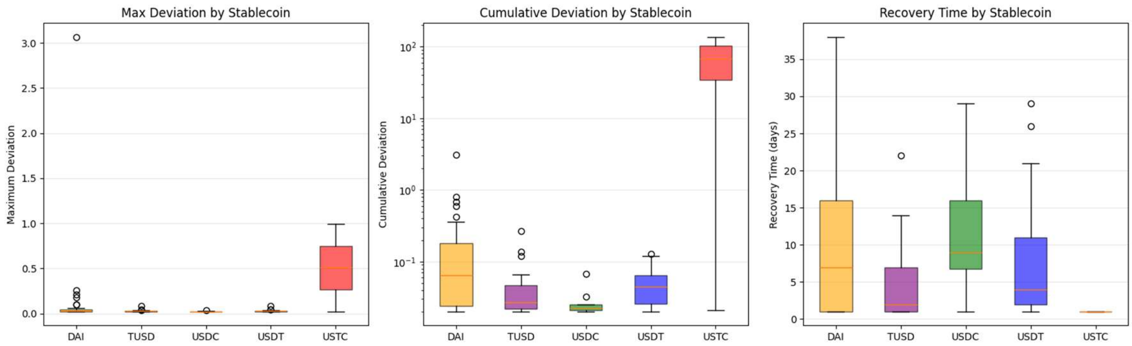


Figure 4: Severity distributions

Source: own elaboration based on data from CryptoCompare (2017–2025).

Eleven episodes meet the criteria for classification as extreme (maximum deviation >10%, cumulative deviation >10, or recovery time >30 days). These include the Terra/USTC collapse, seven early DAI episodes (2017–2020), and three DAI episodes with long recovery times in 2019–2020.

Table 7: Extreme episodes, sorted by maximum deviation

Stablecoin	Start Date	End Date	Duration (days)	Max Deviation	Cum. Deviation	Recovery (days)
DAI	2018-02-08	2018-02-08	1	3.068	3.068	1

Stablecoin	Start Date	End Date	Duration (days)	Max Deviation	Cum. Deviation	Recovery (days)
USTC	2022-05-09	2022-09-30	145	0.993	136.972	—
DAI	2018-04-23	2018-04-28	6	0.256	0.680	11
DAI	2018-04-15	2018-04-21	7	0.208	0.419	1
DAI	2018-02-05	2018-02-05	1	0.181	0.181	1
DAI	2018-01-04	2018-01-11	8	0.100	0.800	1
DAI	2017-12-28	2018-01-02	6	0.100	0.600	10
DAI	2019-03-28	2019-03-28	1	0.024	0.024	31
DAI	2019-03-19	2019-03-21	3	0.023	0.065	38
DAI	2019-03-25	2019-03-25	1	0.021	0.021	34
DAI	2020-03-29	2020-03-29	1	0.020	0.020	34

Source: own elaboration based on data from CryptoCompare (2017–2025).

Note: The first row (DAI, 2018-02-08) is retained for transparency but, as discussed in Sections 3.4 and 5.3, almost certainly reflects a thin-market data artefact rather than a genuine 300% peg deviation.

5.4. Comparison across stablecoin types

Episodes are grouped by stablecoin design type: fiat-backed (USDT, USDC, TUSD, BUSD), crypto-backed (DAI), and algorithmic (USTC). Table 8 consolidates key statistics across types. All cross-type comparisons in this section should be interpreted in light of the heterogeneous sample periods summarized in Table 1: episode counts are not directly comparable across stablecoins with different observation windows, and the fiat-backed category in particular pools coins with substantially different time spans and market exposures. A clear gradient emerges, nonetheless. Fiat-backed stablecoins account for the largest number of episodes (50) but exhibit the shortest duration (median 1 day), lowest severity (mean max deviation 2.8%), and complete recovery (100%). Crypto-backed stablecoins show fewer but longer episodes (33 episodes, median 2 days). Their mean maximum deviation of 14.2% is inflated by the February 2018 outlier flagged in Section 3.4; excluding it, the figure falls to roughly 5%, still above the fiat-backed range but much closer to it. All episodes recovered fully. The single algorithmic stablecoin (USTC) represents the extreme case: only 2 episodes identified, but with a mean duration of 73 days, a mean maximum deviation of 50.7%, and a recovery rate of only 50%.

These patterns are broadly consistent with the theoretical expectations developed in Section 2, though the alignment should be understood as interpretive rather than deterministic. Fiat-backed designs, supported by explicit reserve assets and (in some cases) regulatory oversight, experience frequent but mild and quickly resolved episodes, a profile most naturally interpreted through the lens of first-generation models, where strong fundamentals constrain the depth and duration of speculative pressure. Crypto-backed designs, reliant on volatile collateral, exhibit greater sensitivity to broad market downturns, with crisis dynamics reminiscent of third-generation models emphasizing financial fragility, forced deleveraging, and contagion. Algorithmic designs, dependent entirely on market confidence and arbitrage incentives, show vulnerability to sharp and catastrophic collapse, consistent with the self-fulfilling dynamics central to second-generation models, though third-generation amplification mechanisms were also prominently at work. As discussed further in Section 6, these mappings are heuristic: boundary cases exist, real episodes routinely carry features of more than one generation simultaneously, and the classification of any individual event involves interpretive judgment.

