Stablecoins and credit risk: when do they stop being stable?

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Abstract

Stablecoins are a pivotal and debated topic within decentralized finance (DeFi), attracting significant interest from researchers, investors, and crypto-enthusiasts. These digital assets are designed to offer stability in the volatile cryptocurrency market, addressing key challenges in traditional financial systems and DeFi, such as price volatility, transparency, and transaction efficiency. This paper contributes to the existing literature by estimating the credit risk associated with stablecoins, marking the first study to focus exclusively on this market. Our findings reveal that a substantial portion of stablecoins have failed, aligning with existing literature. Using Feder et al.'s (2018) methodology, we observed that 21% of stablecoins were "abandoned" at least once, with only 36% being later "resurrected," and just 11% maintaining their "resurrected" status. These results support the hypothesis that stablecoins rarely recover once they break their peg, often due to technical issues or loss of user trust. We also found that the time between a statistically significant break in the stablecoin's peg and its subsequent collapse or stabilization averages approximately 10 days. We estimated probabilities of default (PDs) for stablecoins based on market capitalization using various forecasting models. A robustness check further indicated that stablecoins on the Ethereum blockchain are less prone to default, likely due to Ethereum's robust ecosystem and the established presence of older stablecoins. Despite the study's limitations, including a limited dataset of 121 stablecoins and missing market capitalization data, the findings offer practical applications for investors and traders. The techniques and models applied in this research provide tools for evaluating credit risks in the stablecoins market, aiding in portfolio management and investment strategies.

Keywords: stablecoins; crypto-assets; cryptocurrencies; credit risk; default probability; probability of death; ZPP; Cox Proportional Hazards Model.

JEL classification: C32; C35; C51; C53; C58; G12; G17; G32; G33.

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1 Introduction

The issue of stablecoins and digital assets has generated significant interest lately due to their potential to transform financial transactions and the financial system. Stablecoins, pegged to fiat currencies or other assets, aim to provide stability and predictability compared to conventional cryptocurrencies like Bitcoin. Their fewer restrictions relative to Central Bank Digital Currencies (CBDCs) make them attractive to mainstream investors and businesses. Stablecoins can lower transaction costs, broaden financial access, and serve as a medium for international transfers, remittances, and small-scale transactions, contributing to the DeFi landscape. The relevance of this research is underscored by the growing stablecoin market, and numerous regulatory reports focused on digital assets and stablecoins.

However, stablecoins face risks, including credit risks and stability issues that may cause them to deviate from their peg. Existing studies on stablecoins can be grouped into three categories: those categorizing digital assets and stablecoins (Mita et al., 2019; Bullmann et al., 2019; Moin et al., 2020; Quarles, 2021; White et al., 2022; Baughman et al., 2022); those addressing regulatory and risk issues (Zhang et al., 2018; Brent et al., 2019; Adrichem, 2019; Arner et al., 2020; Bellasio et al., 2020; Inozemtsev, 2021; Chen et al., 2022); and those examining concepts like "*dead coins*" and forecasting default probabilities (Feder et al., 2018; Fantazzini, Zimin, 2020; Grobys, Sapkota, 2020; Fantazzini, Calabrese, 2021; Gandal et al., 2021; Briola et al., 2023).

While insightful, these studies do not focus specifically on stablecoins' credit risk. This paper addresses this gap by evaluating the credit risk associated with stablecoins using various models, including several types of regression and hazard models. The study aims to:

1. Identify the proportion of "dead" and "resurrected" stablecoins by replicating Feder et al.'s (2018)[1] methodology.

2. Determine the time between a statistically significant break in the stablecoin's peg and its subsequent collapse or stabilization. Having a potential warning system that allows investors to exit a position in advance and cut losses is of great importance for any crypto-asset investor.

3. Calculate the market-implied probabilities of default/death (PDs) for stablecoins using the ZPP method and the Cox Proportional Hazards model and perform an out-of-sample forecasting analysis.

This study's findings could prove very valuable to investors seeking to safeguard their assets from the risk of stablecoins deviating from their peg. Assessing the credit risk of stablecoins is crucial for investors as it helps in gauging the stability and reliability of these digital assets. This assessment directly impacts

[1] This paper was later published as Gandal et al. (2021).

investor protection by ensuring transparency and reducing the likelihood of value fluctuations or defaults that could affect their investments. Understanding credit risk safeguards investors against potential losses and promotes a more secure environment for their financial transactions.

The remainder of the paper is organized as follows. Section 2 reviews the literature devoted to the assessment of stablecoin credit risks. Section 3 discusses the models used to evaluate the credit risk associated with stablecoins, starting from the identification of ”dead” and “resurrected” stablecoins, followed by the determination of the time between a statistically significant break in a stablecoin's peg and its subsequent collapse or stabilization, and concludes with the computation of market-implied probabilities of default/death. Section 4 describes the empirical results, while a robustness check is discussed in Section 5. Section 6 concludes.

2 Literature review on the assessment of stablecoin credit risks

We will first examine the key factors that cause stablecoins to struggle in maintaining their intended peg, along with some real-world examples. Then, we will review the research focused on the collapse of stablecoins and the estimation of their default probabilities. For readers seeking a broader introduction to stablecoins, including their mechanisms and types, a detailed overview is provided in the Technical Appendix available on the authors' website.

2.1 Challenges and instances of stablecoins deviating from their peg

While stablecoins are typically pegged to specific assets or algorithms, they face various risks, including stability or run risks, transfer risks, concentration risks, regulatory risks, cybersecurity and operational risks, market risks, and credit risks, among others (Parma et al., 2022). Among these, credit risk is particularly significant, with components such as the probability of default (PD) receiving special attention in this paper.

In terms of credit risk, stablecoins are generally considered less risky compared to traditional cryptocurrencies due to their association with stable assets, which helps mitigate the potential for significant price swings. This characteristic often makes stablecoins an attractive option for diversifying a cryptocurrency portfolio effectively (Wang, et al., 2020). However, credit risks associated with stablecoins remain, particularly concerning their collateralization.

