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STABLECOIN FAILURES THROUGH THE LENS OF EXCHANGE RATE CRISIS MODELS: EMPIRICAL INSIGHTS FROM HISTORICAL DE-PEGGING EVENTS

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ABSTRACT

This dissertation investigates the determinants of stablecoin de-pegging events and examines whether their dynamics can be interpreted through the framework of traditional exchange rate crisis models. Using a panel of major stablecoins with heterogeneous designs, the empirical analysis combines pooled logit models to explain the probability of de-pegging and OLS specifications to assess the magnitude of deviations from the peg.

The results reveal a consistent pattern across specifications. Collateral quality emerges as the most robust predictor of stability, significantly reducing both the likelihood and severity of de-pegging episodes. Market capitalisation dynamics also play a central role, with contractions in size strongly associated with increased fragility. By contrast, macro-financial variables such as market sentiment and Bitcoin volatility primarily act as triggers, affecting the probability of de-pegging events but not their magnitude once instability occurs. Coin-level regressions further highlight substantial heterogeneity across stablecoin designs, suggesting that while common mechanisms are present, the transmission of instability depends on structural features such as collateralisation, liquidity, and exposure to decentralised finance ecosystems.

These findings contribute to the literature by bridging the gap between currency crisis theory and stablecoin instability, showing that parity breaks in digital assets can be understood as a reconfiguration of traditional monetary fragilities. From a policy perspective, the results underscore the need for design-specific regulation, as different stablecoin architectures entail distinct risk profiles. Overall, the analysis provides new empirical evidence on the drivers of stablecoin instability and offers insights relevant for both academic research and financial regulation.

Keywords: Stablecoins, De-pegging, Currency crises, Crypto markets, Financial stability, Collateralisation, Market liquidity, Digital Assets, Regulation, DeFi

RESUMEN

Este trabajo analiza los determinantes de los episodios de pérdida de paridad (*de-pegging*) en stablecoins y examina si su dinámica puede interpretarse a la luz de los modelos tradicionales de crisis cambiarias. Utilizando un panel de stablecoins con diseños heterogéneos, el análisis empírico combina modelos logit agrupados para explicar la probabilidad de depeg y especificaciones OLS para evaluar la magnitud de las desviaciones respecto al peg.

Los resultados muestran un patrón consistente entre especificaciones. La calidad del colateral emerge como el determinante más robusto de la estabilidad, reduciendo tanto la probabilidad como la severidad de los episodios de depeg. Asimismo, la dinámica de la capitalización de mercado desempeña un papel central, ya que las contracciones en el tamaño de las stablecoins se asocian estrechamente con un aumento de su fragilidad. Por el contrario, variables macrofinancieras como el sentimiento de mercado o la volatilidad de Bitcoin actúan principalmente como desencadenantes, afectando la probabilidad de los episodios de depeg, pero no su magnitud una vez que la inestabilidad se materializa. Los análisis a nivel individual ponen de manifiesto una notable heterogeneidad entre diseños, lo que sugiere que, si bien existen mecanismos comunes, la transmisión de la inestabilidad depende de factores estructurales como el tipo de colateral, la liquidez y la integración en el ecosistema DeFi.

Estos resultados contribuyen a la literatura al tender un puente entre la teoría de crisis cambiarias y la inestabilidad de las stablecoins, mostrando que las rupturas de paridad en activos digitales pueden interpretarse como una reconfiguración de fragilidades monetarias tradicionales. Desde una perspectiva de política económica, el trabajo subraya la necesidad de una regulación diferenciada por diseño, dado que cada tipo de stablecoin presenta perfiles de riesgo distintos. En conjunto, el análisis aporta nueva evidencia empírica sobre los factores que explican la inestabilidad de las stablecoins y ofrece implicaciones relevantes tanto para la investigación académica como para la regulación financiera.

Palabras clave: Stablecoins, Pérdida de paridad, Crisis cambiarias, Mercado cripto, Estabilidad financiera, Colateralización, Liquidez, Activos digitales, Regulación, DeFi

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1 Introduction

The first functional blockchain technology was launched in 2008 to serve as the decentralised, public ledger for Bitcoin (BTC) (Nakamoto, 2008). Catalini and Gans (2016) expose the reduction of verification and networking costs as the main benefits of the system, thanks to Bitcoin becoming both an incentive and a consensus mechanism to eliminate due diligence behind transactions and their third-party validation, respectively. In this sense, it does not surge as an ideological alternative to fiat money, but like a practical solution to market frictions. Nevertheless, empirical evidence suggests that cryptocurrency adoption is not primarily driven by a desire to replace traditional financial services. Using survey data on U.S. households, Auer & Tercero-Lucas (2022) show that cryptocurrency ownership is more strongly associated with speculative and investment behaviour than with distrust in the traditional financial system. Hence, crypto assets were not designed to become a stable unit of account, and their extreme volatility limits their use to speculative investment, leaving a gap to be filled when the ecosystem requires less price risk and a reliable transactional instrument. The gap evidences why it is not completely correct to speak about cryptocurrencies, given the restrictions in the three basic functions of money – medium of exchange, unit of account, and store of value (Oliver & Otero, 2022). Their use as payment mean is limited, and its extreme volatility makes them insecure units to invest and issue contracts with. Therefore, stablecoins, also called backed tokens, are created to provide a money-alike instrument in digital transactions. Bullman et al. (2019) define them as "digital units of value that are not a form of any specific currency (or basket thereof) but rely on a set of stabilisation tools which are supposed to minimise fluctuations of their price in such currency(ies)"; i.e., crypto assets with values tied to fiat currencies or other assets. These tokens attempt to serve the three basic functions, while bridging the gap with the traditional financial system.

The ECB´s Financial Stability Review report concludes that stablecoins act as "money-like instruments" in the crypto ecosystem (FSB, 2021). First, they are not just crypto assets with a stable price; they are the cash substitute in this market; their 24/7 availability, higher efficiency, and volatility shield allow for stablecoins to be the most popular settlement medium for crypto trading (Higginson, 2025). Secondly, they are also a temporary storage of value that allows participants to preserve purchasing power within the digital ecosystem without converting back to fiat currency – incurring time and fees. Instead, they convert to USDC or USDT to capitalise on market moves, using them as a "parking asset", a typical function of monetary assets (ECB, 2021). In spite of this, it has not got the plein potential to be a unit of account in the

Decentralised Finance (DeFi) scene: whilst some contracts and liquidity pools reference their value in stablecoins, the ultimate pricing unit in decentralised finance continues to be the dollar, reflecting the fact that their stability is pledged rather than intrinsic (Bullman et al., 2019).

Moreover, stablecoins exhibit structural features that distinguish them sharply from traditional stable deposits, and which make their commitment to parity considerably more fragile. Reserves are often held in volatile crypto assets rather than liquid, sovereign-backed instruments; there is no central bank acting as lender of last resort; arbitrage and stabilisation mechanisms are decentralised and algorithmic-dependent; and contagion can propagate at digital speed across interconnected protocols. These features have not prevented severe failures: Tether, the most widely used stablecoin, was fined in October 2021 due to not holding 100% of its reserves available to guarantee dollar convertibility; and TerraUSD collapsed entirely in May 2022, erasing tens of billions of dollars in value within days. As in traditional currency crises, stablecoin issuers face a fundamental trade-off between maintaining the peg and the sustainability of their reserves, the credibility of their design, and user confidence.

This paper tries to disentangle to what extent can de-pegging events and failures of stablecoins be explained through traditional exchange rate crisis models. Existing literature documents individual failures and stablecoin design in detail, but lacks a systematic framework grounded in economic theory that integrates crypto collapse dynamics within the basis of currency crisis models. The gap is consequential: without such a framework, policymakers and designers lack analytical tools to anticipate fragility and distinguish between structurally different failure modes. This paper aims to bridge that research gap by mapping the first-, second-, and third-generation currency crisis models onto the stabilisation architectures of stablecoins, and testing whether the variables derived from those models are statistically associated with de-pegging events. The contribution combines bringing established macroeconomic theory to a modern digital finance problem, building a descriptive taxonomy of instability mechanisms, and deriving design implications for an asset class that has so far been studied largely inside its own ecosystem rather than as a comparable to broader currency crisis literature.

Using a novel daily panel dataset of five stablecoins – DAI, USDC, UST, USDN, and IRON[1] – covering the period 2020–2024 and fiat-backed, crypto-collateralised, and algorithmic architectures, the empirical analysis evaluates whether observed de-pegging events conform to a generational categorisation similar to that proposed by the theoretical framework. The central proposition is that stablecoins do not fail for being crypto assets, nor due to purely technological flaws, but rather because each design architecture replicates a classical stabilisation commitment that is subject to the same categories of fragility identified in sovereign currency systems.

This thesis is structured as follows. Chapter 2 presents the literature review, covering the three generations of currency crisis models, the design and stabilisation mechanisms of stablecoins, relvant case studies, and the actual regulatory landscape. Chapter 3 develops the theoretical framework, establishing a conceptual mapping between crisis model generations and stablecoin architectures and deriving the empirical hypotheses. Chapter 4 describes the data, variable construction, and empirical strategy. Chapter 5 presents the results, comprising both pooled panel regressions and individual coin-level analyses, as well as a synthesis of the findings into a generational typology of stablecoin instability mechanisms. Lastly, Chapter 6 concludes and discusses the implications for research and policy.

2 Literature Review

2.1 Currency crisis models

Currency crisis models offer the main theoretical framework for analysing de-pegging episodes and their causes. The literature usually distinguishes among first-, second-, and third-generation models[2], each of which highlights a different mechanism behind crisis dynamics. These mechanisms range from weak macroeconomic fundamentals and reserve depletion to self-fulfilling shifts in expectations and, later, to financial fragility and balance-sheet mismatches.

[1] Tether (USDT) is excluded from the analysis its brief deviations during the sample period were insufficiently sustained to constitute de-pegging episodes under the threshold adopted in this study. Additionally, opacity regarding its reserve composition during the period covered introduces a data quality concern that cannot be correctly addressed with publicly available information.
[2] Some studies explain a fourth generation of models which argue that the likelihood of a currency crisis depends on how domestic political institutions – such as legislative fragmentation, government stability, and central bank independence – affect the credibility of the exchange-rate commitment and the ability to sustain a peg (Leblang, 2002).

2.1.1 First-generation models

Krugman (1979) explains how currency crises are the inevitable outcome of inconsistent macroeconomic policies. It defines "balance-of-payments" crises, which occur when state resources used to sustain the fixed rate are saturated. These models evolved in response to crises in developing countries with fixed exchange rate regimes such as Mexico (1973-82), Argentina (1978-81), and Chile (1983); a period which was marked by the breakdown of the Bretton Woods system (1971)[3], oil shocks (1974,1979) and severe political and macroeconomic imbalances in the international atmosphere.