Table 8: Severity metrics by stablecoin type

Type	**N Episodes**	**Avg Duration (days)**	**Median Duration (days)**	**Avg Max Dev**	**Recovery Rate**
Fiat-backed	50	1.90	1.0	0.028	100%
Crypto-backed	33	3.36	2.0	0.142	100%
Algorithmic	2	73.00	73.0	0.507	50%

Source: own elaboration based on data from CryptoCompare (2017–2025).

These patterns provide the empirical foundation for the comparison with currency crisis frameworks in Section 6 and the discussion of findings in Section 7.

6. DISCUSSION

6.1. Interpretation through the currency crisis framework

The episodes documented in Section 5 exhibit patterns worthy of analysis. Each stablecoin design type produces a recognizable profile: frequent but mild for fiat-backed coins, fewer but deeper for DAI, catastrophic and irreversible for USTC. Each profile is moreover most naturally read through one of the three currency crisis generations reviewed in Section 2.3 (though the mapping is interpretive rather than classificatory). The three generations are not mutually exclusive frameworks but complementary lenses on the same underlying dynamics, real episodes routinely carry features of more than one generation simultaneously, and boundary cases are frequent. What follows identifies the dominant dynamic for each design type while flagging the most important cross-generation overlaps.

Fiat-backed stablecoins (USDT, USDC, TUSD, BUSD) account for 50 of the 85 identified episodes, the largest share in the sample. The episodes themselves are mild: median duration of 1 day, mean maximum deviation of 2.8%, and full recovery in every case. BUSD, supervised by NYDFS, registered no episodes at all during its active period.

This is what the first-generation models of Flood & Garber (1984) and Krugman (1979) would predict for an issuer with credible reserves: speculative pressure shows up but never escalates, because arbitrageurs can profitably close the gap before expectations turn. The 4-day median recovery for USDT and 2-day median for TUSD are short enough to suggest the redemption channel was actually doing the work, not just that markets eventually returned to equilibrium. The contrast between BUSD (zero episodes) and TUSD (21 episodes) is also telling since both are fiat-backed, but BUSD operated under direct NYDFS supervision with regular Paxos attestations and TUSD did not. Reserves matter, but verifiable reserves matter more, which is exactly the first-generation point about credibility rather than mere existence of fundamentals.

The USDC SVB episode of March 2023 sits in this category. The de-peg was not caused by reserve inadequacy but by uncertainty about whether the reserves could be accessed in time, given Circle's exposure to the failing bank. That puts it on the boundary between first-generation dynamics (anything reserve-related) and second-generation dynamics (an expectations-driven move despite adequate fundamentals). The fact that the peg snapped back as soon as Circle confirmed reserve access supports the second reading: the crisis resolved the moment expectations re-coordinated, which is what Obstfeld (1984) framework predicts.

The USTC collapse is best interpreted as an expectations-driven peg failure, amplified by third-generation mechanisms related to leverage, liquidity withdrawals, and DeFi contagion. The empirical fingerprint is consistent with this dual reading: only 2 episodes identified, but a mean duration of 73 days, a mean maximum deviation of 50.7%, and a recovery rate of 50%. The catastrophic episode beginning May 9, 2022 lasted 145 days within the analysis window and never recovered. With no real reserves behind it and only the UST–LUNA arbitrage and the Anchor yield holding confidence in place, USTC's peg was always a coordination problem, the second-generation core. Once the Anchor withdrawals started, the bad equilibrium took over: holders rushed to exit, the arbitrage mechanism inverted, and the price fell irreversibly. Layered on top of this expectations-driven core, third-generation amplifiers operated simultaneously: leveraged positions across Anchor and adjacent DeFi protocols were unwound at fire-sale prices, liquidity withdrawals from interconnected pools propagated stress across the ecosystem, and contagion reached unrelated stablecoins such as MIM (Section 2.3.3).

The speed of the collapse points to a real difference between sovereign and stablecoin second-generation crises. A sovereign facing speculative pressure can usually do something: raise rates, sell reserves, accept reputational damage in exchange for time… and this “menu” of costly options is what produces Obstfeld's zone of ambiguity, where multiple equilibria coexist for a while before the crisis resolves. An algorithmic stablecoin has no such “menu”. Once the arbitrage mechanism stops working there is no second move, which is why the transition from one equilibrium to the other looked closer to instantaneous than gradual.

DAI’s profile may fit the third-generation models of Kaminsky & Reinhart (1999) and Krugman (1999), which were written precisely to capture currency crises that travel through balance sheets. The mechanism is direct: DAI is collateralized by volatile crypto, primarily ETH; when ETH falls hard, vault ratios drop, and the protocol auto-liquidates collateral to cover positions. Those forced sales push ETH down further and squeeze DAI in the same direction: a fire-sale loop in code rather than in commercial banks, but the same mechanism. The empirical fingerprint is the clustering of DAI episodes during periods of broad crypto stress: 14 of 16 episodes in 2020 fell during or after the March 2020 crash, and the 2018 episodes coincide with the broader crypto bear market.