As previously mentioned, stablecoins often rely on reserves of assets held by an intermediary (custodian). If this custodian or the issuer encounters financial difficulties or collapses, it may undermine confidence in the stablecoin and expose stablecoin holders to potential losses (Cermak et al., 2021). Additionally, certain stablecoins use unstable and volatile cryptocurrencies or, in some cases, algorithms as collateral, which can increase the risk of credit defaults or other credit-related concerns. Furthermore, since stablecoins are not subject to the same regulations as currencies within the traditional financial system, particularly concerning anti-money laundering and combating the financing of terrorism standards (AML/CFT - US Treasury, 2021), there may be an increased risk of fraudulent behavior or mismanagement by the stablecoin issuer or involved third parties, such as custodians.

The potential for stablecoins to deviate from their peg is a consequence of credit risk, but it is distinct from credit risk itself. Credit risk refers to the probability of losses resulting from the default of the stablecoin's issuer or custodian. Factors such as insufficient backing assets, mishandling of assets held as reserves in bank accounts, or fraudulent activities by the issuer or custodian can lead to credit risk (BIS, 2021).

Stablecoins break their peg when their value diverges from the asset they are collateralized by, such as the US dollar. For example, when a stablecoin is pegged to the US dollar, it should remain valued at one dollar. However, if its value falls below one dollar, it is considered to have broken the peg (Moin et al. 2020). Numerous factors, ranging from market volatility or insufficient backing assets to malfunctioning algorithmic mechanisms (including bugs in the algorithm itself or issues with smart contract specifications), can contribute to the risk of breaking the peg (Klages-Mundt et al., 2020). Although the deviation of stablecoins from their peg is usually a result of credit risk, this is not always the case. Factors like market volatility can cause a stablecoin to deviate from its peg, even if the financial stability of the issuer or custodian is not in question. Similarly, a stablecoin can maintain its peg despite concerns regarding the issuer's or custodian's creditworthiness.

There have been instances where stablecoins have deviated from their peg due to specific events:

1. DAI: On March 12, 2020, DAI faced issues when Ethereum's value dropped sharply, causing network congestion and liquidity problems. An emergency auction of collateral was initiated to stabilize its value, see Berentsen and Schär (2019), Klages-Mundt (2020) and Kjäer et al. (2021).

2. Basis: This algorithmic stablecoin ceased operations in April 2018 due to regulatory concerns. The SEC classified its stabilization mechanism as involving unregistered securities, leading to a decline in confidence (Piech, 2022).

3. Steem Dollar: It lost its peg in December 2018 due to system debt and experienced further devaluation in 2020 following a hostile takeover of the Steem blockchain (Guidi, 2021).

4. Tether (USDT): In 2017 and in 2018, Tether briefly lost its peg, raising concerns about its reserves and stability. Market skepticism grew due to newly minted Tether and the broader crypto market crash (Bolger and Hon, 2022).

5. TerraClassicUSD: In May 2022, Terra lost its peg when the value of supporting cryptocurrencies plummeted. This led to a loss of trust in its governance, resulting in a downward spiral for both Terra and its asset, LUNA, see Hileman (2019) and Lyons and Viswanath-Natraj (2023). Moreover, Briola et al. (2023) provided a detailed analysis of events leading to the Terra collapse, highlighting broader economic factors and market dependencies, while ruling out coordinated attacks.

2.2 Studies on stablecoins' death and their probability of default

Research specifically focused on the probability of death for cryptocurrencies or predicting their collapse is relatively scarce. Most studies in this field tend to address the broader cryptocurrency market rather than concentrating on stablecoins. Feder et al. (2018) made a significant contribution by introducing the concept of a "dead coin" and distinguishing between active and abandoned cryptocurrencies. Their study, which was the first to define cryptocurrency "death," used a dataset of 1,082 cryptocoins and found that cryptocurrencies with lower trading volumes were more prone to abandonment. Their work explored the dynamics of "*creation, competition, and destruction*" in the cryptocurrency ecosystem by introducing the concepts of abandoned cryptocurrencies and those later "resurrected". Feder et al. (2018) developed methodologies for identifying peaks in price and trade volume over a five-year period, covering a wide array of cryptocurrencies. Their findings revealed that 44% of the cryptocoins analyzed experienced temporary abandonment, with 71% eventually being recovered and 18% failing permanently. Furthermore, the study examined the relationship between a cryptocurrency's market entry and exit, its price, volume, and market capitalization to provide insights into the factors influencing cryptocurrency performance. Cryptocurrencies with higher trading volumes were found to be less likely to default, while those with lower volumes were more susceptible to abandonment but also showed greater potential for price spikes. The study also observed that both newly introduced and resurrected cryptocurrencies benefited from the overall growth trajectory of the cryptocurrency market, despite increasing competition.

In a related study, Fantazzini and Zimin (2020) pioneered models for predicting cryptocurrency defaults or deaths. They explored various approaches to modeling and estimating market and credit risks within the cryptocurrency market. To validate their findings, they used two distinct datasets: one comprising 5 and 15 cryptocurrencies for market risk forecasting and another including 42 cryptocurrencies for credit risk forecasting. The study applied several methods to evaluate credit risk, including the Zero-Price-Probability (ZPP) method, which estimates default probabilities solely based on market prices, as initially proposed by Fantazzini et al. (2008). Classical credit scoring models such as logit and probit were also employed. The results indicated that the ZPP method was the most effective for estimating credit risk compared to other models.

Further expanding on this topic, Fantazzini and Calabrese (2021) conducted a comprehensive study focusing on cryptocurrency exchanges and the credit risks associated with them. Analyzing a dataset of 144 crypto exchanges operating from 2018 to the first quarter of 2021, they employed a series of models that combined traditional credit scoring techniques with machine learning to predict the probability of exchange closures. Their findings suggested that the presence of a public developer team was the key determinant of exchange closure. Other significant factors included the CER cybersecurity grade, the exchange's age, and the number of traded cryptocurrencies. These factors were consistent in both in-sample and out-of-sample forecasts. The research advised investors to choose exchanges with public developer teams, high CER cybersecurity grades, long operational histories, and a diverse range of tradable crypto-assets to ensure substantial transaction volumes and enhanced security. Robustness checks confirmed that variables such as centralization, decentralization, and compliance with local regulations regarding AML/CFT did not significantly impact the model's performance. Although the study acknowledged the limitation of a relatively small dataset, the researchers were confident that expanding the dataset would not compromise the robustness of their findings.