The logic behind the theory is that inconsistent expansionary monetary and fiscal policies lead to a speculative attack and the collapse of the currency peg. The starting point is a country´s persistent fiscal deficit, which is monetised by its central bank by issuing domestic currency, a phenomenon called fiscal dominance[4]. Because of this, apart from the inflationary burden that the policy entails, Krugman describes how, in order to maintain a fixed exchange rate, the Treasury needs to simultaneously sell foreign currency to counteract the excess domestic supply. However, if continued, the gradual depletion of foreign reserves makes the fixed price unsustainable. The mechanism of failure is the launch of a speculative attack from investors, who anticipate the break due to reserves reaching zero, and buy all the remaining, thereby provoking the collapse of the regime with the devaluation of the currency and inflation. It is important to note that the de-pegging is unavoidable, the fundamentals of those systems were bound to fail; investors just anticipate the crisis through an act of rational arbitrage, not a shift in expectations as in second-generation models (Dabrowski, 2022).

The main contribution of Krugman's work is showing that inconsistent policies such as domestic credit expansion in a fixed exchange rate regime involves a predictable complete exhaustion of international reserves and a devaluation of the rate, forcing the abandonment of the peg. However, some criticisms include the strict assumptions under which the triggering factors are simplified to flawed fundamentals and rationality. Cuaresma and Slacík (2008) argue that it does not explain "surprise" crises occurring in an economic environment with coherent macro decisions and speculative attacks based on market sentiment. Moreover,

[3] The Bretton Woods system (1944–1971) was the first negotiated monetary order, setting fixed exchange rates by pegging world currencies to the U.S. dollar.
[4] The situation forces a central bank to prioritise financing the government over controlling inflation, effectively ending central bank independence (ECB, 2020).

another limitation is underestimating the Treasury´s independence from the government; to not be forced to fiscal dominance, and its tools to peg the exchange rate apart from the sale of reserves. Realistically, the central bank could use other policies such as open-market sale of securities or intervention in the forward market (Broner, 2008).

2.1.2 Second-generation models

Obstfeld (1994), on the other hand, did consider the role of expectations and self-fulfilling crises when approaching second-generation models. He explains situations under sound economic policies with no structural fiscal issue where the peg is a contingent commitment. Implying that its sustainability depends on the government´s willingness – not ability – to support it, and on how investors perceive this promise. These crises can be framed in the European Exchange Rate Mechanism (ERM) collapse on "Black Wednesday", September 16, 1992; when market pressure forced countries like the UK and Italy to exit the ERM, as governments, after efforts of rising interest rates and spending in reserves, failed to keep their currencies within the agreed band due to divergent economic procedures among member states and speculative attacks on weaker currencies (Xiao, 2024).

In this case, there is multiple equilibria, with investor confidence in the government's willingness to maintain the rate being the factor most responsible for the different outcomes. Policy makers have a trade-off between defending the peg and its economic costs, e.g., if the economy demands lower interest rates due to lack of jobs, perhaps the costs of maintaining the fixed rate at expense of a recession exceed its benefits and the country is forced to abandon it. In truth, agents (investors) are key to this model because, despite the will to sustain the fixed rate, what matters most is its credibility to them. Obstfeld remarks the vital importance of expectations because they trigger the crisis by a self-fulfilling prophecy[5]; if they expect restrictive monetary policy to not hold, they will prompt a speculative attack by selling domestic currency; forcing the break, whatever the scheme would have been.

Second-generation models highlight that the distinction between fundamentals-driven crises and expectation-driven crises is misleading. It is not a dichotomic event, they emerge from government credibility problems among an interaction in which bearing policy costs depend

[5] A self-fulfilling prophecy in economics occurs when a widely held expectation about the future alters behaviour, causing the predicted event to occur (O'Rourke, 2016).

on market expectations and vice versa, leading to multiple possible equilibria (Xiao, 2024).[4] Nevertheless, some scholars argue that the model considers a narrow scope of actors, focusing on central banks and forgetting about private large financial institutions, who play a big role in trading volume which will be introduced in the third-generation models (Rangvid, 2002). Furthermore, inquiries have been made about the challenge of empirically distinguishing the timing and type of equilibrium that will occur in each economic area, and even why it was Black Wednesday and not Black Tuesday. Criticising the inaccuracy of the theory, which just mentions the attack, but does not precise the break point at which investors lose confidence and "cash out" (Naef, 2022).

2.1.3 Third-generation models

The outburst of the Asian crisis in 1997-1998 gave place to the third-generation models, which Corsetti et al. (1998) used to introduce financial institutions as key to explaining how the sustainability of a fixed exchange rate is questioned when the surrounding financial environment is struggling. These models extend the analysis by incorporating interactions between currency markets and financial systems; relationship that Kaminsky & Reinhart (1999) present as closely linked and mutually reinforcing in their "Twin Crises" paper. In fact, Krugman (1999) exemplifies this generation by describing the feedback loop caused by high foreign-currency-denominated debt and weak corporate balance sheets, implying that currency devaluation acts contractionarily by reducing domestic firms´ net worth; in turn harming their borrowing capacity. Different fundamentals´ problems appear in overleveraged economies with a high moral hazard, which has pushed them to take excessive risks. In fact, the study defines these countries as "paper tigers"[5], referring to the expanding size of their asset market in spite of its weak sustain, which fell apart quickly with contagious expectations.

The approach links currency crises to weaknesses in the domestic financial system through the combination of macro and micro factors. It emphasises on how the over-borrowing syndrome left a fragile ecosystem with implicit guarantees from the government to fix these microeconomic flaws. Thus, the currency mismatch is not the endgame problem, it is just a symptom of an economy featuring indebted banks and companies, and a large presence of

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[4] The failure of the ERM evidenced the need for a more stable currency union, laying the basis for stronger institutional arrangements and integration, eventually becoming the EU and a single European currency in 1999.
[5] Paper tiger: *a Chinese expression first used by Chairman Mao, a person, country, etc., that appears outwardly powerful or important but is actually weak or ineffective* (Oxford English Dictionary, 2nd edition.)

foreign investment, a mix which is bound to fail. Likewise, Chang & Velasco (1998) address the Asian currency crisis "as a product of a bank run". Following a sudden change in expectations caused by capital flight in foreign currency, the government intervenes to bail out the banks with expansionary tools, perhaps at the expense of losing the fixed rate. Again, here, the speculative attack is not irrational, the financial fragilities that were in place made it rational for investors to withdraw. The difference lies in that, this time, expectations do not affect government incentives to act; they directly affect balance sheets.

As in the second generation, these models attempt to explain how triggers are not just macroeconomic fundamentals, or expectations; they are a systemic interaction in which a third, much more unpredictable factor, appears to shift the exchange rate environment. Moreover, as examined by Kaminsky and Reinhart (1999), it gives rise to a "twin crises" relation where a currency crisis surges from a banking crisis and then they reinforce each other. Eyraud et al. (2018) also note a limitation in that, when attempting to consider multiple variables, it creates complex models hard to be predictive; they sacrifice parsimony in order to capture complex financial interactions yet jeopardising its forecasting power.[6]

2.2 Stablecoin literature

2.2.1 Design and stabilisation mechanisms

The stability of stablecoins is not an automatic property but rather depends on the credibility of their backing mechanism and the possibility of exchange, which in turn depends on the design behind them, meaning that their parity is not guaranteed. The most common categorisation of stablecoins is based on the type of collateral used to stabilise their value. The classification typically yields three distinct types: asset-backed – comprising fiat and commodity basis, cryptocurrency-collateralised, and non-collateralised (algorithmic) tokens.

Firstly, the price of centralised fiat- and asset-collateralised stablecoins is supported by units of an asset (or basket of them) against which users can claim their holdings. However, due to the fluctuation of the collateral´s price, its parity is redemption-based (Bullman et al., 2019). For instance, the issuer promises that each token is worth 1:1 with the US dollar and can be "cashed in" for such at any moment. Whenever its price falls under US$1, arbitrageurs will

[6] It looks for explanatory simplicity. A model is parsimonious if it explains something with the fewest possible assumptions or variables while maintaining good predictive power.

stabilise it back to parity by buying and redeeming it with the issuer at the dollar´s value; reducing the offer and raising its price back to 1:1. For this mechanism to work, the issuer must maintain sufficient reserves to meet the claims, which poses redemption and liquidity risk to this system when under-collateralised. Ma et al. (2025) show that asset illiquidity coupled with fixed redemption values reinstate panic runs among investors. Here, the run-risk – exacerbated if reserves are illiquid or perceived insufficient – resembles first- and third-generation crises in which liquidity mismatches caused peg instabilities.

Next, decentralised unbacked algorithmic stablecoins use algorithms to maintain the peg. In the case of a shift in the price above or below a threshold, the mechanism automatically increases or decreases the supply through code and market incentives. In contrast to dollar-backed stablecoins, there is no clear arbitrage mechanism to restore values given the lack of equivalent collateral (Lyons & Viswanath-Natraj, 2022). Instead, other backings are used; such as the two-token system, which aims to provide a decentralised alternative by relying on mint-and-burn[7] of a secondary token rather than holding tangible reserves (McKenna, 2025). Algorithms are controversial due to its complete reliance on expectations. In fact, a self-fulfilling second-generation kind crisis happened when TerraUSD (UST), an algorithmic stablecoin that used LUNA – a secondary coin – to absorb its volatility, suffered a bank run caused by a loss of confidence and collapsed on May 2022. Briola et al. (2023) highlight the dangerous loop that can be observed when credibility drops and the selloff leads to "death spirals" in which the secondary token´s price crashes and no longer guarantees the value of the stablecoin being redeemed at 1:1; causing investors to panic-sell both assets, and the entire ecosystem to collapse.

Finally, crypto-backed stablecoins, which are also decentralised, attempt to combine collateral backing with automated adjustment mechanisms. Typically overcollateralised with crypto assets in place of fiat reserves, their stability relies on excess collateral requirements and automatic liquidation rules – e.g., predefined collateral ratios – placed in on-chain smart contracts[8] (Bullmann et al., 2019). However, because the underlying crypto collateral is itself volatile, abrupt market downturns can trigger forced liquidations, amplifying price declines

[7] Minting and burning refer to creating new tokens and destroying existing ones, respectively. These are used to regulate the supply, value, and circulation of assets, serving as a digital, automated equivalent of central bank currency issuance or destruction.

[8] On-chain actions are recorded directly on the public blockchain, validated by decentralised nodes; while off-chain transactions occur outside the main blockchain, via payment channels or private ledgers.

and fostering procyclicality.[9] As noted by the BIS (2023), such structures may transmit stress through declining asset values, resembling balance-sheet effects observed in the Asian crises; showing not only an expectations problem, but endogenous financial fragility.