“Black Thursday” (March 12, 2020) is the textbook case. A 43% ETH price crash hit at the same time as Ethereum network congestion, which prevented MakerDAO's oracles from updating prices and its liquidation auctions from clearing. The system was solvent on paper but operationally broken, close to the digital analogue of the twin crises in Kaminsky & Reinhart (1999), where banking and currency stress reinforce each other through shared infrastructure rather than through pure fundamentals.

The contagion dimension of third-generation models also shows up clearly in the data. The March 2023 SVB episode hit USDC, DAI, and TUSD simultaneously, which represent three structurally different stablecoins linked through traditional banking exposure and shared DeFi liquidity pools. DAI’s vulnerability to USDC's de-peg in particular reflects its partial reliance on USDC as collateral within MakerDAO's vaults, a textbook cross-market transmission channel. Similarly, the Terra collapse of May 2022 propagated stress to MIM and other stablecoins through shared DeFi positions, as discussed in Section 2.3.3.

6.2. Comparison with sovereign currency crises

The mapping of stablecoin crises onto currency crisis models reveals both meaningful parallels and important differences with sovereign experience.

In terms of parallels, the fundamental logic of peg maintenance and failure is strikingly similar across domains. Both sovereign currencies and stablecoins face the trilemma of maintaining a fixed parity while managing reserves, confidence, and external shocks. The gradient observed in the data, fiat-backed stablecoins experiencing frequent but mild crises; crypto-backed stablecoins showing vulnerability to market-wide stress; and algorithmic stablecoins suffering catastrophic confidence-driven collapse, mirrors the spectrum observed across different exchange rate arrangements, from hard pegs backed by ample reserves to soft pegs with limited defenses (Eichengreen et al., 1995). However, this comparison should be interpreted with caution: the stablecoins in each design category do not share identical observation windows (see Table 1 for detailed observation windows per stablecoin), and cross-type episode counts are accordingly descriptive rather than controlled.

The role of reserve transparency in determining crisis severity (BUSD vs. TUSD) echoes findings in the sovereign literature about reserve adequacy as a determinant of vulnerability to speculative attacks (Eichengreen et al., 1995). The contagion from SVB to USDC to DAI mirrors the cross-country transmission channels documented in third-generation models, where common creditors and shared exposures propagate crises across otherwise unrelated economies (Kaminsky & Reinhart, 1999). The collapse of USTC shares features with second-generation crisis models, particularly the role of self-fulfilling dynamics in accelerating peg failure, though it also reflects underlying fundamental weaknesses (notably the absence of collateral and reliance on an unsustainable yield mechanism) that distinguish it from the canonical case of expectations-driven crises in otherwise sound regimes (Obstfeld, 1984).

Stablecoin crises also differ from their sovereign counterparts in important ways. The speed of resolution is dramatically faster: the median stablecoin crisis lasts 1 day, while sovereign currency crises typically unfold over weeks or months. This reflects the 24/7 operation of crypto markets, the absence of policy deliberation lags, and the automated nature of many stabilization mechanisms. Stablecoins also lack a lender of last resort: there is no central bank to provide emergency liquidity or coordinate a defense, which may explain why algorithmic stablecoins, once destabilized, collapse more completely than sovereign currencies, which can often be defended through policy intervention even under severe pressure. And the recovery rate for fiat-backed and crypto-backed stablecoins (100%) is higher than for many sovereign crises, suggesting that collateralized designs, when they survive the initial shock, are effective at restoring parity.

One difference has no sovereign analogue at all: BUSD's termination by regulatory order in 2023 represents a kind of "crisis" (the death of a stablecoin) that simply cannot happen to a state-issued currency, since states cannot be ordered to cease issuing their own money.

6.3. Implications for stablecoin design and regulation

Within the limits of this descriptive sample, the choice of stabilization mechanism appears as a key differentiator across stablecoins' behavior under stress, with practical consequences for design, risk assessment, and regulation alike.

On the design side, collateral-backed approaches (whether fiat or crypto) proved substantially more resilient than algorithmic ones across every dimension measured. Within collateral-backed designs, the quality, transparency, and regulatory oversight of reserves appear to matter more than the mere presence of collateral, a finding consistent with the first-generation emphasis on the credibility of fundamentals.

Investors should not treat stablecoin risk as homogeneous. The near-zero crisis rate of BUSD and the brief, moderate episodes experienced by USDC represent a fundamentally different risk profile than the existential vulnerability of algorithmic designs. The concentration of episodes in 2017-2019, followed by a marked decline, may reflect maturation of the stablecoin market through improved reserve practices, regulatory scrutiny, and market learning, though this interpretation should be treated with caution given the limited post-2020 sample for some stablecoins.