Finally, Fantazzini (2022) conducted a study assessing credit risk across over 2,000 crypto-assets from 2015 to 2020. This study focused on predicting the likelihood of cryptocurrencies "dying" using a variety of models, three definitions for dead crypto-assets, and different forecasting horizons. The analysis employed credit-scoring models, machine-learning models, and time-series methods based on the ZPP model. The study's key findings indicated that the definition of a "dead" cryptocurrency influenced the selection of the most effective forecasting models, though the top-performing models remained generally consistent across different definitions. The analysis identified the *cauchit* and the ZPP models based on a random walk or MS-GARCH(1,1) as optimal for newly established coins, while credit-scoring models and machine-learning techniques proved more effective for mature cryptocurrencies. Robustness checks were conducted to ensure the reliability and comparability of results across different data samples. It was found that the cauchit model performed best for cryptocurrencies with limited time series data or low trading volumes and Google searches. For short-term forecasting with extensive datasets, the random forests model was most effective. For long-term forecasting, ZPP-based models using either the simple random walk or the MS-GARCH(1,1) were favored.

3 Methodology

This paper aims to evaluate the credit risk associated with stablecoins by employing various models. The analysis begins by identifying the proportion of "dead" and "resurrected" stablecoins, followed by determining the time between a statistically significant break in a stablecoin's peg and its subsequent collapse or stabilization, and concludes with the computation of market-implied probabilities of default (PDs) to perform an out-of-sample forecasting analysis.

3.1 Proportion of "dead" and "resurrected" stablecoins

To address the first goal —identifying the proportion of “dead” and “resurrected” stablecoins and distinguishing between these concepts— we adopted the approach proposed by Feder et al. (2018) and Gandal et al. (2021). The process begins by identifying a “candidate peak,” defined as the day when the 7-day rolling average closing price surpasses any value within a 30-day window (both forward and backward). These peaks are then filtered to include only those that are at least 50% higher than the minimum value observed in the preceding 30 days and represent at least 5% of the stablecoin’s maximum peak value. Each of the peak values are then compared to all of the subsequent daily volume values, and a stablecoin is subsequently categorized as “dead/abandoned” if its average daily trading volume falls below 1% of its peak volume. Conversely, a “dead” stablecoin is reclassified as “resurrected” if its average daily trading volume exceeds 10% of its peak value.

This methodology provides critical insights into the stability of the stablecoin market by calculating the proportion of “dead” (or “abandoned”) stablecoins. More importantly, it also reveals whether stablecoins commonly recover by calculating the proportion of “resurrected” stablecoins among those classified as “dead” or “abandoned”. Understanding these dynamics is essential because it offers insights into market trends and investor sentiment, enables stakeholders to assess risks and make informed decisions, supports regulatory efforts to protect investors and maintain stability, identifies areas for improvement in stablecoin design and governance, and enhances transparency, thereby boosting investor confidence in the cryptocurrency ecosystem.

Overall, this approach provides a comprehensive overview of the stablecoin framework, particularly concerning “abandoned” and “resurrected” stablecoins, and it can contribute to a more robust and resilient stablecoin ecosystem.

3.2 Time Between Significant Peg Break and Stablecoin Collapse/Stabilization

To address the second goal of this study, we examined the presence of any significant structural break in a stablecoin’s price peg using a simple linear regression model, where the price was regressed against a constant of 1 to detect any substantial deviation from the peg. As most stablecoins are pegged to the U.S. dollar at a 1:1 ratio, this model was deemed appropriate for our study framework. In this regard, generalized fluctuation tests can be used to test for structural stability. Generalized fluctuation tests involve fitting a model to the data and generating an empirical process that reflects fluctuations in either the residuals or the parameter estimates. The limiting processes for these empirical processes are well-defined, allowing for the calculation of boundaries with a crossing probability of α under the null hypothesis. If the empirical process exceeds these boundaries, it indicates that the observed fluctuations are unusually large, leading to the rejection of the null hypothesis of structural stability at the α significance level. We note that if the price of a stablecoin were to decrease from 1 to 0.95, for instance, but no significant break was detected by the previous tests, this price movement would not be considered a depeg but rather an insignificant price fluctuation.

The first type of process that can be computed for a generalized fluctuation test is the cumulative sum (CUSUM) process, which involves the cumulative sums of standardized residuals. Alternatively, structural changes can be detected by analyzing moving sums of residuals (MOSUM) rather than cumulative sums. A third approach involves using fluctuation processes based on estimates of the unknown regression coefficients. These coefficients can be estimated either recursively as the number of observations grows or within a moving data window of fixed bandwidth h, and then compared to estimates derived from the entire sample. Detailed discussions on generalized fluctuation tests are available in works like Kuan, Hornik (1995), Zeileis et al. (2002), Zeileis et al. (2005). Empirical processes such as CUSUM, MOSUM, and other variants, as well as generalized fluctuation tests based on these processes, are implemented in the R *strucchange* package.

We employed generalized fluctuation tests to determine the number of days before the official collapse of the stablecoin or its price recovery, when a significant break in the peg occurs. In our work, we used three types of processes to perform generalized fluctuation tests for structural change: the empirical process based on recursive estimates (RE), an OLS-based CUSUM process, and an empirical process based on moving estimates (ME).