Table 1. Stablecoin classification by stabilisation mechanism

Feature	*Asset-backed stablecoins*	*Algorithmic stablecoins*	*Crypto-backed stablecoins*
Stabilisation mechanism	1:1 peg through off-chain reserve backing (cash, t-bills, equivalents).	Via algorithmic supply adjustments and minting/burning a secondary token.	Through on-chain overcollateralisation (crypto assets) and auto-liquidation mechanisms.
Source of credibility	Credible redemption promise at par value.	Market confidence in the stabilising token.	Value of pledged collateral and liquidation rules.
Balance sheet structure	Off-chain assets backing on-chain liabilities.	No equivalent reserve asset; synthetic token absorbs shocks.	On-chain collateral exceeding issued supply.
Role of arbitrage	Arbitrageurs create and redeem tokens to restore parity.	Arbitrage between stablecoin and absorber token.	Liquidation arbitrage restores collateral ratios.
Main vulnerability	Run risk if reserves are illiquid or perceived insufficient.	Self-fulfilling "death spirals" if confidence breaks.	Procyclical liquidations during market stress.
Type of fragility	Liquidity mismatch; redemption pressure.	Expectation-driven failure.	Collateral price volatility.
Example	USDT, USDC	TerraUSD (UST)	DAI

Source: Authors's elaboration.

2.2.2 Case studies

In order to illustrate the previous fragilities, the following case studies are, among others, important to analyse. Rather than presenting them chronologically, they are organised by stabilisation mechanism, moving from more fragile designs to more robust ones. This structure allows the analysis to highlight how different architectures – algorithmic, crypto-collateralised, and fiat-backed – generate different vulnerabilities to de-pegging events.

[9] Amplification of economic cycles; exaggerating booms and crashes.

The most paradigmatic episode is the Terra USD (UST) collapse, which accelerated global efforts to regulate stablecoins; lawmakers consider it to be a clear example of systemic risk (OECD, 2022). UST aimed to maintain a value of 1:1 with the U.S. dollar through an algorithmic mechanism that used the floating rate coin LUNA as counterweight. The Anchor Protocol was designed to allow the exchange of 1 UST for US$1 worth of LUNA and stabilise the price: when UST traded above the peg, arbitrageurs could mint new UST by burning LUNA, increasing UST supply until the price returned to parity; when it traded below the peg, UST could be burned to mint LUNA, reducing supply and restoring the peg (Briola et al., 2023).

However, a series of events in 2022 evidenced the system´s heavy reliance on market confidence. On May 7th, 2022, a large market participant withdrew substantial liquidity from the UST–3CRV pool on Curve and simultaneously executed large sell orders of UST (approximately US$350 million).[10] This move unbalanced the liquidity pool and pushed the price of UST below its peg for the first time, starting arbitrage activity and amplifying market concern (Ba et al., 2025). After the first signs of the run in Anchor[11], and due to Blockchain technology allowing depositors to monitor each other's actions, the accelerated selling pressure caused the UST-LUNA mechanism to enter a "death spiral" (Liu et al., 2023). As investors sold UST for LUNA, the hyper-issuance of the latter caused its price to reach almost zero, and the sustained de-peg of UST, falling to US$0.12 in one week. The impact resulted in the vanishing of US$50 billion in market value of UST/LUNA, and the set off of a broader crypto currency market crash with over US$400 billion in losses (Loo, 2022). As analysed by Briola et al. (2023), the episode illustrates how algorithmic stablecoin designs may be particularly vulnerable to self-fulfilling run dynamics. Because the system relied primarily on market trust in LUNA instead of on exogenous collateral, once investors began to doubt the sustainability of the peg, their attempts to exit positions accelerated the collapse they feared. The Terra crisis therefore provides a clear example of how expectation-driven coordination and liquidity shocks can spread within DeFi architectures, producing instability mechanisms similar to classical financial runs.

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[10] Curve Finance is a decentralised exchange for stablecoin trading that uses an Automated Market Maker (AMM) algorithm and liquidity pools.

[11] 75% of UST supply had been deposited in Anchor to earn 20% annual yields, as claimed by the platform. Liu et al. (2023) show that both the deposit and lending rates on Anchor were heavily subsidised: newly issued UST were used to pay the interest; cycle that became unsustainable as the volume of deposits skyrocketed.

While TerraUSD represents the most prominent example of a purely algorithmic stablecoin collapse, earlier and smaller episodes had already revealed the fragility of stabilisation mechanisms that rely on endogenous tokens. An earlier episode was the collapse of IRON stablecoin issued by Iron Finance in June 2021. Unlike purely algorithmic stablecoins, its design attempted to combine 25% of algorithmic endogeneous stabilisation with 75% of partial collateral backing. To mint IRON, users deposited a mixture of USDC and TITAN, meaning that the stability of the system depended simultaneously on external collateral and on the market valuation of the protocol's native token; an architecture that exposed the system to both liquidity risk and reflexive price dynamics.While the presence of USDC provided an initial liquid base, a significant share of the backing relied on a floating coin (Saengchote, 2021; Federal Reserve, 2022).

The crisis unfolded in June 2021 following a sudden wave of selling pressure on TITAN after a period of vertical speculative growth and high yield-farming returns. As early investors began to realise profits, the token's price started to decline, weakening the collateralisation of IRON. The value decrease triggered redemptions of the stablecoin, which generated additional issuance of TITAN through the protocol. As observed in subsequent analyses, the expansion of TITAN supply during falling market demand rapidly intensified the price collapse and destabilised the peg (Federal Reserve, 2022). Within hours, TITAN fell from roughly US$60 to near zero, effectively erasing the endogenous component of the collateral structure. Although smaller in scale than the Terra crisis, this episode provided an illustration of how algorithmic architectures can become vulnerable to expectation-driven runs when confidence in the asset deteriorates, even if liquid collateral has been added. As noted by Briola et al. (2023), the event highlighted the structural fragility of designs that rely partly on endogenous tokens, where redemption mechanisms may amplify market stress rather than absorb it.

To further illustrate crypto-collateralised designs, the repeated de-pegging of Neutrino USD (USDN), issued by the Neutrino Protocol, exemplifies a mechanism that relies on crypto collateral to support its peg, replacing the purely algorithmic backing. Users could mint USDN by locking WAVES tokens into the protocol, while redemptions returned the underlying collateral. The stability of the system therefore depended primarily on the market valuation of WAVES rather than exclusively on arbitrage expectations (Feng et al., 2024). In theory, the protocol stabilised the peg during temporary imbalances between supply and demand. However, because the collateral consisted of a highly volatile asset, market swings coul cause the backing to fluctuate significantly. When the value of WAVES declined, the collateral ratio supporting the stablecoin weakened, creating incentives for investors to exit positions and increasing pressure on the peg (Au, 2024).

These vulnerabilities became particularly visible during the turmoil that followed the collapse of TerraUSD in 2022. The loss of confidence in algorithmic and cryprto stablecoins triggered widespread market stress across decentralised finance. In this environment, USDN experienced selling pressure as investors doubted the credibility of stablecoins. At the same time, the price of WAVES declined sharply, reducing the value of the collateral and intensifying market concerns (Abrams, 2022). Consequently, USDN lost its dollar parity in numerous occasions, at times falling below US$0.90 and remaining below the peg for extended periods. As opposed to the fast collapse observed in purely algorithmic systems, this episode was gradual, reflecting the interaction between falling collateral values and investor expectations. Although market sentiment still played a role, the main destabilising factor here was the deterioration of the asset backing the stablecoin. Over time, these persistent deviations from the peg harmed the credibility of the project's proposition. The protocol eventually abandoned the objective of maintaining the 1:1 parity with the U.S. dollar, and USDN evolved into a token whose value is indexed to protocol reserves; transforming it into a different type of asset (Neutrino Protocol Official Website, 2026).

Finally, overcollateralised and automated models show structural vulnerabilities under systemic stress, as it can be observed in DAI´s – a crypto-backed stablecoin managed by MakerDAO – behaviour. Unlike systems such as USDN, it requires overcollateralisation, meaning that users deposit collateral whose value significantly exceeds the amount of DAI minted. This creates a buffer against fluctuations in collateral prices and allows the protocol to liquidate positions when collateral ratios fall below defined thresholds (MakerDAO white paper; BIS, 2023). In this case, Zhang (2022) explains, DAI´s several temporary deviations from the peg are related to external inputs that evidence cycle-amplification dynamics and collateral interdependence risks. Namely, the "Black Thursday" crash – on March 2020, on account of the COVID-19 recession – exposed the "collateral cascade" risk and operational fragility of crypto-backed coins when the price of Ethereum[12] fell sharply and caused large-scale liquidations across decentralised finance. Moreover, oracles failed to update due to high

[12] DAI was launched on the main Ethereum network with a mechanism: users could lock up ETH as collateral and mint DAI against it (Kurt, 2025).

gas prices[13,14], so normal liquidation bots could not place bids for DAI; ultimately disrupting its liquidation mechanism reducing the availability of collateral backing (Hadi, 2025). Usually, arbitrageurs would mint more to cover the supply shock; however, volatility, congestion, and information delays impeded them to take such actions; causing a de-pegging in which DAI reached US$1.10 (Kurt, 2025). More recently, because a significant portion of DAI's backing consists of other stablecoins – particularly USD Coin – external shocks affecting them influence DAI's stability. For example, the banking stress surrounding Silicon Valley Bank in March 2023 affected USDC reserves and temporarily generated market uncertainty about the collateral structure. That said, it is important to note that, compared with other crypto-collateralised designs such as USDN, the overcollateralisation framework implemented by MakerDAO has generally allowed the protocol to restore the peg after periods of market turbulence (BIS, 2023).

Lastly, a key episode of fiat-backed stablecoins is the temporary de-pegging of USD Coin (USDC) in March 2023. It is issued by Circle Internet Financial and maintains its peg through reserves composed primarily of cash deposits and short-term U.S. Treasury securities. Here, the trigger was rooted in the traditional banking system and the crisis began following the collapse of Silicon Valley Bank (SVB), alongside the failures of Silvergate Bank and Signature Bank, institutions that were heavily exposed to cryptocurrency markets. Circle disclosed that approximately US$3.3 billion of USDC reserves were held at SVB at the time of its failure. The uncertainty regarding the recoverability of these deposits caused panic among investors and prompted large-scale redemptions, pushing the market price of USDC as low as US$0.88 (Hadi, 2025).

In this case, the instability did not stem from flaws in algorithmic stabilisation mechanisms or from the volatility of crypto collateral, but rather from a classic liquidity shock affecting the banking institutions holding the underlying reserves. As Moody's Ratings (2023) notes, fiat-backed stablecoins depend on the safety and accessibility of the financial intermediaries managing their reserves. If access to those reserves becomes hindered, market participants may question the issuer's ability to maintain convertibility, generating short-term price mismatches.