The findings also support differentiated supervisory approaches based on design type. The stability of BUSD under NYDFS supervision, contrasted with the instability of less regulated alternatives, suggests that regulatory oversight contributes meaningfully to peg maintenance. The contagion dynamics observed during the SVB episode (where stress in traditional banking transmitted to stablecoins and then propagated across the DeFi ecosystem) underscores the importance of monitoring interconnections between stablecoins and the broader financial system. The catastrophic collapse of USTC supports the case for particular scrutiny of algorithmic designs. Recent regulatory frameworks move in this direction. In the EU, the Markets in Crypto-Assets Regulation (MiCA) imposes reserve, disclosure, and authorization requirements on stablecoin issuers, and its insistence on tangible reserves effectively rules out uncollateralized algorithmic designs. In the US, the GENIUS Act of 2025 establishes a federal licensing regime for payment stablecoins, requires 1:1 backing with high-quality liquid assets, and mandates monthly public disclosure of reserve composition.

7. CONCLUSIONS AND LIMITATIONS

7.1. Conclusions

This thesis has systematically identified and characterized 85 stablecoin de-pegging episodes across six major stablecoins (USDT, USDC, TUSD, BUSD, DAI, USTC) over the period July 2017 – December 2025, using crisis identification methods adapted from the sovereign currency crisis literature.

Three principal findings emerge. The first is that stablecoin crises are not rare events: the sample documents 85 episodes at the 2% deviation threshold, distributed unevenly across stablecoins and over time. It is important to recall that the identified episodes are conditional on the empirical specification: a 2% threshold on absolute price deviation, a one-day minimum persistence criterion, daily closing prices, and the sample filters described in Section 3.4 (notably the exclusion of USTC observations after September 2022 and BUSD observations after December 2023). Alternative specifications produce different episode counts, although the cross-sectional ranking across stablecoin design types is preserved (Section 5.4). Crisis frequency is concentrated in the 2017–2019 period, which accounts for 69% of all episodes, and has declined markedly in subsequent years. However, the most severe episodes, the Terra/USTC collapse of May 2022 and the USDC/SVB contagion of March 2023, occurred in the later period, indicating that reduced frequency does not imply reduced severity.

Second, design type is the primary determinant of crisis characteristics, even after accounting for the heterogeneous sample coverage across stablecoins (see Table 1 for exact observation windows). Fiat-backed stablecoins experience frequent but mild episodes (median duration 1 day, mean maximum deviation 2.8%, 100% recovery rate). Crypto-backed stablecoins exhibit fewer but longer and more severe episodes, driven by their exposure to volatile collateral. Algorithmic stablecoins, represented by USTC, are vulnerable to catastrophic and irreversible collapse. Within the fiat-backed category, regulatory oversight appears to contribute meaningfully to stability, as evidenced by the zero-episode record of BUSD under NYDFS supervision.

The third finding is the most conceptually important: the patterns observed in the data are broadly consistent with the three generations of currency crisis theory developed for sovereign currencies, suggesting that the underlying monetary logic transcends the institutional context in which it operates. Fiat-backed episodes exhibit dynamics most consistent with first-generation models, where the credibility of reserves constrains the depth and duration of speculative pressure. The USTC collapse is most naturally interpreted through the lens of second-generation models, where the absence of hard reserves leaves the peg exposed to self-fulfilling expectations and irreversible equilibrium shifts (though third-generation amplification mechanisms operated simultaneously and were central to the speed of the collapse. Crypto-backed episodes show behaviour most reminiscent of third-generation mechanisms, with balance-sheet effects, forced liquidation, and contagion concentrated in periods of broad market stress. This interpretive mapping is heuristic rather than conclusive: the three generations are not mutually exclusive, individual episodes regularly exhibit features of more than one framework, and alternative theoretical readings of the same data are possible. What the evidence supports is a structural analogy (not a precise one-to-one classification) between stablecoin and sovereign currency crisis dynamics.

7.2. Limitations

Several limitations should be acknowledged, falling into two broad groups: data limitations and methodological ones.

On the data side, the analysis relies on a single source (CryptoCompare), and data quality and coverage vary across stablecoins and over time. Older observations, particularly from the early years of USDT's existence, may reflect thinner markets and less reliable reporting, and for smaller or less liquid stablecoins reported volumes and prices may be more susceptible to manipulation, wash trading, or reporting errors. The reliance on daily closing prices also abstracts from intraday dynamics. Stablecoin de-pegs can be highly volatile events, with prices fluctuating significantly within a single day, so daily data may obscure the severity or speed of intraday stress; for particularly fast-moving crises such as the TerraUSD collapse, this may result in underestimating the intensity of market pressure during the most acute phase. The sample also includes only six stablecoins. Although these represent the main design categories, the algorithmic category is represented by a single coin (USTC), limiting the generalizability of conclusions about algorithmic designs. Several targeted filters were also necessary: exclusion of BUSD's early illiquid period (pre-October 2019) and post-wind-down observations (post-December 2023), truncation of USTC at September 2022 to remove post-collapse speculative noise, and exclusion of USDT data prior to July 2017. Each filter is documented and justified individually, but together they introduce researcher discretion into sample construction.