The central concept of all generalized fluctuation tests is that the null hypothesis of no structural change in the price peg should be rejected when the fluctuation of the empirical process at time t, $efp(t)$, becomes improbably large compared to that of the limiting process. For one-dimensional residual-based processes, this comparison is made using an appropriate boundary $b\,(t)$, which the limiting process crosses with a given probability α. If the empirical process exceeds $b\,(t)$ or falls below $-\,b\,(t)$ at any time t, it indicates that the fluctuation is unusually large, leading to the rejection of the null hypothesis at the α significance level. A similar approach is used for k-dimensional estimate-based processes, but instead of setting a boundary for the process itself, a boundary is applied to $||efp_i(t)||$, where $||\cdot||$ is an appropriate functional applied to each component. Common functionals include 'max' or 'range'. In our analysis we set the confidence level α at 5%.

Testing for structural change in the price peg is crucial for the following reasons:

1. It allows us to identify breakpoints, i.e., pinpoint the exact moment when a stablecoin's peg begins to break down. This information is essential for investors and market participants to make informed and timely decisions about their investments.

2. Detecting structural changes early can serve as an early warning system for investors, allowing them to take proactive measures to manage risks associated with holding or trading stablecoins, mitigate potential losses, and adjust their investment strategies accordingly.

3. By analyzing structural changes, researchers can gain insights into the underlying market dynamics that contribute to stablecoin instability. This understanding can contribute to regulatory efforts aimed at stabilizing the stablecoin market as well as improving stablecoin design.

3.3 Computation of market-implied probabilities of default (PDs)

The last goal of our work was to calculate the market-implied probabilities of default/death (PDs) for stablecoins using a set of competing models to perform an out-of-sample forecasting analysis.

We first computed market-implied probabilities of default or "death" (PDs) using the *Zero Price Probability* (*ZPP*) method, as described in detail by Fantazzini (2022, 2023). However, instead of relying on prices as in the original approach, we used the asset's market capitalization. Market capitalization was chosen over price because it represents the total value of a stablecoin, reflecting both its price and circulating supply. This makes market capitalization a more comprehensive measure of market sentiment and valuation, making it a suitable metric for assessing stability. In contrast, volume only represents the total number of coins traded within a specific timeframe, which can fluctuate significantly and may not accurately reflect the overall market sentiment or stability of the stablecoin. Therefore, market capitalization is preferred over volume for computing the market-implied probability of default/ death of stablecoins. Using the ZPP has several advantages: we can employ more realistic distributions than the log-normal distribution and compute estimations for any future time period. This method estimates the market-implied probability that the market capitalization of a stablecoin will be less than or equal to zero, $P\left(MCap_{\tau} \leq 0\right)$, within a specified time horizon ($t < \tau \leq t+T$), considering that the market capitalization (and the price) of a traded stablecoin is a truncated variable that cannot drop below zero. The Zero Price Probability (ZPP) reflects the likelihood of the price/market capitalization reaching or falling below the truncation level of zero, thereby acting as an indicator of default. For more details, see Fantazzini et al. (2008).

The method involves three main steps:

1. First, use a general conditional model for the differences in market capitalizations (MCap):

$$
\begin{aligned}
X_t &= \mu_t + \varepsilon_t \quad \text{where,} \quad X_t = MCap_t - MCap_{t-1}, \\
\varepsilon_t &= \sqrt{\sigma_t} z_t, \quad z_t \sim iid(0,1)
\end{aligned} \tag{1}
$$

where μ_t and σ_t are the conditional mean and standard deviation, respectively.

2. Generate multiple trajectories N for market capitalizations up to time $t+T$ using the model (1) estimated in the previous step.

3. Finally, calculate the probability of default/death $P\left(MCap_{\tau} \leq 0\right)$ as the ratio of n to N, where n represents the number of instances out of N when the market capitalization fell to zero along the simulated trajectory.

We considered the 1-day-ahead, 30-day-ahead, and 365-day ahead probability of death for each stablecoin, that is, $T = \{1, 30, 365\}$. The rationale for using different forecast horizons stems from the possibility that distinct factors drive the collapse of different stablecoins over varying time intervals. For instance, one stablecoin might experience a long-term fraud, while another might face technical issues over a short period. In this context, Fantazzini et al. (2008) found that the default probabilities estimated with the ZPP model for a set of bankrupt Italian stocks exceeded 50% well before the defaults –sometimes even years in advance–while for a set of American defaulted stocks, this increase only occurred in the final 100 trading days. They explained this difference by referencing justice probes conducted at the time, which revealed that large-scale illegal schemes to siphon money from the Italian companies were set up much earlier, as far back as the 1990s, unlike the American cases. Similar variations are also possible among stablecoins, as our review in Section 2 highlighted, making the use of different forecasting time horizons, computed at various points before the default, a sensible approach.

Additionally, we also considered the *Cox Proportional Hazards Model* (*CPHM*), a widely used model in survival analysis, see Cox (1972), Breslow (1975) and Kalbfleisch and Schaubel (2023) for more details. As a survival model, the CPHM analyzes the time until a specific event occurs in relation to various covariates and examines the impact of these covariates on the likelihood of this event. In this setting, the effect of a one-unit increase in a covariate is multiplicative on the hazard rate, indicating how the risk of the event changes over time. In our study, the event could be the death of the stablecoin or a significant break in its peg. The impact of different factors is measured by "hazard ratios" (HR). The CPHM uses a function, denoted as the hazard function $h(t)$, which represents the likelihood of an event, such as death (risk of death) in our case, occurring at time t:

$$h(t|\boldsymbol{X}) = h_0(t) \cdot \exp(b_1 x_1 + b_2 x_2 + \ldots + b_p x_p), \tag{2}$$

where the vector $\boldsymbol{X}$ is a vector of covariates, while $h_0\,(t)$is the baseline hazard, corresponding to the function value when all covariates equal to zero.