[13] Oracles are third-party services that bridge blockchains with off-chain, real-world data, enabling smart contracts to execute based on external inputs like price feeds, weather, or API data (Coinbase, 2026).

[14] Ethereum depends on gas prices because gas is the native transaction fee mechanism for its network, which requires users to pay for the computational resources used for transactions and smart contracts. The gas (in units) represents the effort, while the price, paid in Ether (ETH), is the cost per unit (Rasure, 2025).

Nevertheless, the episode also illustrates the relative resilience of fully collateralised designs. Following the announcement by U.S. authorities guaranteeing depositors of SVB, confidence gradually returned to the market and the peg was restored within days. As highlighted in a Fed´s report by Du et al. (2025), public intervention played a decisive role in stabilising expectations and preventing further contagion across crypto markets. However, this report also revealed a potential systemic flaw: had Circle been forced to liquidate large portions of its reserves – including U.S. Treasury bills and other liquid assets – the shock could caused a spillover into broader financial markets.

Taken together, the USDC episode demonstrates that even the most conservative stablecoin architectures remain exposed to external sources of instability. While algorithmic and crypto-collateralised models are primarily vulnerable to endogenous market dynamics within DeFi, fiat-backed stablecoins inherit risks from the traditional financial institutions that safeguard their reserves. As argued by Duan and Urquhart (2023), this reflects a structural trade-off between decentralisation and peg stability: designs that minimise reliance on financial intermediaries reduce custodial and regulatory risk but tend to be more exposed to endogenous volatility, whereas fully reserved stablecoins achieve tighter pegs at the cost of reintroducing centralised intermediation risks.

2.2.3 Regulation

Regulatory authorities have increasingly framed stablecoins as financial instruments capable of generating systemic risk if widely adopted. Arner et al. (2020) emphasises that stablecoins replicate core traditional banking functions, such as deposit-taking, maturity transformation and payment intermediation, without being subject to equivalent preventive measures. In particular, the BIS highlights run risk, reserve opacity and pro-cyclical dynamics as potential channels of instability, advocating the principle of "same risk, same regulation" and robust reserve requirements, transparency standards, and effective (perhaps, centralised) supervision.

Similarly, regulatory responses from the U.S. Federal Reserve (2021) argue that payment stablecoin issuers should be subject to bank-like regulation, including capital, liquidity, and risk-management requirements. These concerns materialised in the GENIUS Act, which establishes the first comprehensive federal framework for USD-denominated stablecoins. The legislation requires issuers to maintain 100% reserve backing with highly liquid assets, e.g., U.S. dollars or short-term Treasury securities, demands regular disclosure of reserve composition and audits, and restricts certain riskier assets such as equities, as well as adding diversification requirements. Such provisions aim to reduce redemption risk and strengthen consumer protection while allowing stablecoins to operate within a clearer regulatory perimeter (U.S. Senate Committee on Banking, Housing and Urban Affairs, 2025).

Within the euro area, the ECB has emphasised the dependency of privately issued digital money on its convertibility into central bank money (Panetta, 2021). From this perspective, stablecoins are structurally fragile as long as their credibility hinges on access to safe and liquid backing assets, particularly under market turmoil. The E.U.´s approach to establish common rules towards crypto-asset issuers and service providers across member states is the Markets in Crypto-Assets Regulation (MiCA). Under it, stablecoins classified as asset-referenced tokens or e-money tokens – essentially, the first category mentioned in section 2.2 – must comply with strict requirements regarding authorisation, governance, reserve management and redemption rights.[15] Issuers are required to maintain adequate reserve assets, ensure full exchange at par value and disclose detailed reserve composition (European Securities and Markets Authority, 2023).

Essentially, regulatory actors converge on the view that stablecoins reintroduce classical financial stability risks in digital form. They reiterate that the different backing designs do not represent evolutions to more stable mechanisms, they just determine whether risks emerge via redemption channels, collateral valuation or interdependent balance sheets; thereby calling for stricter oversight comparable to that applied to traditional financial institutions (BIS, 2023).

3 Theoretical Framework

This section elaborates on a conceptual analogy between fiat crisis models and stablecoin disparities – considering that these assets differ in institutional backing and legal status, it will focus on their commitment to maintain the peg – and illustrates how classical mechanisms can be reinterpreted within a DeFi monetary environment.

[15] Because MiCA mandates that stablecoins be backed by asset reserves, pure algorithmic tokens — which rely on code and cannot replace reserve backing — are considered non-compliant.

3.1 Conceptual mapping

Four concepts are important to map in order to establish a practical framework: peg, reserves, central banks, and speculative attacks – considering the analogy in terms of functional equivalence as opposed to institutional identity.

- The peg: in both cases, a pledge is made to hold a fixed conversion rate against a reference asset, typically the US dollar. Stability, therefore, depends on the credibility of this promise rather than on intrinsic value.
- Reserves: foreign exchange reserves in traditional crisis models find its counterpart in the collateral pool of assets of stablecoins. The credibility of the peg depends on the quality, liquidity, and transparency of these backing assets.
- Central bank: in fiat systems, it acts as guarantor and potentially as lender of last resort. In stablecoins, this role is either performed by a private issuer (e.g., USDC) or by code and governance mechanisms (e.g., protocols). The absence of a true lender of last resort increases fragility.
- Speculative attacks: coordinated selling of domestic currency in sovereign crisis models translates into mass redemptions, "death spirals", or continued secondary market exits in the stablecoin ecosystem. In both settings, if agents believe the peg cannot be sustained, simultaneous exits can make collapse self-fulfilling.

3.2 Reinterpretation of crisis models in stablecoin context

Building on this analogy, the three generations of currency crisis models can be reinterpreted within the structure of stablecoins. In first-generation models, fixed exchange rates collapse when reserves become insufficient to sustain monetary commitments. The attack is rational and driven by observable inconsistencies between policy decision and reserve availability. Applied to stablecoins, this mechanism relates to illiquid or insufficient reserves relative to redemption pressure. If collateral cannot satisfy withdrawals, de-pegging becomes mechanically inevitable. The collapse mechanism is predetermined: once liabilities exceed credible reserves, parity cannot be defended. Fully reserved stablecoins (e.g., asset-backed tokens) exposed to liquidity mismatches exhibit behaviours closest to this framework.

Second-generation models introduce the possibility of multiple equilibria and self-fulfilling crises. Even if fundamentals are not necessarily inconsistent, shifts in expectations make the peg unsustainable. This mechanism is particularly relevant for algorithmic currencies, as their stabilisation depends on market incentives and confidence in the value of tokens; a sudden loss of confidence can lead to increases in supply and collapses in parity, regardless of reserve capacity.

Finally, third-generation models highlight financial sector vulnerabilities and interconnected balance sheets in which currency mismatches and leveraged positions increase the effects of the crisis. In crypto-collateralised (hybrid) stablecoins, declining asset prices similarly weaken collateral ratios, activating liquidations cascades and broader systemic contagion.

In conclusion, these reframings suggest that stablecoin instability does not surge from a single structural flaw, but from several channels of weaknesses that have already been studied for classical crisis mechanisms.

3.3 Implications and research design

This theoretical framework advances three empirically testable hypotheses on how to extend the classic ways in which peg breaks to stablecoins' failures.

- Hypothesis 1 – Reserve composition and liquidity (first-generation mechanism): stablecoins with weaker or less liquid collateral backing exhibit a higher probability of de-pegging and, in case of deviating, experience larger downside departures from parity. This hypothesis is tested using the collateral score – a categorical measure of backing strength – alongside market performance metrics as a proxy for liquidity depth and arbitrage capacity.

- Hypothesis 2 – Expectations and market sentiment (second-generation dynamics): deteriorating market sentiment, measured by the Crypto Fear and Greed Index, significantly raise the probability of de-pegging, consistent with self-fulfilling run dynamics in which declining confidence triggers exit behaviour independently of reserve fundamentals.

- Hypothesis 3 – DeFi ecosystem fragility and balance-sheet interdependence (third-generation mechanism): deeper liquidity in decentralised exchange markets is expected to reduce deviations, whilst higher levels of leveraged on-chain activity may amplify them through liquidation cascades and collateral interdependence – consistent with balance-sheet feedback dynamics.

The central proposition of this thesis is that stablecoins do not fail for the fact of being crypto assets or purely due to technological flaws. Instead, each design structure tends to respond to a classical stabilisation architecture: fiat-backed structures are primarily exposed to liquidity issues, algorithmic designs are particularly sensitive to expectation-driven collapse, and crypto-collateralised systems are vulnerable to weak financial systems. On that account, this empirical analysis evaluates whether observed de-pegging events conform to this generational categorisation.

4 Data and empirical Strategy

A novel panel dataset of major stablecoins featuring different stabilisation architectures has been constructed by combining market, blockchain, and macro-financial data from multiple sources. The sample includes five stablecoins – DAI, USDC, UST, USDN, and IRON – with daily frequency coverage over the period from January 1, 2020 to January 1, 2024, including all relevant de-pegging episodes. Coin´s price[16] and market data are obtained from CoinGecko, while DeFi-related variables such as Total Value Locked (TVL) are sourced from DeFiLlama. Macroeconomic and financial indicators are collected from Investing (VIX and gold prices) and Alternative.me (Crypto Fear & Greed Index). All series are merged at daily frequency using dates as the common key, resulting in a coin-date panel dataset. Missing observations arise due to differences in data availability (e.g., DeFi variables only available for certain assets, gold prices not quoted on weekends, or short-lived stablecoins such as IRON). These are handled through cubic spline interpolation where appropriate.

The resulting panel is unbalanced because the data availability differs across stablecoins and over time. In particular, some assets have shorter effective sample periods due to structural breaks or regime changes (UST, IRON, and USDN). These assets remain in the pooled sample when data are available, while coin-level regressions are estimated on coin-specific windows chosen to reflect their relevant operating periods.

[16] This study uses the daily closing price for all assets.

4.1 Dependent variable

The dependent variable captures the extent to which a stablecoin deviates from the parity with the U.S. dollar. In this case, the empirical analysis focuses on explaining deviations using multiple complementary measures.

First, a binary indicator of de-pegging events is defined as:

$$depeg_{dummy_{i,t}} = 1 \quad \text{if} \quad 1 - price_{i,t} > \tau$$

where τ denotes a threshold set at 1% for the main regression scheme[17]. To be considered a depeg episode, it is filtered by positive differences – i.e. coin depreciation episodes, which are typically associated with crisis dynamics – and a depeg duration of >24h.