On the methodological side, the crisis identification relies on threshold-based rules (2% and 5% deviation) that are transparent and replicable but inherently arbitrary. The robustness check using a two-consecutive-day persistence criterion is, in this regard, reassuring rather than merely neutral: the stricter criterion removes 47 single-day events (55% of the primary catalog, including economically significant episodes such as the USDC/SVB de-peg and DAI's Black Thursday) yet the qualitative ranking of design types by frequency, severity, and duration is entirely preserved. The fact that the central findings survive the removal of these well-documented events strengthens confidence that they reflect genuine structural differences across stablecoin designs, rather than an artefact of the identification methodology. Nonetheless, the sensitivity of raw episode counts to specification choices should be acknowledged when drawing quantitative comparisons. Finally, the discussion in Section 6 maps empirical patterns onto theoretical frameworks through qualitative interpretation rather than formal model estimation. The alignment between stablecoin crisis dynamics and currency crisis generations is suggestive rather than conclusive, and alternative theoretical interpretations of the same data may be possible.

7.3. Future research

Three directions for future research stand out. The first is to widen the design coverage: incorporating hybrid and fractional-algorithmic stablecoins such as FRAX or frxUSD, using data sources beyond CryptoCompare, would test whether their crisis characteristics fall between fully collateralized and purely algorithmic designs, as theory would predict. This is the most direct extension of the present sample.

A second avenue is to push the analysis to higher frequency. Hourly or minute-level data would provide a much sharper picture of crisis dynamics, particularly for fast-moving events like the USDC/SVB episode of March 2023, which is largely flattened by daily closing prices. Higher-frequency data would also enable formal econometric work (survival models linking design features to crisis probability and severity, or event studies of contagion timing) that the descriptive approach taken here cannot support.

The third direction concerns regulation. The EU's Markets in Crypto-Assets Regulation, the emerging US frameworks including the CLARITY Act, and comparable regimes elsewhere create natural experiments for studying the causal effect of regulation on stablecoin stability. As the stablecoin ecosystem continues to mature and these regimes take effect, extending the sample forward in time and exploiting the cross-jurisdictional variation will allow for the kind of causal claims that the present descriptive analysis deliberately avoids.

Declaración de Uso de Herramientas de Inteligencia Artificial Generativa en Trabajos Fin de Grado

Por la presente, yo, Álvaro Moroño Moreno, estudiante de ADE y Business Analytics de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado titulado "WHEN THE PEG BREAKS: CHARACTERIZING STABLECOIN CRISES", declaro que he utilizado la herramienta de Inteligencia Artificial Generativa ChatGPT u otras similares de IAG de código sólo en el contexto de las actividades descritas a continuación:

1. **Interpretador de código**: Para realizar análisis de datos preliminares.
2. **Constructor de plantillas**: Para diseñar formatos específicos para secciones del trabajo.
3. **Corrector de estilo literario y de lenguaje**: Para mejorar la calidad lingüística y estilística del texto.
4. **Sintetizador y divulgador de libros complicados**: Para resumir y comprender literatura compleja.
5. **Revisor**: Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.

Afirmo que toda la información y contenido presentados en este trabajo son producto de mi investigación y esfuerzo individual, excepto donde se ha indicado lo contrario y se han dado los créditos correspondientes (he incluido las referencias adecuadas en el TFG y he explicitado para que se ha usado ChatGPT u otras herramientas similares). Soy consciente de las implicaciones académicas y éticas de presentar un trabajo no original y acepto las consecuencias de cualquier violación a esta declaración.

Fecha: 18 de mayo de 2026

Firma: ___Álvaro Moroño Moreno___

8. REFERENCES

Ahmed, R., Aldasoro, I., & Duley, C. (2025). *Public information and stablecoin runs* (BIS Working Papers No. 1164). Bank for International Settlements.

Aldasoro, I., Aquilina, M., Lewrick, U., & Lim, S. H. (2025). Stablecoin growth-policy challenges and approaches. *BIS Bulletins*, (108).

Ante, L., Fiedler, I., Willruth, J. M., & Steinmetz, F. (2023). A Systematic Literature Review of Empirical Research on Stablecoins. *FinTech*, *2*(1), 34–47. https://doi.org/10.3390/fintech2010003

Briola, A., Vidal-Tomás, D., Wang, Y., & Aste, T. (2023). Anatomy of a Stablecoin's failure: The Terra-Luna case. *Finance Research Letters*, *51*, 103358. https://doi.org/10.1016/j.frl.2022.103358

CFTC. (2021). *CFTC Orders Tether and Bitfinex to Pay Fines Totaling $42.5 Million*. https://www.cftc.gov/PressRoom/PressReleases/8450-21

CoinDesk. (2020). *DeFi Leader MakerDAO Weighs Emergency Shutdown Following ETH Price Drop*. https://www.coindesk.com/tech/2020/03/12/defi-leader-makerdao-weighs-emergency-shutdown-following-eth-price-drop

Du, C., Sonawane, R., & Watsky, C. (2025). *In the Shadow of Bank Runs: Lessons from the Silicon Valley Bank Failure and Its Impact on Stablecoins* [FEDS Notes]. Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/econres/notes/feds-notes/in-the-shadow-of-bank-run-lessons-from-the-silicon-valley-bank-failure-and-its-impact-on-stablecoins-20251217.html