The Hazard ratios (HR), denoted by $exp(b_i)$ for each covariate, indicate the relationship between the covariate $i$and the likelihood of a particular event, such as the death of a stablecoin in our case. A HR greater than 1 suggests a positive association with the event, while a HR less than 1 indicates a negative association. If HR equals 1, no effect is indicated. The use of the Cox Proportional Hazards Model offers several advantages, including its compatibility with both categorical and quantitative predictors. Recently, Gatabazi et al. (2022) used the hazard model to assess the risk of cryptocurrencies based on factors such as their blockchain platform (Ethereum or Standalone), regional origin, and period of existence (2009–2013 or 2013–2017). Their findings showed that cryptocurrencies issued between 2013–2017 faced higher risks compared to those issued between 2009–2013. Additionally, the model identified crypto-assets with undisclosed headquarters as being at increased risk. This model can be computed using the *survival* or *survminer* R packages. We employed the Cox Proportional Hazards Model with each stablecoin over time to assess its probability of death, given the occurrence of a peg break. As with the ZPP method, we estimated the probabilities of death for three forecasting horizons: 1-day-ahead, 30-days-ahead, and 365-days-ahead.

3.4 Forecasting model evaluation

The predictive accuracy of different models regarding the probability of death was assessed by comparing the predicted probabilities of default (PDs) with the actual outcomes of the stablecoins. Traditional forecast evaluation metrics, including the Area Under the Receiver Operating Characteristic Curve (AUC or AUROC), Brier Score, accuracy, sensitivity, and specificity, were then computed.

The AUC measures a binary classification model's ability to distinguish between positive and negative classes. It is derived from the area under the ROC curve, which plots the true positive rate against the false positive rate at various classification thresholds. The AUC value ranges from 0 to 1, with higher scores indicating better model performance. For more information, refer to Sammut and Webb (2011), pp. 869–75, and the references therein.

The Brier Score represents the mean squared error (MSE) applied to binary outcomes, as outlined by Brier (1950). This score can be combined with the Model Confidence Set (MCS) method by Hansen et al. (2011) to identify the best forecasting models at a specified confidence level. In this regard, consider the difference between the MSEs of models i and j at time t, that is, $d_{i,j,t} = MSE_{i,t} - MSE_{j,t}$. The MCS approach involves testing the hypothesis of equal predictive ability $H_{0,M} : \mathrm{E}(d_{i,j,t}) = 0$, across all models i, j in the set M. First, t-statistics are computed for each model $i \in M$, denoted as $t_{i\cdot} = \bar{d}_{i\cdot}/\widehat{var}(\bar{d}_{i\cdot})$, where $\bar{d}_{i\cdot} = m^{-1}\sum_{j\in M}\bar{d}_{ij}$ is the simple loss of model i relative to the average losses across models in M, $\bar{d}_{ij} = T^{-1}\sum_{t=1}^{T} d_{ij,t}$ represents the sample loss differential between models i and j, and $\widehat{var}(\bar{d}_{i\cdot})$ is an estimate of $var(\bar{d}_{i\cdot})$. Next, the test statistic $T_{\max} = \max_{i\in M}(t_{i\cdot})$ is computed to evaluate the null hypothesis. This statistic follows a non-standard distribution, so its distribution under the null hypothesis is estimated using bootstrap methods with 1,000 replications and a minimum block length of 7 days. If the null hypothesis is rejected, one model is removed from the analysis, and the testing procedure is repeated.

Accuracy refers to the rate of correct classifications, calculated as the ratio of correct predictions to the total predictions made. Although it is a commonly used metric for evaluating binary classification models, it can be misleading when dealing with imbalanced datasets. Sensitivity, also known as recall, indicates the percentage of true positive predictions among all actual positive instances in the dataset. In our context, it reflects how effectively the model identifies dead stablecoins. Specificity, on the other hand, represents the percentage of true negative predictions among all actual negative instances, assessing the model's ability to correctly identify stablecoins that are still functioning.

4 Empirical analysis

4.1 Data

The dataset used for the analysis was obtained from CoinMarketCap.com. This platform is a widely recognized resource in the cryptocurrency space, providing comprehensive information on various crypto assets, including cryptocurrencies, stablecoins, collectibles, and NFTs. The dataset includes historical data on prices (open, close, high, and low), market capitalization, and trading volume. CoinMarketCap offers real-time data on thousands of cryptocurrencies and tokens, making it an invaluable resource for researchers, investors, traders, and enthusiasts. Additionally, the platform provides news, analysis, educational content, and tools to help users monitor and understand the cryptocurrency market. We compiled a dataset of 121 stablecoins, with the complete list presented in Table 1. For further analysis, we used daily data of close prices, market capitalization, and trading volume for these stablecoins.