Second, a continuous measure of deviation is constructed as:

$$depeg\_abs_{i,t} = | \, 1 - price_{i,t} \, |$$

which captures the magnitude of deviations regardless of direction and threshold, capturing both downward and upward breaks from the US$1 peg.

Third, a continuous downside deviation measure is extracted from the previous metric as:

$$depeg\_down_{i,t} = \max\,(0, 1 - price_{i,t})$$

This distinction allows us to focus on negative shocks (loss of confidence), differentiating from positive deviations (excess demand).

Additionally, de-pegging events are classified by an intensity scale based on the magnitude of the deviation which can take values between 0 and 3, following the empirical literature (Lyons & Viswanath-Natraj, 2023; BIS, 2023). Deviations are then classified into increasing levels of severity – mild (>1%), moderate (>3%), and severe de-pegs (>5%)[18] – which are interpreted as initial confidence losses, significant stress, and possible collapse of the system, if sustained. This approach allows the model to account for heterogeneity in crisis dynamics, as larger deviations are typically associated with structural failures and contagion effects across the

[17] A threshold of 5% will be used in robustness analysis to closely analyse severe episodes.

crypto ecosystem (Castello et al., 2024). Event counts per period and coin are presented in Appendix C.

4.2 Explanatory variables

Firstly, to capture broader traditional financial market stress, the model includes the CBOE Volatility Index (VIX). The VIX measures the implied volatility of options on the S&P 500 and is widely interpreted as a forward-looking indicator of global financial uncertainty and risk aversion. Higher values of the index typically correspond to periods of market turbulence and heightened demand for hedging, conditions that may trigger liquidity pressures and portfolio reallocations affecting digital asset markets (Cboe Global Markets, n.d.; Whaley, 2009). Moreover, gold returns are calculated as a proxy for traditional safe-haven demand; allowing to test whether investors exit the crypto ecosystem during periods of stress.

On the other hand, representing cryptocurrency ecosystem stress, the model includes a measure of volatility for Bitcoin. The reason behind it lies on its use as the reference asset because it represents the largest and most liquid cryptocurrency market and often is a benchmark for the broader digital asset ecosystem. It also tracks investor sentiment within the cryptocurrency market using the Crypto Fear & Greed Index published by Alternative.me, where lower values indicate extreme fear and higher values indicate extreme greed. The index aggregates several indicators including market volatility, trading volume, social media activity, Google Trends search intensity, market dominance, and surveys (Alternative.me, n.d.).[19]

Finally, the analysis incorporates a set of coin-specific fundamentals capturing market activity, size, and DeFi integration. Market variables include circulating supply, market capitalisation, and trading volume. To mitigate scale effects and non-stationarity, growth rates are used for market capitalisation and volume, capturing dynamic changes. Additionally, to measure the extent to which a stablecoin is embedded in DeFi protocols and its reliance on decentralised liquidity, Total Value Locked (TVL) and the ratio of TVL to circulating supply are included. Besides, a collateral quality index variable ("collateral score") classifies stablecoins according to the strength and nature of their backing.

[19] Daily data to use Google Trends as a variable itself is not available at a comparable frequency, as it is normalised over variable time intervals. For this reason, we rely exclusively on the Fear & Greed Index as a consistent daily measure of crypto sentiment. A visual analysis of "Stablecoin" Google Trends [2020-2024] is provided in Appendix A.

Table 2 presents a summary and a general view of the explanatory variables included in the analysis to determine the depeg probability. Moreover, in Appendix A, additional information about their sourcing and construction is given.

Table 3 presents the descriptive statistics of the explanatory variables.

Table 2: Potential factors influencing a price depeg

Variable	*Code*	*Brief definition*
Market capitalisation growth	*market_cap_growth_w*	Growth rate of stablecoin market capitalisation
Trading volume growth	*volume_growth_w*	Growth rate of coin´s trading volume
Net supply change	*net_supply_change_pct_w*	Change in circulating supply
DeFi TVL	*log_dex_tvl*	Total value locked linked to the stablecoin in DeFi protocols
DeFi TVL / Supply	*dex_tvl_supply_ratio_w*	Ratio of DeFi TVL to circulating supply
Collateral score	*collateral_score*	Index of collateral strength and design quality
Bitcoin return	*btc_return*	Daily return of Bitcoin
Bitcoin volatility	*log_btc_volatility_w*	Bitcoin volatility in a monthly basis
VIX	*vix*	Volatility index capturing global financial uncertainty
Fear & Greed Index	*fear_greed_sentiment*	Index measuring the overall sentiment of the cryptocurrency market
Gold return	*gold_return*	Daily return of gold

Source: Authors's elaboration.
Appendix A provides an expanded description of the variables and their construction.

Table 3: Descriptive statistics table

Variable	*N*	*Mean*	*Std. Dev.*	*Min*	*Max*
VIX	7309	22.7025	8.3486	12.0700	82.6900
BTC volatility (log, 30d)	7310	-3.5094	0.3895	-4.3788	-2.3658
BTC return	7305	0.0012	0.0351	-0.4337	0.1760
Fear & Greed Index	7310	46.9514	22.5447	6.0000	95.0000

Gold return	7195	0.0004	0.0088	-0.0499	0.0595
Volume growth	6532	-0.0032	0.8991	-5.1855	5.4819
Market cap growth	5165	0.0019	0.0412	-0.2204	0.3154
DEX TVL	3671	15.5956	6.2916	0.1823	21.6729
DEX TVL / Supply Ratio	2804	0.0419	0.0470	0.0000	0.4961
Net Supply Change	5108	0.0021	0.0184	-0.0892	0.1402
Collateral score	7310	2.8000	1.4698	1.0000	5.0000

Source: Authors's elaboration.

4.3 Methodological detail of the collateral score

A central contribution of the paper is the construction of a collateral score that summarises the strength of each stablecoin's backing. The index ranges from 1 (weakest) to 5 (strongest) and is designed to capture three dimensions emphasised in the literature and in protocol documentation: the type of collateral, its quality and liquidity, and the degree of overcollateralisation. Fiat-backed stablecoins backed by liquid reserves are generally considered more stable, while algorithmic designs without credible collateral are structurally more fragile. Overcollateralised crypto-backed designs occupy an intermediate position, with resilience depending on the volatility and liquidity of the underlying assets (Ahmed et al., 2024; Castello et al., 2024).

In particular, it reflects the idea that stablecoin stability depends on the credibility of the redemption mechanism and the extent to which the design is vulnerable to reflexive or "death spiral" dynamics. This approach is consistent with Maker documentation on overcollateralised stablecoins, ECB assessments of algorithmic stablecoins as effectively unbacked or weakly backed, and recent work stressing the role of reserve risk and reflexivity in stablecoin instability (ECB, 2022; MakerDAO, n.d.).

Table 4: Collateral score assigned by stablecoin

Score	*Design type*	*Stablecoins*
5 (very strong)	Fiat-backed, liquid reserves	USDC
4 (strong)	Crypto-backed, overcollateralised	DAI
3 (weak)	Crypto-backed with volatile collateral	USDN

2 (weak)	Hybrid design (partial collateral + endogenous token)	IRON
1 (very weak)	Pure algorithmic design	UST

Source: Author´s elaboration

4.4 Methodology

The empirical strategy aims to analyse both the probability of de-pegging events and the magnitude of deviations from the peg across different types of stablecoins. To do so, the analysis combines complementary approaches: a pooled logit model as the main specification, a pooled OLS model for continuous outcomes, and a set of individual coin-level regressions to capture heterogeneity across stablecoin designs. The main specification is a pooled logistic regression model, defined as:

$$Pr(\text{ depeg}_{i,t} = 1 \mid\mid X_i) = \Lambda(\beta 0 + \beta 1\text{Macro}_{i,t} + \beta 2\text{Crypto}_{i,t} + \beta 3\text{Fundamentals}_{i,t} + \epsilon_{i,t})$$

where $\Lambda(\cdot)$denotes the logistic cumulative distribution function. The model is estimated by maximum likelihood, and results are reported in terms of average marginal effects (AMEs).

The set of explanatory variables $X_{i,t}$is structured along three main dimensions. First, macro-financial variables capture global market conditions, including indicators of financial stress, risk sentiment, and alternative safe-haven assets. Second, crypto-market variables reflect broader dynamics within the cryptocurrency ecosystem, such as Bitcoin returns and volatility. Third, stablecoin-specific fundamentals capture the internal characteristics of each asset, including supply dynamics, liquidity conditions, and DeFi-related activity.

The use of a pooled logit specification is motivated by the characteristics of the dataset. The number of cross-sectional units is limited and some assets exhibit relatively short time series due to collapses. In addition, de-pegging events are relatively infrequent and quasi-separation problems appear. In this context, panel logit models with fixed effects would substantially reduce the available variation and may lead to unstable estimates. The pooled specification therefore provides a more robust and parsimonious framework. Nevertheless, to complement the binary analysis, the empirical strategy also considers continuous measures of de-pegging using pooled panel OLS regressions. These specifications allow to assess the magnitude of deviations from the peg and provide a useful robustness check for the main results. Coefficients are reported directly for ease of interpretation. In some specifications, time fixed effects are included to control for common shocks affecting all stablecoins simultaneously, such as market-wide stress or crypto-specific events. However, their inclusion involves a trade-off, as they may absorb part of the variation in macro-financial variables. In addition, across all models, standard errors are clustered at the stablecoin level to account for serial correlation within assets.

Next, to address the possible masking of important differences across stablecoin designs, separate regressions are estimated for each asset, providing for heterogeneity in collateral structures and market behaviour. Each coin is analysed through a set of progressively enriched specifications during their active circulation periods.[20] The baseline model includes macro-financial and crypto-market variables. Additional specifications incorporate growth variables, capturing changes in market capitalisation and trading activity, as well as supply dynamics. For stablecoins with relevant data availability, DeFi-related variables are also included to account for on-chain liquidity conditions. Here, the choice of dependent variable also differs across assets. For fiat-backed and overcollateralised stablecoins, the analysis focuses on absolute deviations from the peg, capturing both upward and downward movements. In contrast, for more fragile designs, the focus is placed on downward deviations, which are more closely associated with loss of confidence and crisis dynamics.

Finally, the robustness of the results is assessed by varying the threshold used to define de-pegging events. While the baseline specification uses a 1% threshold, a stricter threshold of 5% is also considered – particularly to distinguish between temporary deviations and structurally significant events.

It is important to acknowledge that the analysis focuses on identifying economically meaningful episodes rather than isolated fluctuations. In this context, an episode is understood as a transition into a de-pegging state followed by a sequence of consecutive periods until the peg is restored. To complement the econometric analysis, event-count tables are constructed (found in Appendix C) to document the frequency and distribution of de-pegging episodes across assets and the periods previously mentioned, as well as classified according to their intensity.