Duan, K., & Urquhart, A. (2023). The instability of stablecoins. *Finance Research Letters*, *52*, 103573. https://doi.org/10.1016/j.frl.2022.103573

Eichengreen, B., Rose, A. K., & Wyplosz, C. (1995). Exchange market mayhem: The antecedents and aftermath of speculative attacks. *Economic Policy*, *10*(21), 249–312. https://doi.org/10.2307/1344591

Flood, R. P., & Garber, P. M. (1984). Collapsing exchange-rate regimes: Some linear examples. *Journal of International Economics*, *17*(1), 1–13. https://doi.org/10.1016/0022-1996(84)90002-3

Flood, R. P., Garber, P. M., & Kramer, C. (1996). Collapsing exchange rate regimes: Another linear example. *Journal of International Economics, Symposium on Mexico*, *41*(3), 223–234. https://doi.org/10.1016/S0022-1996(96)01435-3

Flood, R. P., & Marion, N. P. (2000). Self-fulfilling risk predictions: An application to speculative attacks. *Journal of International Economics*, *50*(1), 245–268. https://doi.org/10.1016/S0022-1996(98)00039-7

Frankel, J. A., & Rose, A. K. (1996). *Currency Crashes in Emerging Markets: Empirical Indicators* (Working Paper No. 5437). National Bureau of Economic Research. https://doi.org/10.3386/w5437

Girton, L., & Roper, D. (1977). A Monetary Model of Exchange Market Pressure Applied to the Postwar Canadian Experience. *The American Economic Review*, *67*(4), 537–548.

Gregory, G., Alessio, C., Vito, L., & Patrice, S. (2024). Break a peg! A study of stablecoin co-instability. *International Review of Financial Analysis*, *96*, 103608. https://doi.org/10.1016/j.irfa.2024.103608

Gubareva, M., Bossman, A., & Teplova, T. (2023). Stablecoins as the cornerstone in the linkage between the digital and conventional financial markets. *The North American Journal of Economics and Finance*, *68*, 101979. https://doi.org/10.1016/j.najef.2023.101979

Hoang, L. T., & Baur, D. G. (2024). How stable are stablecoins? *The European Journal of Finance*, *30*(16), 1984–2000. https://doi.org/10.1080/1351847X.2021.1949369

Kaminsky, G. L., & Reinhart, C. M. (1999). The Twin Crises: The Causes of Banking and Balance-of-Payments Problems. *American Economic Review*, *89*(3), 473–500. https://doi.org/10.1257/aer.89.3.473

Krugman, P. (1979). A Model of Balance-of-Payments Crises. *Journal of Money, Credit and Banking*, *11*(3), 311–325. https://doi.org/10.2307/1991793

Krugman, P. (1999). Balance Sheets, the Transfer Problem, and Financial Crises. *International Tax and Public Finance*, *6*(4), 459–472. https://doi.org/10.1023/A:1008741113074

Lee, Y.-H., Chiu, Y.-F., & Hsieh, M.-H. (2025). Stablecoin depegging risk prediction. *Pacific-Basin Finance Journal*, *90*, 102640. https://doi.org/10.1016/j.pacfin.2024.102640

Obstfeld, M. (1984). *Rational and Self-Fulfilling Balance-of-Payments Crises* (Working Paper No. 1486). National Bureau of Economic Research. https://doi.org/10.3386/w1486

Watsky, C., Allen, J., Daud, H., Demuth, J., Little, D., Rodden, M., & Seira, A. (2024). *Primary and Secondary Markets for Stablecoins* [FEDS Notes]. Board of Governors of the Federal Reserve System. https://www.federalreserve.gov/econres/notes/feds-notes/primary-and-secondary-markets-for-stablecoins-20240223.html

Wen, H., Li, S., & Zhang, J. (2025). *Hybrid Monetary Ecosystems: Integrating Stablecoins and Fiat in the Future of Currency Systems* (arXiv:2505.10997). arXiv. https://doi.org/10.48550/arXiv.2505.10997

9. APPENDIX

APPENDIX A: Full Crisis Episodes Catalog

Table A.1 lists all 85 crisis episodes identified under the primary specification (2% deviation threshold, 1-day minimum persistence). Episodes are grouped by stablecoin and sorted chronologically. Maximum deviation is measured as |P_t − 1|. Cumulative deviation is the sum of daily absolute deviations over the episode duration. Recovery time indicates the number of days until the price returned to the ±1% parity band; "—" indicates no recovery within the sample period. BUSD is excluded from this table as it registered zero episodes.