N.	Abbreviation	Full Name	N.	Abbreviation	Full Name	N.	Abbreviation	Full Name
1	AGEUR	Angel Protocol	41	mCUSD	Moola Celo USD	81	USX	sForce USD
2	BAC	Basis Cash	42	MIM	Magic Internet Money	82	UUSDS	SpiceUSD
3	BIDR	BIDR	43	MIMATIC	MAI	83	v1JPYC	JPY Coin v1
4	BITCNY	bitCNY	44	MONEY	Moremoney USD	84	VAI	Vai
5	BRCP	BRCP TOKEN	45	MSUSD	mStable USD	85	vBUSD	Venus BUSD
6	BUSD	Binance USD	46	MTR	Meter Stable	86	vDAI	Venus DAI
7	CADC	CAD Coin	47	MUSD	Mad USD	87	vUSDC	Venus USDC
8	cCUSD	Coin98 Dollar	48	MXNT	Mexican Peso Tether	88	vUSDT	Venus USDT
9	CEUR	Celo Euro	49	nUSD	nUSD (HotBit)	89	WANUSDT	wanUSDT
10	COFFIN	Coffin Finance	50	ONC	One Cash	90	XCHF	CryptoFrank
11	CUSD	Celo Dollar	51	ONEICHI	ONEICHI	91	xDAI	xDAI
12	CUSDT	Compound USDT	52	OUSD	Origin Dollar	92	XIDR	XIDR
13	DAI	Dai	53	PAR	Parallel	93	XSGD	XSGD
14	DFUSD	DefiDollar	54	RSV	Reserve	94	XSTUSD	SORA Synthetic USD
15	DGD	DigixDAO	55	SBD	Steem Dollars	95	XUSD	xUSD Token
16	DGX	DigixGoldToken	56	SEUR	sEUR	96	xXUSD	xDollar Stablecoin
17	DJED	Djed	57	STATIK	Statik	97	YUSD	YUSD Stablecoin
18	DOLA	DOLA	58	sUSD	sUSD	98	FDUSD	First Digital USD
19	DPT	Diamond Platform Token	59	TOR	TOR	99	USDe	Ethena USDe
20	DSD	Dynamic Set Dollar	60	TRIBE	Tribe	100	PYUSD	PayPal USD
21	DUSD	Decentralized USD	61	TRYB	BiLira	101	QC	Qcash
22	EOSDT	EOSDT	62	TUSD	TrueUSD	102	ITL	Italian Lira
23	ESD	ESD	63	USDB	USD Bancor	103	USDSC	Stably USD Classic
24	EUROC	Euro Coin	64	USDC	USD Coin	104	USDQ	USDQ
25	EURS	STASIS EURO	65	USDD	USDD	105	BSD	Basis Dollar
26	EURT	Tether EURt	66	USDEX	USDEX	106	MDS	Midas Dollar Share
27	F1GOLD	1GOLD	67	USDH	USDH	107	MDO	Midas Dollar
28	FEI	Fei USD	68	USDI	USDi	108	ALUSD	Alchemix USD
29	FFUSD	Fuse Dollar	69	USDJ	USDJ	109	FLOAT	Float Protocol
30	FRAX	Frax	70	USDK	USDK	110	fUSDT	Frapped USDT
31	FUSD	Fantom USD	71	USDP	Pax Dollar	111	ARTH	ARTH Valuecoin
32	GUSD	Gemini Dollar	72	USDPS	USDP Stablecoin	112	BEAN	Bean
33	HUSD	HUSD	73	USDR	Ratio Stable Coin	113	COUSD	Coffin Dollar
34	IDRT	Rupiah Token	74	USDS	Stably USD	114	AUSD	Alpaca USD
35	IRON	Iron	75	USDs	Sperax	115	FUSDT	FEG Wrapped USDT
36	JPYC	JPY Coin	76	USDT	Tether	116	H2O	H2O
37	KBC	Karatgold Coin	77	USDX	USDX [Kava]	117	IUSDS	Inflation Adjusted USDS
38	KRT	TerraKRW	78	USDZ	ZEDXION	118	EUROS	SpiceEURO
39	LUSD	Liquity USD	79	USN	USN	119	QCAD	QCAD
40	mCEUR	Moola Celo EUR	80	USTC	TerraClassicUSD	120	SBC	Stable Coin
						121	RUBCASH	Rubcash

Table 1: List of downloaded stablecoins with their abbreviations and full names.

4.2 Key findings: proportion of "dead" and "resurrected" stablecoins

We applied the method proposed by Feder et al. (2018) and Gandal et al. (2021) to our dataset of 121 stablecoins to identify which stablecoins had changed their status to "abandoned" and/or "resurrected," and how many times this occurred, see Table 2.

Our findings revealed that only 21% of the stablecoins in our dataset had changed their status to "abandoned" at least once. Among these, 36% were resurrected (7% of the total sample); however, the majority were subsequently considered abandoned once again. Only 11% of the stablecoins that had been resurrected at least once retained the status of "resurrected" as their final status (1% of the total sample).

Unlike Feder et al. (2018) and Gandal et al. (2021) with cryptocurrencies, we found a relatively low percentage of stablecoins that were classified as abandoned. One possible reason for this discrepancy is that the methodology proposed by Feder et al. (2018) begins with identifying a "candidate peak," which requires the price to be somewhat elevated before the collapse of the cryptocurrency. However,

№	Abbreviation	Name	N. of times "Abandoned"	N. of times "Resurrected"	Date "Abandoned"	Date "Resurrected"
1	BITCNY	bitCNY	1	0	2023-11-01	-
2	BRCP	BRCP TOKEN	1	0	2023-11-08	-
					2022-04-19	2023-01-14
3	CADC	CAD Coin	3	2	2023-05-01	2023-06-01-
					2023-07-01	-
4	COFFIN	Coffin Finance	1	0	2023-07-01	-
5	DGD	DigixDAO	2	1	2022-11-01	2022-12-01-
					2023-02-01	-
6	DGX	Digix Gold Token	2	1	2021-07-01	2021-10-01-
					2023-11-01	-
7	DPT	Diamond Platform T.	2	1	2021-05-15	2021-10-23-
					2022-07-01	-
8	DSD	Dynamic Set Dollar	1	0	2022-05-01	-
9	EOSDT	EOSDT	2	1	2022-02-01	2022-05-01-
					2022-07-01	-
10	ESD	ESD	1	0	2022-06-01	-
11	IRON	Iron	1	0	2024-01-01	-
12	KBC	Karatgold Coin	1	0	2020-11-01	-
13	KRT	TerraKRW	1	0	2022-06-01	-
14	nUSD	nUSD (HotBit)	1	0	2022-11-12	-
15	SBD	Steem Dollars	2	1	2021-05-01	2021-06-01-
					2023-06-01	-
16	USDB	USD Bancor	1	0	2024-02-01	-
17	USDR	Ratio Stable Coin	1	0	2023-12-01	-
18	USDS	Stably USD	1	0	2021-08-06	-
19	USX	sForce USD	1	0	2021-12-09	-
20	v1JPYC	JPY Coin v1	1	0	2022-04-06	-
21	XIDR	XIDR	1	1	2024-02-01	2024-04-01
22	ITL	Italian Lira	2	1	2020-04-01	2020-08-03-
					2021-09-01	-
23	USDSC	Stably USD Classic	1	0	2021-08-06	-
24	USDQ	USDQ	2	2	2021-02-13	2021-06-15-
					2022-05-01	-
25	BSD	Basis Dollar	1	1	2022-05-01	-

Table 2: List of stablecoins that acquired the status of "abandoned" and/or "resurrected" according to the methodology of Feder et al. (2018) and Gandal et al. (2021).

stablecoins, unlike cryptocurrencies, are designed to maintain their peg and exhibit lower volatility. As a result, many stablecoins that broke their peg did not experience a price increase prior to this event. To gain more insight, it is helpful to examine a few examples. Let's consider the behavior of the close prices for three stablecoins: TerraClassicUSD, Iron, and EOSDT, see Figure 1.