[20] IRON´s subperiod comprises from 2020-01-01 to 2021-06-24, a week after its collapse. USDN is only considered from 2020-01-01 until 2022-12-31, when it changed its regime to XDN – an indexed coin. Lastly, the subperiod 2020-01-01 to 2022-05-15 is used for UST, the cutoff represents the definitive collapse.

5 Results

5.1 Main regressions

Table 5 reports the main pooled regressions explaining stablecoin de-pegging. Columns (1) and (2) present the logit specifications, reported as average marginal effects, while Columns (3) and (4) show OLS estimates using the continuous downside deviation measure. It is worth noting two features of the table. First, the number of observations decreases from 7,195 in Column (1) to 5,085 in Columns (2) and (3), reflecting the inclusion of growth variables with more limited availability. Column (4), which includes time fixed effects, is estimated on a slightly different sample (5,165 observations) due to the inclusion of additional non-missing observations in the restricted specification. Second, model fit improves notably across specifications: the pseudo-R^2 increases from 0.40 in the baseline logit model to 0.53 in the extended specification, while the OLS model achieves an $R^2$of 0.43; suggesting that internal stablecoin dynamics contribute meaningfully to predicting de-pegging behaviour. Despite the model fit improvement, the focus of the analysis is not on predictive performance but on identifying statistically significant relationships between the explanatory variables and stablecoin instability.

Moving on to analyse the coefficients, a first key result in Column (1) concerns the collateral score, which is negative and highly significant. This indicates that stablecoins with higher scores – stronger and more credible backing structures – exhibit a lower probability of de-pegging. In terms of economic magnitude, the AMEs suggest that moving up one category in the collateral score reduces the probability of a de-pegging event by approximately 14 – 15 percentage points. This finding is consistent with the literature emphasising the importance of stabilisation mechanisms and reserve quality in maintaining price stability (Bullmann et al., 2019). In particular, designs backed by liquid and credible reserves appear significantly more resilient than weaker or partially endogenous systems.

Regarding crypto-market variables, the model also highlights the role of market sentiment. The Fear & Greed Index is negative and strongly significant, implying that periods of heightened fear are associated with a higher likelihood of de-pegging. Quantitatively, a one-point increase in the index (i.e. a shift towards more “greedy” sentiment) reduces the probability of de-pegging by around 0.4 – 0.5%. Similarly, Bitcoin volatility is highly significant. The negative coefficient suggests that stablecoins may act as a relative safe asset within the crypto ecosystem during periods of turbulence, as investors rebalance away from riskier assets. This interpretation aligns with the role of stablecoins as liquidity buffers within crypto markets (Gurrado & Masciandaro, 2025). By contrast, Bitcoin returns are not statistically significant. This suggests that the direction of price movements is less relevant than overall uncertainty and activity in explaining de-pegging events. That said, it is important to stress that these results should be interpreted as statistical associations rather than causal effects; some variables may be subject to reverse causality. For instance, Ba et al. (2025) explain, the collapse of UST in 2022 triggered a sharp deterioration in market sentiment and a sustained increase in perceived risk across the crypto ecosystem.

Column (2) extends the baseline model by incorporating internal stablecoin dynamics, namely volume growth and market capitalisation growth. This specification leads to a substantial increase in explanatory power, suggesting that these variables capture an important dimension of de-pegging risk. The most notable result is the strong negative coefficient on market capitalisation growth, whose marginal effects indicate that a one-unit decrease in market capitalisation growth increases the probability of de-pegging by approximately 33 percentage points. This can be interpreted as evidence that declining demand and shrinking liquidity pools increase fragility. Larger and expanding stablecoins benefit from more usage; which in turn means liquidity, deeper markets, and more effective arbitrage mechanisms that help stabilise prices, as pointed out previously by Lyons and Viswanath-Natraj (2023). In spite of this, the relationship should be interpreted with caution, as market size may itself respond to de-pegging events. On the other hand, volume growth is not statistically significant, suggesting that overall market size is more informative than trading activity per se.

Remarkably, the inclusion of growth variables does not alter the core findings. The collateral score remains highly significant, reinforcing the importance of design quality. Similarly, the Fear & Greed Index and Bitcoin volatility remain significant, indicating that market sentiment and systemic risk continue to play a central role. Specifically, a 1% increase in Bitcoin volatility causes a decrease of 0.0031 percentage points in depeg probability due to the logarithmic nature. Moreover, unlike in the baseline specification, gold returns become positive and significant. While not a primary result, given that it loses significance in the third model, this may reflect episodes in which investors exit the crypto ecosystem altogether and reallocate towards traditional safe-haven assets.

In Column (3), the focus shifts from the probability of de-pegging to the magnitude of downside deviations by moving to a continuous dependent variable. In this specification, collateral score remains negative and statistically significant. Economically, moving up one category in the collateral score is associated with a reduction of approximately 0.13 units in the magnitude of downside deviations, under the assumption of a linear relationship between collateral quality and stability. This suggests that stronger backing structures not only reduce the likelihood of instability but also limit its severity once it occurs; making it one of the most robust findings in the paper. Similarly, market capitalisation growth remains negative and highly significant, indicating that expansions in market size are associated with firmer adherence to the peg, and reinforcing the importance of internal market dynamics in amplifying instability once it emerges.

On the contrary, macro-financial variables such as VIX, Bitcoin volatility, and Fear & Greed lose statistical significance. It is an important finding, as it suggests that these variables primarily influence the onset of de-pegging events rather than the magnitude of deviations. In particular, heightened sentiment and market stress may trigger the attack, but its severity and instability appears to depend more strongly on arquitectural and structural factors. Indeed, recent work emphasises the role of attention, sentiment, and coordination in triggering self-fulfilling runs (Briola et al., 2023; Liu et al., 2023).

Finally, Column (4) introduces daily time fixed effects. The main interest here lies in assessing whether stablecoin-specific variables remain significant after controlling for time-specific shocks. In this respect, both collateral score and market capitalisation growth remain statistically significant, providing further support for the central role of structural fundamentals. As a whole, the results reveal a consistent pattern across specifications. Structural characteristics – particularly collateral quality and market size – play a role in explaining stablecoin stability, while market-wide factors such as sentiment and volatility act as triggers that increase the likelihood of de-pegging events.

Table 5: Determinants of stablecoin de-pegging

	(1) Logit	*(2) Logit*	*(3) OLS*	*(4) OLS with time-fixed effects*
Vix	-0.0154***	-0.0021***	-0.0010	
	(0.002)	(0.000)	(0.002)	
Btc volatility	-0.2985***	-0.3105***	-0.3016	
	(0.037)	(0.063)	(0.202)	
Btc return	-0.0113	0.1409	0.1209	
	(0.150)	(0.212)	(0.172)	
Fear & greed index	-0.0046***	-0.0025***	-0.0005	
	(0.001)	(0.000)	(0.001)	
Gold return	-0.0832	0.4147***	0.3187*	
	(0.181)	(0.128)	(0.173)	
Collateral score	-0.1487***	-0.1400***	-0.1308***	-0.1326***
	(0.037)	(0.020)	(0.019)	(0.023)
Volume growth		0.0015	-0.0016	-0.0016
		(0.005)	(0.004)	(0.007)
Market cap growth		-0.3332***	-0.5248***	-0.2746**
		(0.073)	(0.089)	(0.133)
Observations	7,195	5,085	5,085	5,165
Pseudo r² / r²	0.4015	0.5304	0.425	0.597

Source: Authors's elaboration.
Notes: Logit models report average marginal effects. OLS model reports coefficients. Logit models explain the dicotomic probability of de-peg at 1% (depeg_dummy_1pct), while OLS models explain depreciations through a continuous variable (depeg_down). Standard errors clustered at the coin level are reported in parentheses. Symbols ***, **, and * indicate statistical significance at p<0.01, p<0.05, and p<0.1, respectively.

Additionally, the robustness exercise with a higher 5% de-peg threshold[21] confirms the main results of the paper. In particular, collateral quality and market capitalisation growth remain the two most stable predictors across thresholds, preserving their sign, significance, and broadly similar magnitude. Bitcoin volatility also continues to matter for the probability of severe de-pegging events in roughly the same magnitude as in 1% deviations. By contrast, the effect of market sentiment becomes somewhat weaker under the stricter threshold; its coefficient remains significant, but it implies that a 1-point increase in sentiment reduces the probability of mild de-pegs by around 0.25 – 0.45 percentage points, and the same change only reduces the probability of severe de-pegs by approximately 0.14 – 0.26 percentage points, suggesting that extreme and persistent parity breaks are driven strongly by structural fragilities than by confidence fluctuations alone. These findings indicate that the core relationships identified in the main analysis are not sensitive to the choice of threshold and therefore appear to capture broader patterns of stablecoin instability.

5.2 Individual coin-level regressions

Table 6 reports the individual regressions. Unlike the pooled estimations, which exploit common variation across the full panel, these specifications are estimated separately for each stablecoin and therefore rely on much smaller samples and much less variation. This point is important when interpreting the results. The number of observations ranges from 534 for UST and 536 for IRON to 1,439 for USDC; a difference that already suggests that the individual regressions should not be read symmetrically. In some cases, the models are informative and economically interpretable; in others, they are better understood as suggestive evidence rather than as strong causal statements. A second relevant point is that the dependent variable is not equal across all coins. For IRON and USDN, the specification focuses on downside deviations (depeg_down), for UST the dependent variable is the continuous distance_peg, and for DAI and USDC the model uses depeg_abs. The choice reflects differences in empirical behaviour across stablecoins, but it also limits direct comparability of coefficient magnitudes across columns. The purpose of Table 6 is therefore not to compare all coefficients one by one, but to assess which variables appear informative within each stablecoin's own dynamics.

To begin with, Column (1) presents the baseline regression for IRON and – not overlooking its short-term and limited sample – the regression shows several significant variables. Again, VIX

[21] Results can be found in Appendix C.

and Fear & Greed Index show an inverse significant relationship; causing a 0.0007 and 0.0003 decrease in peg deviation per point increase, respectively. Added to this, Bitcoin, too, is significant and causes a light increase of 0.000092 increase in deviations per additional 1% volatility. This pattern suggests that IRON's downside deviations were associated with broader stress conditions and deteriorating sentiment. In other words, once the coin entered a vulnerable state, turbulence in the wider market appears to have been linked to larger deviations. At the same time, neither Bitcoin returns nor gold returns are significant, again pointing to the greater importance of uncertainty and sentiment over directional price movements.