Table A.1: Complete crisis episodes catalog (2% threshold)

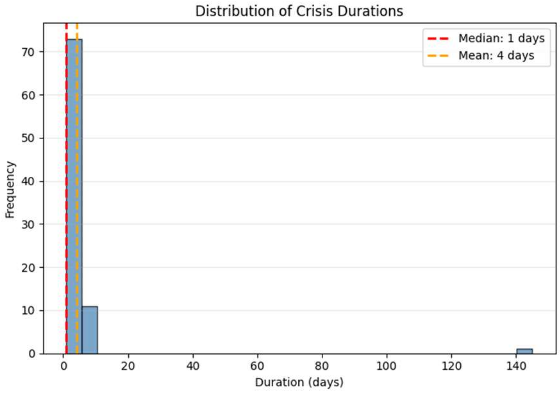
#	Stablecoin	Start Date	End Date	Duration (days)	Max Dev.	Cum. Dev.	Recovery (days)
1	DAI	2017-12-28	2018-01-02	6	0.100	0.600	10
2	DAI	2018-01-04	2018-01-11	8	0.100	0.800	1
3	DAI	2018-02-05	2018-02-05	1	0.181	0.181	1
4	DAI	2018-02-08	2018-02-08	1	3.068	3.068	1
5	DAI	2018-04-15	2018-04-21	7	0.208	0.419	1
6	DAI	2018-04-23	2018-04-28	6	0.256	0.680	11
7	DAI	2018-04-30	2018-05-08	9	0.030	0.270	1
8	DAI	2018-06-21	2018-06-21	1	0.026	0.026	1
9	DAI	2018-08-22	2018-08-22	1	0.024	0.024	1
10	DAI	2018-11-19	2018-11-20	2	0.022	0.044	1
11	DAI	2019-03-07	2019-03-08	2	0.031	0.057	2
12	DAI	2019-03-19	2019-03-21	3	0.023	0.065	38
13	DAI	2019-03-25	2019-03-25	1	0.021	0.021	34
14	DAI	2019-03-28	2019-03-28	1	0.024	0.024	31
15	DAI	2019-03-31	2019-04-01	2	0.025	0.050	27
16	DAI	2019-04-03	2019-04-12	10	0.047	0.363	16
17	DAI	2019-04-14	2019-04-20	7	0.032	0.174	8
18	DAI	2019-04-22	2019-04-26	5	0.030	0.133	2
19	DAI	2020-03-12	2020-03-12	1	0.062	0.062	13
20	DAI	2020-03-14	2020-03-18	5	0.043	0.155	7
21	DAI	2020-03-23	2020-03-23	1	0.022	0.022	2
22	DAI	2020-03-29	2020-03-29	1	0.020	0.020	34
23	DAI	2020-04-01	2020-04-03	3	0.026	0.069	29

#	Stablecoin	Start Date	End Date	Duration (days)	Max Dev.	Cum. Dev.	Recovery (days)
24	DAI	2020-04-07	2020-04-09	3	0.031	0.072	23
25	DAI	2020-04-11	2020-04-11	1	0.023	0.023	21
26	DAI	2020-04-16	2020-04-16	1	0.022	0.022	16
27	DAI	2020-07-12	2020-07-12	1	0.020	0.020	7
28	DAI	2020-07-22	2020-07-24	3	0.035	0.092	1
29	DAI	2020-07-28	2020-08-02	6	0.032	0.148	12
30	DAI	2020-08-08	2020-08-08	1	0.020	0.020	6
31	DAI	2020-09-07	2020-09-15	9	0.037	0.259	6
32	DAI	2020-09-17	2020-09-17	1	0.022	0.022	4
33	DAI	2023-03-11	2023-03-11	1	0.030	0.030	1
34	TUSD	2018-05-19	2018-05-21	3	0.080	0.120	1
35	TUSD	2018-05-25	2018-05-25	1	0.020	0.020	1
36	TUSD	2018-05-27	2018-05-28	2	0.020	0.040	1
37	TUSD	2018-08-14	2018-08-14	1	0.030	0.030	1
38	TUSD	2018-10-14	2018-10-14	1	0.023	0.023	1
39	TUSD	2018-11-14	2018-11-14	1	0.026	0.026	4
40	TUSD	2018-12-16	2018-12-16	1	0.020	0.020	5
41	TUSD	2018-12-25	2018-12-25	1	0.026	0.026	22
42	TUSD	2018-12-28	2019-01-02	6	0.032	0.138	14
43	TUSD	2019-02-13	2019-02-13	1	0.042	0.042	1
44	TUSD	2019-02-27	2019-02-27	1	0.025	0.025	2
45	TUSD	2019-04-26	2019-04-26	1	0.027	0.027	13
46	TUSD	2019-04-28	2019-04-29	2	0.024	0.044	10
47	TUSD	2019-05-02	2019-05-02	1	0.021	0.021	7
48	TUSD	2022-12-24	2022-12-24	1	0.021	0.021	2
49	TUSD	2023-05-08	2023-05-08	1	0.022	0.022	1
50	TUSD	2024-02-16	2024-02-17	2	0.025	0.047	12
51	TUSD	2024-02-19	2024-02-28	10	0.039	0.269	1
52	TUSD	2024-03-24	2024-03-26	3	0.026	0.066	1
53	TUSD	2024-12-07	2024-12-08	2	0.027	0.049	4
54	TUSD	2024-12-11	2024-12-11	1	0.020	0.020	1
55	USDC	2018-10-15	2018-10-17	3	0.026	0.068	7
56	USDC	2018-11-14	2018-11-14	1	0.022	0.022	16