The graph shows that all of these stablecoins deviated from their pegs. Terra collapsed in May 2022 and was unable to recover. Iron collapsed in December 2022, but after a year, it experienced a price increase with some peaks. EOSDT also broke its peg, but unlike the other stablecoins mentioned, it was more volatile before the peg break. Terra did not exhibit price peaks or noticeable volatility before the peg break, which is why the methodology proposed by Feder et al. (2018) did not classify it as "abandoned." The same applies to Iron, whose price was relatively stable before the peg break. However, after its recovery, the price experienced a sudden peak at the end of 2023. A closer examination of the

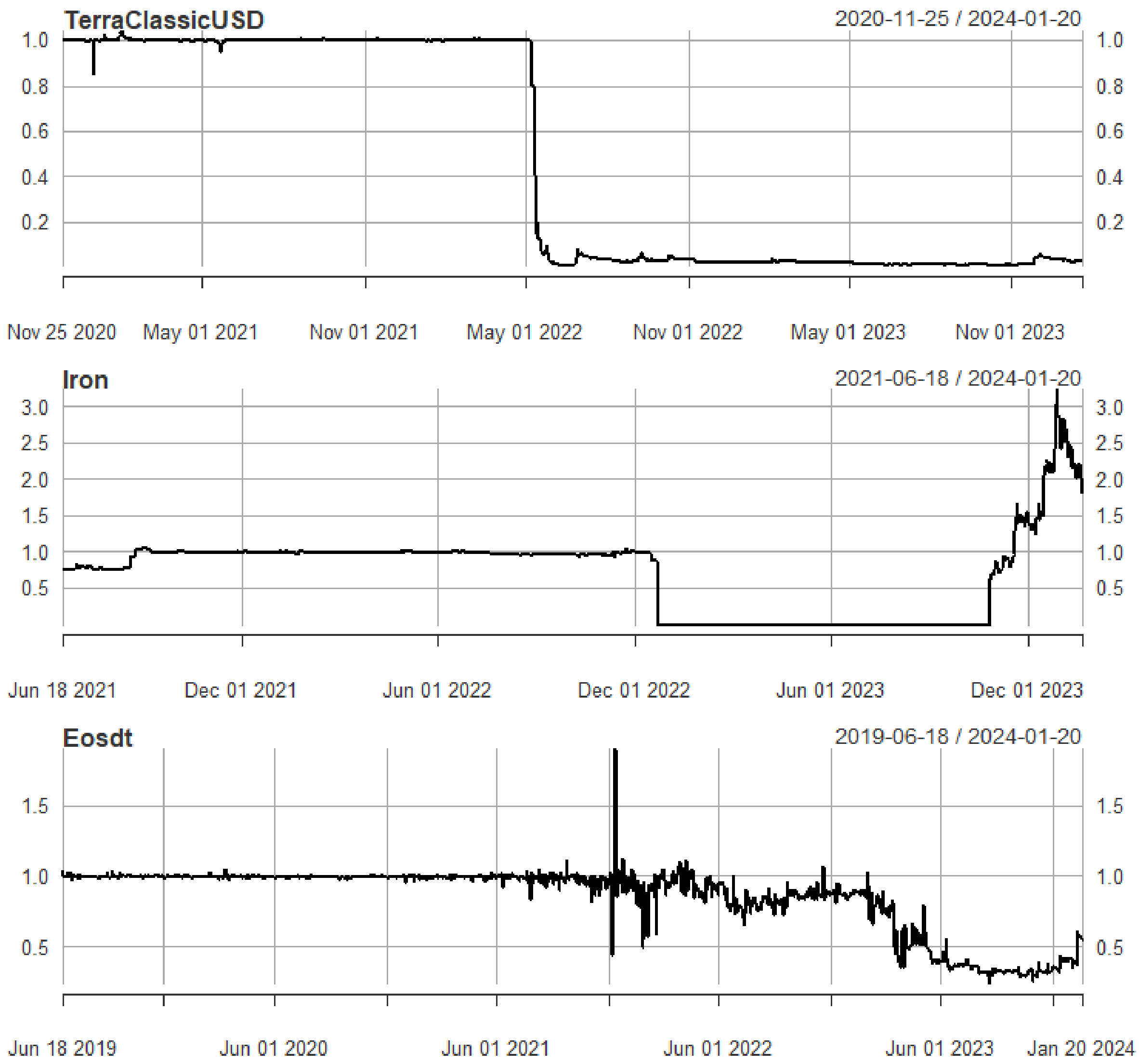

Figure 1: The behavior of close prices for 3 stablecoins: TerraClassicUSD, Iron, and EOSDT.

price behavior around this peak reveals that it was a sudden jump, meeting the criteria required by the method to be considered "dead". The last example, EOSDT —a more volatile stablecoin— demonstrates that a stablecoin can receive a status of "resurrected."

Conceptually, the design of stablecoins is the primary reason why the results of this methodology for stablecoins differ from those obtained by Feder et al. (2018) for cryptocurrencies. While cryptocurrencies are more volatile and likely to experience significant price fluctuations, it is uncommon for investors to reinvest in stablecoins that have broken their peg, as this involves substantial risks and uncertainties (including potential technical errors in the algorithm maintaining the peg), which may outweigh the potential benefits.

Unfortunately, there are currently no better alternatives to the method proposed by Feder et al.

(2018). Schmitz and Hoffmann (2020) suggested a simplified version of Feder et al. (2018)'s method, where a crypto-asset is classified as dead if its average daily trading volume for a given month is less than or equal to 1% of its previous historical peak. Conversely, a crypto-asset is classified as "resurrected" if this average daily trading volume rises to 10% or more of its past historical peak. However, it is evident that such an approach would be even less effective with stablecoins, rendering it unsuitable. Similarly, the widely recognized professional rule that defines a crypto-asset as dead if its value falls below 1 cent, and alive if its value rises above 1 cent, is difficult to apply to stablecoins. For example, in Figure 1, out of the three abandoned stablecoins, only Iron dropped below the price of 1 cent. For a detailed comparison of these three criteria for classifying a crypto-asset as dead or alive, see Fantazzini (2022).