Secondly, Column (2) show perhaps the clearest example of why the individual regressions need to be interpreted carefully. Although VIX is marginally significant and positively related, most other coefficients are not, including Bitcoin volatility, Bitcoin returns, the Fear & Greed Index, gold returns, volume growth, and market capitalisation growth. The model may fail not because fundamentals were unimportant, but because the collapse unfolded too quickly and too discontinuously for these variables to explain much of the day-to-day variation. For that reason, the UST results should be interpreted as evidence of the limitations of the empirical framework in extreme collapse events, rather than as evidence that UST was unaffected by market conditions or internal pressures.

Now, USDN´s preferred specification is presented in Column (3), which includes the growth variables. Here, as for IRON, VIX and Fear & Greed are negative and significant; producing 0.0004 and 0.0009 increase in deviations for a 1 unit decrease in their respective indexes. Likewise, Bitcoin volatility and, especially, market capitalisation growth are negative and significant; with the latter being the strongest in the study; causing a 0.57% increase in distance to parity per 1% loss in market size. While Bitcoin returns, gold returns, and volume growth do not appear to matter. The clearest takeaway is that USDN instability is associated both with wider crypto stress and with contractions in market size. In that sense, the coin appears more systematically responsive to the explanatory variables than IRON or UST. Still, causal relationships cannot be confirmed and the results are best read as a match in USDN´s nature with the main regressions; showing that shrinking size and deteriorating market conditions are closely associated with downside deviations.

Focusing on the DAI specification in Column (4), several coefficients are both statistically and economically meaningful. First, market capitalisation growth enters positively and is highly significant. Economically, a one-unit increase in market capitalisation growth is associated with an increase of approximately 0.056 units in the absolute deviation from the peg. Interpreting this in more realistic terms, a 10% increase in market capitalisation is associated with an increase of around 0.0056 in the deviation, suggesting that periods of expansion are linked to slightly larger pricing effects. This contrasts with the pooled results and indicates that, in the case of DAI, expansions in scale coincide with greater usage intensity, or periods of heightened demand in which deviations can also become temporarily larger, which could explain why DAI´s deviations tend to be apreciations. In other words, the role of size may depend on the specific collateral of the coin and the channels through which it is used. DAI is also the clearest example that coin-specific regressions are not miniature versions of the pooled model; once the coin is analysed on its own, different mechanisms may dominate.

A truly insightful set of results is found here. First, the relatively high R^2suggests that DAI's deviations are better captured by observable market and on-chain variables than those of the more fragile designs. Second, the significance of the DeFi variables indicates that DAI's peg behaviour is closely linked to its ecosystem integration; which is within reason given its crypto-backing element. In particular, the negative coefficient on DEX TVL suggests that deeper DeFi liquidity is associated with smaller deviations, which is reasonable for an overcollateralised stablecoin heavily embedded in decentralised finance. At the same time, the positive coefficient on the DEX TVL-to-supply ratio – which would imply a 10% increase in this ratio to increase by approximately 0.0013 the deviation distance – indicates that higher relative on-chain activity may coincide with greater short-term imbalances, reflecting periods of intensified trading pressure rather than purely stabilising liquidity. In such environments, deviations can become larger due to liquidation cascades, rebalancing pressures, and the interconnection of on-chain protocols

To end with, Column (5) reports the results for USDC using the baseline specification. In contrast to other stablecoins, the model identifies only one statistically significant variable: Bitcoin volatility, which enters with a positive coefficient; implying that a 1% increase in crypto-market turbulence is associated with a slightly larger deviation of 0.000014 units from the peg, even for a highly collateralised and fiat-backed stablecoin such as USDC. Although the magnitude of this effect is relatively small, it indicates that even the most stable designs are not completely insulated from broader market conditions.

All other variables – VIX, Bitcoin returns, the Fear & Greed Index, and gold returns – are statistically insignificant. In this sense, the model does not contradict the pooled results, but rather complements them. While the main models identify general patterns across stablecoins, the USDC specification highlights that highly collateralised coins may be less sensitive to the same set of explanatory variables; pointing to a form of heterogeneity across stablecoin designs: whereas some coins appear to react strongly to market sentiment and internal dynamics, others are largely anchored by the credibility and liquidity of their backing assets. It indicates that USDC's four year deviations are either too small, too infrequent, or too short to be well explained by the selected daily elements; therefore less econometrically "traceable" in this framework. Overall, the coin-level evidence suggests heterogeneity, but not with enough precision to claim a general design-specific rule. What it does support is a more modest conclusion: some stablecoins appear to respond more strongly to market dynamics and ecosystem variables, whereas others are dominated by their pledged assets´ nature and require a deep study of collateral vaults.

Table 6: Determinants of stablecoin de-pegging at coin-level

	(1) IRON	*(2) UST*	*(3) USDN*	*(4) DAI*	*(5) USDC*
Dependent variable	Depeg down	Distance peg	Depeg down	Depeg abs	Depeg abs
VIX	-0.0007***	0.0018**	-0.0009**	0.0002***	0.0000
	(0.000)	(0.001)	(0.000)	(0.00003)	(0.00001)
BTC volatility	0.0092***	0.0045	-0.0864***	-0.00004	0.0014***
	(0.003)	(0.004)	(0.018)	(0.000)	(0.000)
BTC return	-0.0213	0.0330	0.0093	-0.0112	-0.0013
	(0.037)	(0.078)	(0.041)	(0.010)	(0.002)
Fear & Greed Index	-0.0003***	-0.0002	-0.0004***	0.00001**	0.000003
	(0.000)	(0.000)	(0.00007)	(0.000006)	(0.000003)
Gold return	-0.0401	0.0178	0.1459	0.0052	0.0066
	(0.054)	(0.144)	(0.318)	(0.023)	(0.005)
Volume growth		-0.0083	-0.0000	0.0007**	
		(0.013)	(0.006)	(0.0003)	

Market cap growth		-0.2592	-0.5713***	0.0558***	
		(0.628)	(0.217)	(0.015)	
Log DEX TVL				-0.0009***	
				(0.000)	
DEX TVL / Supply				0.0129**	
				(0.006)	
Intercept	0.0734***	-0.0057	-0.2227***	0.0141***	0.0060***
	(0.023)	(0.013)	(0.052)	(0.004)	(0.000)
Observations	536	534	739	1385	1439
R^2	0.096	0.069	0.209	0.453	0.084

Source: Authors's elaboration.

5.3 Descriptive clustering of stablecoin instability mechanisms

The empirical evidence is compatible with organising stablecoin de-pegging dynamics into three descriptive clusters, each broadly aligned with a generation of currency crisis models. The first cluster covers fundamental fragility, and is most clearly associated with reserve quality and liquidity constraints. Across all pooled panels, the collateral score is the single most robust determinant of de-pegging: a stronger backing structure is associated with both a lower probability of peg deviation and reduced severity once instability materialises. This finding is reinforced by the strong negative coefficient on market capitalisation growth, which can be interpreted as a proxy for liquidity depth and arbitrage capacity – a contraction of market size indicates a withdrawal of the stabilising mechanisms that sustain redemption commitments. These elements form the setting for first-generation logic: where reserve backing is weak, illiquid, or eroding, the peg becomes mechanically difficult to defend, as the USDC episode corroborates it from a different angle: even fully collateralised reserves can fail to sustain the peg if their liquidity becomes temporarily constrained. The slight de-pegging triggered by Silicon Valley Bank's failure illustrates how even a fully collateralised stablecoin remains vulnerable to external liquidity shocks affecting its underlying reserves – a dynamic that resembles Krugman's (1979) reserve depletion mechanism before crypto-native pathologies. Yet, the cross-sectional data limitations and small sample sizes do not allow strong causal inference; the collateral score is an unrefined measure, and design heterogeneity across coins introduces noise and differences that a structural test would need to address more rigorously.

A second cluster, broadly aligned with second-generation frameworks, concerns confidence-driven instability. The Fear & Greed Index is negative and strongly significant in the pooled probability models, suggesting that periods of market fear are associated with a materially higher likelihood of de-pegging. Crucially, however, this variable loses significance when the dependent variable captures the magnitude of deviations rather than their occurrence, implying that sentiment may function primarily as a trigger rather than as a structural amplifier; whoch aligns with the second-generation idea that expectations shift the economy from a stable to an unstable equilibrium to participate in self-fulfilling dynamics and provoking a crisis. The case of TerraUSD most directly exemplifies this cluster: the collapse unfolded too rapidly and discontinuously for daily regressors to capture, yet the Fear & Greed coefficient remains negtive and qualitative evidence points straight to a self-fulfilling coordination failure, in which the loss of confidence in the Luna-UST arbitrage mechanism induced the death spiral investors feared. Reverse causality is also a valid option here – the UST collapse demonstrably deteriorated broader market sentiment, so the relationship between the sentiment index and de-pegging cannot be interpreted as strictly unidirectional.

The third cluster reflects endogenous financial fragility, and is most visible in the coin-level results for DAI and, to a lesser extent, USDN. For DAI, deeper DeFi liquidity – captured by DEX TVL – is associated with smaller deviations, while a higher TVL-to-supply ratio is associated with larger ones, suggesting that intensive, leveraged on-chain activity can amplify short-term imbalances rather than absorb them. This pattern, alongside the well-documented liquidation cascades during Black Thursday and the collateral interdependence introduced by DAI's partial USDC backing, is suggestive of third-generation balance-sheet dynamics: endogenous feedback between collateral valuations and redemption pressure, analogous to the currency-financial sector interactions described by Corsetti et al. (1998) and Kaminsky and Reinhart (1999). For USDN, the combination of significance in both market capitalisation contractions and broader crypto stress indicators points to a gradual erosion of collateral credibility – a structural and more traceable deterioration rather than an abrupt confidence shock – evidencing the distinction between this cluster and the second.

As a matter of fact, the clustering proposed here is descriptive, not taxonomic: most stablecoins exhibit elements of more than one mechanism, and the available data cannot establish which channel dominates within a given episode. What this mapping does demonstrate, however, is that stablecoin instability does not represent a novel form of monetary fragility, but rather a digital restructuring of classical currency crisis mechanisms. In this way, the principal contribution of this analysis is to show that the generational framework of currency crisis theory, far from being obsolete in a decentralised context, provides a well-grounded economic lens thorugh which levers of modern stablecoin architectures can be understood.

6 Conclusions

This paper set out to examine whether stablecoin de-pegging events can be understood through the lens of traditional exchange rate crisis models. The central conclusion is that they can, to a considerable extent. Stablecoin instability does not emerge as a purely technological phenomenon, nor as an entirely novel form of financial disruption. Rather, it reflects familiar patterns of fragility long identified in fixed exchange rate regimes: weak fundamentals, shifts in expectations, and self-reinforcing runs. Hence, the main contribution of the paper lies in bridging two literatures that have largely evolved in parallel – currency crisis theory and the growing field of digital asset markets – and showing that the former retains strong explanatory power in the latter context.