#	Stablecoin	Start Date	End Date	Duration (days)	Max Dev.	Cum. Dev.	Recovery (days)
57	USDC	2018-11-24	2018-11-24	1	0.023	0.023	6
58	USDC	2018-12-16	2018-12-16	1	0.020	0.020	29
59	USDC	2018-12-29	2018-12-29	1	0.020	0.020	16
60	USDC	2019-04-28	2019-04-28	1	0.023	0.023	11
61	USDC	2019-05-02	2019-05-02	1	0.021	0.021	7
62	USDC	2023-03-11	2023-03-11	1	0.032	0.032	1
63	USDT	2017-07-02	2017-07-02	1	0.030	0.030	11
64	USDT	2017-09-02	2017-09-06	5	0.040	0.120	5
65	USDT	2017-09-10	2017-09-10	1	0.027	0.027	1
66	USDT	2017-11-26	2017-11-26	1	0.021	0.021	1
67	USDT	2017-11-29	2017-11-29	1	0.020	0.020	2
68	USDT	2017-12-12	2017-12-12	1	0.045	0.045	3
69	USDT	2017-12-22	2017-12-24	3	0.081	0.127	2
70	USDT	2018-01-16	2018-01-16	1	0.035	0.035	3
71	USDT	2018-01-18	2018-01-18	1	0.020	0.020	1
72	USDT	2018-10-15	2018-10-17	3	0.027	0.072	2
73	USDT	2018-11-14	2018-11-14	1	0.030	0.030	4
74	USDT	2018-11-19	2018-11-20	2	0.029	0.053	8
75	USDT	2018-11-24	2018-11-26	3	0.023	0.065	2
76	USDT	2018-12-22	2018-12-22	1	0.024	0.024	29
77	USDT	2018-12-25	2018-12-25	1	0.023	0.023	26
78	USDT	2018-12-27	2018-12-30	4	0.028	0.100	21
79	USDT	2019-01-01	2019-01-02	2	0.026	0.048	18
80	USDT	2019-01-04	2019-01-06	3	0.028	0.072	14
81	USDT	2019-01-08	2019-01-10	3	0.022	0.064	10
82	USDT	2019-01-12	2019-01-14	3	0.022	0.064	6
83	USDT	2020-03-12	2020-03-12	1	0.026	0.026	1
84	USTC	2020-10-22	2020-10-22	1	0.021	0.021	1
85	USTC	2022-05-09	2022-09-30	145	0.993	136.972	—

APPENDIX B: Supplementary Figures

Figure B.1 shows the distribution of crisis episode durations across all 85 episodes. The distribution is heavily right-skewed, with the majority of episodes lasting between 1 and 3 days. The USTC collapse (145 days) is the only episode exceeding 90 days.



APPENDIX C: Robustness Check — Alternative Persistence Criterion

As discussed in Section 4.2, the primary analysis uses a one-day minimum persistence criterion. This appendix reports results under an alternative two-consecutive-day requirement. Table C.1 compares the two specifications. Table C.2 disaggregates the comparison by stablecoin.

Table C.1: Impact of persistence criterion on episode identification

Metric	Primary (1-day)	Robust (2-day)
Total episodes	85	38
Episodes dropped	—	47 (55.3%)
Median duration (days)	1.0	2.0
Mean max deviation	0.0837	0.0706
Median recovery time (days)	5.0	7.0

Table C.2: Episodes by stablecoin under both specifications

Stablecoin	Primary (1-day)	Robust (2-day)	Dropped
BUSD	0	0	0
DAI	33	18	15
TUSD	21	8	13
USDC	8	1	7
USDT	21	10	11
USTC	2	1	1

All 47 dropped episodes have a duration of exactly one day. Notable episodes excluded by the two-day criterion include the USDC de-peg of March 11, 2023 (SVB episode, max deviation 3.21%), DAI's "Black Thursday" episode of March 12, 2020 (max deviation 6.2%), and DAI's $4.07 spike of February 8, 2018 (max deviation 306.8%). The exclusion of these well-documented events supports the choice of one-day persistence as the primary specification.

The core findings are robust to the alternative criterion. The ranking of stablecoins by crisis frequency is preserved. The type-level severity gradient, fiat-backed exhibiting the mildest profiles, crypto-backed occupying an intermediate position, and algorithmic exhibiting the most extreme, holds in its entirety. The qualitative conclusions of Section 6 are unchanged. This result is particularly noteworthy given the demanding nature of the test: the two-day criterion excludes the USDC de-peg of March 2023 (a benchmark event in the recent stablecoin literature, max deviation 3.21%), DAI's Black Thursday episode of March 2020 (the canonical third-generation case study, max deviation 6.2%), and DAI's February 2018 outlier (max deviation 306.8%). The fact that these well-documented, economically significant events can be dropped wholesale while the cross-sectional ranking remains fully intact suggests that the main findings are driven by genuine structural differences across stablecoin designs, not by the identification of borderline single-day events. This reinforces the credibility of the primary specification and supports the choice of a one-day minimum persistence criterion as a deliberate methodological feature rather than a default.

APPENDIX D: Source Code

The full code employed for the development of this thesis can be accessed through the following public repository:

https://github.com/alvaromoronomoreno/TFG_Morono_Moreno_Alvaro