The empirical analysis supports this interpretation. Across pooled specifications, collateral quality consistently results to be the most robust variable of stability, reducing both the likelihood and severity of de-pegging events. Furthermore, market capitalisation dynamics also play a central role, concluding that contractions in size are closely associated with heightened fragility; which seems reasonable as, the larger the market, the better the setting for stabilisers to operate. By contrast, market-wide variables such as sentiment and volatility appear to operate primarily as triggers: they increase the probability of de-pegging episodes but do not systematically explain their magnitude once instability begins. At the coin level, the evidence points to meaningful heterogeneity, suggesting that while common mechanisms are present, the transmission of instability depends on design. Fiat-backed coins remain exposed to liquidity and intermediary risk; algorithmic structures are particularly vulnerable to confidence breakdowns; and crypto-collateralised designs are shaped by DeFi-specific feedback loops and collateral interdependence.

These findings have direct regulatory implications. They suggest that stablecoins should not be treated as a homogeneous asset class. While the principle of "same risk, same regulation" is appropriate, the relevant risks differ across architectures. For fiat-backed stablecoins, reserve transparency and liquidity management are critical. For crypto-collateralised and hybrid designs, greater attention must be paid to leverage, liquidation dynamics, and on-chain interconnectedness. The results therefore support a regulatory approach that is not only stricter, but also design-specific. Recent frameworks such as MiCA and the GENIUS Act represent important steps in this direction; however, the evidence suggests that disclosure requirements alone may be insufficient unless complemented by credible safeguards against liquidity stress and mechanisms that address endogenous fragility.

This perspective opens several paths for future research. In particular, further work could explore the microstructure of arbitrage mechanisms, the role of large holders and liquidity providers, and the interaction between stablecoins and the broader financial system during periods of stress. As digital assets continue to integrate with traditional markets, understanding these dynamics will become increasingly important not only for academic analysis, but also for the design of effective and forward-looking financial regulation.

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

Por la presente, yo, María Chao Arrese, estudiante de Administración de Dirección de Empresas y Relaciones Internacionales de la Universidad Pontificia Comillas al presentar mi Trabajo Fin de Grado, titulado "Stablecoin failures through the lens of exchange rate crisis models: empirical insights from historical de-pegging events", 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. Brainstorming de ideas de investigación: Utilizado para idear y esbozar posibles áreas de investigación.
2. Referencias: Usado conjuntamente con otras herramientas, como Science, para identificar referencias preliminares que luego he contrastado y validado.
3. Metodólogo: Para descubrir métodos aplicables a problemas específicos de investigación.
4. Corrector de estilo literario y de lenguaje: Para mejorar la calidad lingüística y estilística del texto.
5. Generador previo de diagramas de flujo y contenido: Para esbozar tablas.
6. Sintetizador y divulgador de libros complicados: Para resumir y comprender literatura compleja.
7. Revisor: Para recibir sugerencias sobre cómo mejorar y perfeccionar el trabajo con diferentes niveles de exigencia.
8. Interpretador de código: Para realizar análisis de datos preliminares

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: 26 de marzo de 2026

Firma: ___________________________

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9 Appendix

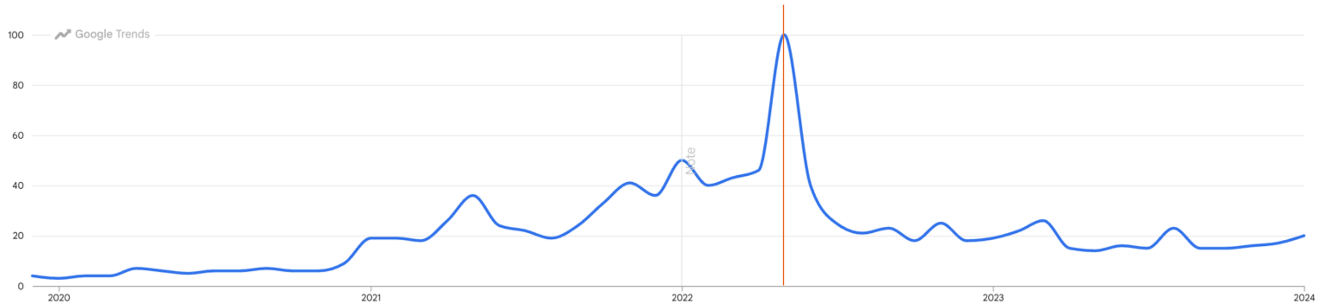
9.1 Appendix A: Variables

Table A1: Extended description of explanatory variables

Variable	Code	Categories / values / construction
Market capitalization growth	*market_cap_growth_w*	Weekly percentage growth of market capitalisation; winsorised at 1%
Trading volume growth	*volume_growth_w*	Weekly percentage growth of trading volume; winsorised at 1%
Net supply change	*net_supply_change_pct_w*	Weekly percentage change in circulating supply; winsorised at 1%
Defi tvl	*log_dex_tvl*	Total value locked linked to the stablecoin in DeFi, transformed in logarithms; available only for some coins
Defi tvl / supply	*dex_tvl_supply_ratio_w*	Ratio of DeFi TVL to circulating supply; winsorised at 1%; available only for some coins
Collateral score	*collateral_score*	Discrete scale from 1 to 5 reflecting collateral type, liquidity, quality, and overcollateralisation
Bitcoin return	*btc_return*	Daily % change in Bitcoin close price
Bitcoin volatility	*log_btc_volatility_w*	Natural logarithm of the 30-day rolling standard deviation of daily Bitcoin returns
Vix	*vix*	CBOE Volatility Index; continuous variable, higher values indicate greater expected equity-market volatility and global risk aversion
Fear & greed index	*fear_greed_sentiment*	Scale from 0 to 100. Categories: 0–24: Extreme Fear; 25–44: Fear; 45–54: Neutral; 55–74: Greed; 75–100: Extreme Greed
Gold return	*gold_return*	Daily % change in gold closing prices

Source: Authors's elaboration.

Figure A1: Evolution of the term "Stablecoin" in worldwide Google searches over 2020-2024



Source: Google Trends
Notes: Terra USD collapse is marked in red to show the peak of stablecoin sentiment volatility. Data is normalised throughout the 4 year period.

9.2 Appendix B: Correlation and Multicolinearity VIF tests

Table B1: Correlation matrix (main models)

Variable	*VIX*	*BTC vol.*	*BTC ret.*	*Fear & Greed*	*Gold ret.*	*Collat. score*	*Volume growth*	*MCap growth*
VIX	1.000	0.341	-0.057	-0.379	-0.019	0.137	-0.000	-0.001
BTC volatility	0.341	1.000	-0.011	-0.121	-0.029	-0.001	0.001	0.051
BTC return	-0.057	-0.011	1.000	0.209	0.035	0.007	-0.059	0.094
Fear & Greed	-0.379	-0.121	0.209	1.000	0.016	0.017	0.001	0.085
Gold return	-0.019	-0.029	0.035	0.016	1.000	0.007	-0.012	-0.006
Collat. score	0.137	-0.001	0.007	0.017	0.007	1.000	0.006	0.020
Volume growth	-0.000	0.001	-0.059	0.001	-0.012	0.006	1.000	0.163
Market cap growth	-0.001	0.051	0.094	0.085	-0.006	0.020	0.163	1.000

Source: Authors's elaboration.
Notes: Values do not indicate a correlation problem for the model.

Table B2: Correlation matrix (including DeFi variables)

Variable	*VIX*	*BTC vol.*	*BTC ret.*	*Fear & Greed*	*Log DEX TVL*	*DEX TVL / Supply*	*Net supply change*
VIX	1.000	0.381	-0.044	-0.385	-0.662	-0.043	0.061
BTC volatility	0.381	1.000	-0.018	-0.172	-0.207	0.075	0.084
BTC return	-0.044	-0.018	1.000	0.193	-0.004	-0.015	0.108
Fear & Greed	-0.385	-0.172	0.193	1.000	0.033	-0.033	0.118
Log DEX TVL	-0.662	-0.207	-0.004	0.033	1.000	0.331	-0.104
DEX TVL / Supply	-0.043	0.075	-0.015	-0.033	0.331	1.000	0.095
Net supply change	0.061	0.084	0.108	0.118	-0.104	0.095	1.000

Source: Authors's elaboration.
Notes: Values do not indicate a correlation problem for the model.

Table B3: VIF multicollinearity test (main specification)

Variable	*VIF*
VIX	1.339
BTC volatility (log, 30d)	1.139
BTC return	1.060
Fear & Greed Index	1.231
Gold return	1.002
Collateral score	1.028
Volume growth	1.033
Market cap growth	1.048

Source: Authors's elaboration.
Notes: Values indicate absence of multicolinearity problems.

9.3 *Appendix C: 5% threshold robustness test and event counts by intensity*

Table C1: Event counts per coin and period

Coin	*2020–2021*	*2022*	*2023–2024*	*Total*
1% threshold				
DAI	1	0	1	2
IRON	18	40	1	59
USDC	1	1	1	3
USDN	58	35	0	93
UST	7	1	0	8
3% threshold				
DAI	0	0	1	1
IRON	5	17	1	23
USDC	0	0	1	1
USDN	9	11	0	20
UST	2	1	0	3
5% threshold				
DAI	0	0	0	0
IRON	8	3	1	12
USDC	0	0	0	0
USDN	2	7	0	9
UST	0	1	0	1

Source: Authors's elaboration.
Notes: Each cell reports the number of de-pegging episodes per coin and sub-period. An episode is defined as a sequence of consecutive days recording a deviation above the indicated threshold; a new episode is counted each time such a sequence begins after at least one day of no deviation.

Table C2: Determinants of stablecoin de-pegging

	(1) Logit	*(2) Logit*
Dependent variable	Depeg dummy 5%	Depeg dummy 5%
VIX	-0.0181***	-0.0067
	(0.004)	(0.005)
BTC volatility	-0.2734***	-0.2959***
	(0.021)	(0.033)
BTC return	0.1200***	0.2163**
	(0.043)	(0.097)
Fear & Greed index	-0.0026**	-0.0014*
	(0.001)	(0.001)
Gold return	-0.1014	0.5211***
	(0.132)	(0.108)
Collateral score	-0.1375***	-0.1333***
	(0.022)	(0.013)
Volume growth		0.0020
		(0.004)
Market cap growth		-0.2740***
		(0.036)
Observations	7,195	5,085
Pseudo (R^2) / (R^2)	0.4625	0.5714

Source: Authors's elaboration.
Notes: Average marginal effects from pooled logit models estimated using depeg_dummy_5pct. Standard errors clustered at the coin level are reported in parentheses. Symbols ***, **, and * indicate statistical significance at p<0.01, p<0.05, and p<0.1, respectively.