4.3 Key findings: time between significant peg break and stablecoin collapse/stabilization

The second objective of our study was to perform structural tests using a simple linear regression model (against a constant of 1) to analyze the price behavior of stablecoins. This approach aimed to determine the number of days occurring between a structural change and the subsequent collapse of the stablecoin or its price recovery.

The algorithm to calculate the days leading up to a stablecoin's collapse involved several steps. First, we examined each stablecoin individually to identify the point when its price began to significantly deviate from its peg, utilizing one of the previously discussed structural break tests. To illustrate this approach, we consider two stablecoins that did not experience a peg break, such as Moremoney USD (MONEY) and mStable USD (MSUSD). The close prices and the Recursive Estimates (RE) processes are shown in Figure 2.

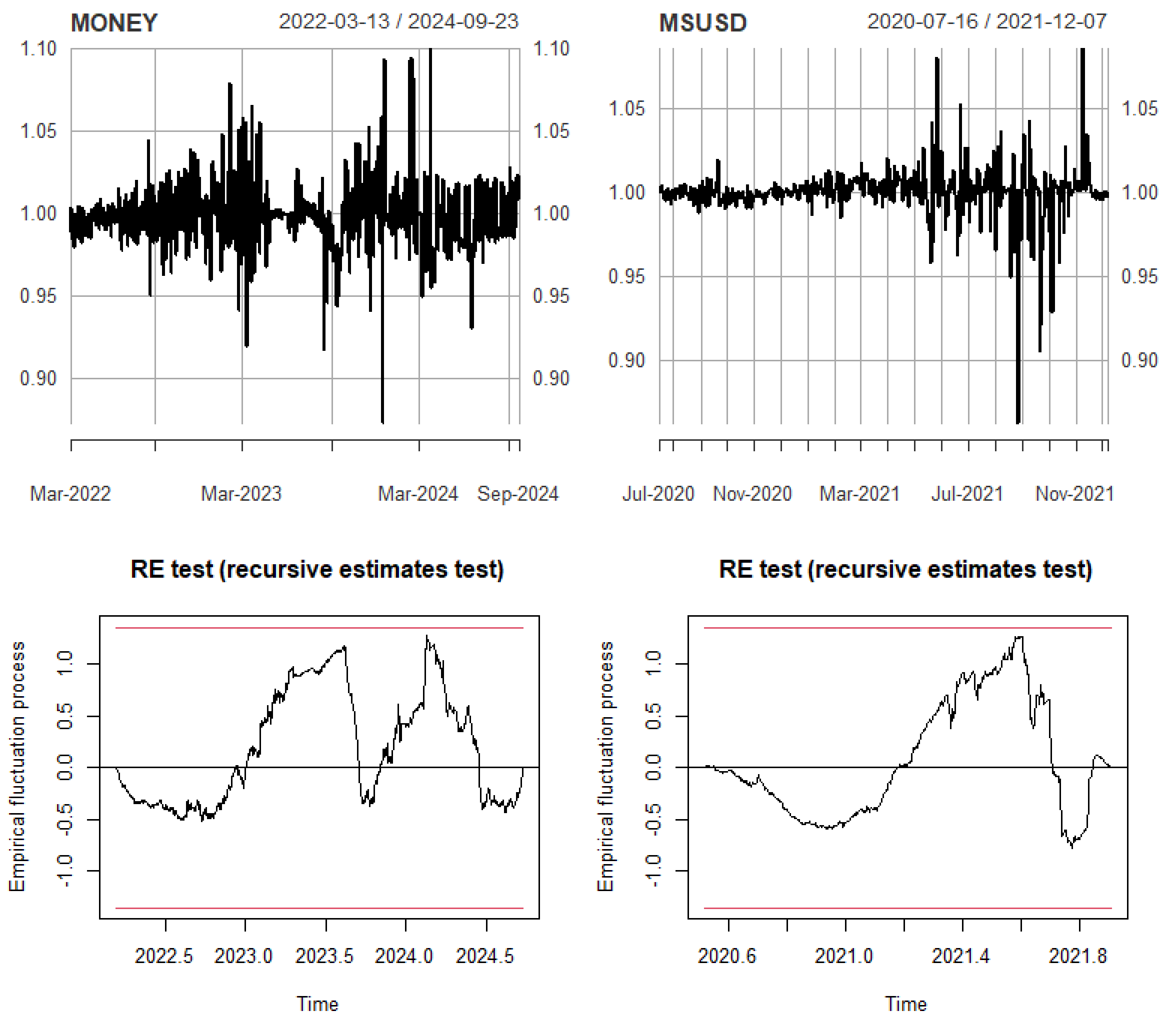

Figure 2: Prices behavior and assumed RE processes for two stablecoins: Moremoney USD (MONEY) and mStable USD (MSUSD).

It is evident from the graph that both stablecoins remained relatively stable, experiencing only minor fluctuations around their peg. After computing the RE process and plotting the results, no significant structural change in the price process of these stablecoins was observed. Structural change tests based on these RE processes did not reject the null hypothesis of no break in the price peg, with p-values of 0.43 and 0.15, respectively.

Next, we consider a stablecoin that did break its peg –TerraClassicUSD (USTC)– which lost its peg in May 2022, making it a significant example. We used data from September 2020 to early May 2022, a period during which Terra's price fell from \$1 to \$0.4, raising uncertainty about whether the stablecoin could recover its peg. The price behavior, along with three empirical processes based on recursive estimates (RE), the OLS-based CUSUM process, and moving estimates (ME), are presented in Figure 3. The p-values for the structural change tests based on these processes are 0.02, 0.02 and 0.01, respectively, and the null hypothesis is rejected at the 5% significance level for all three tests.

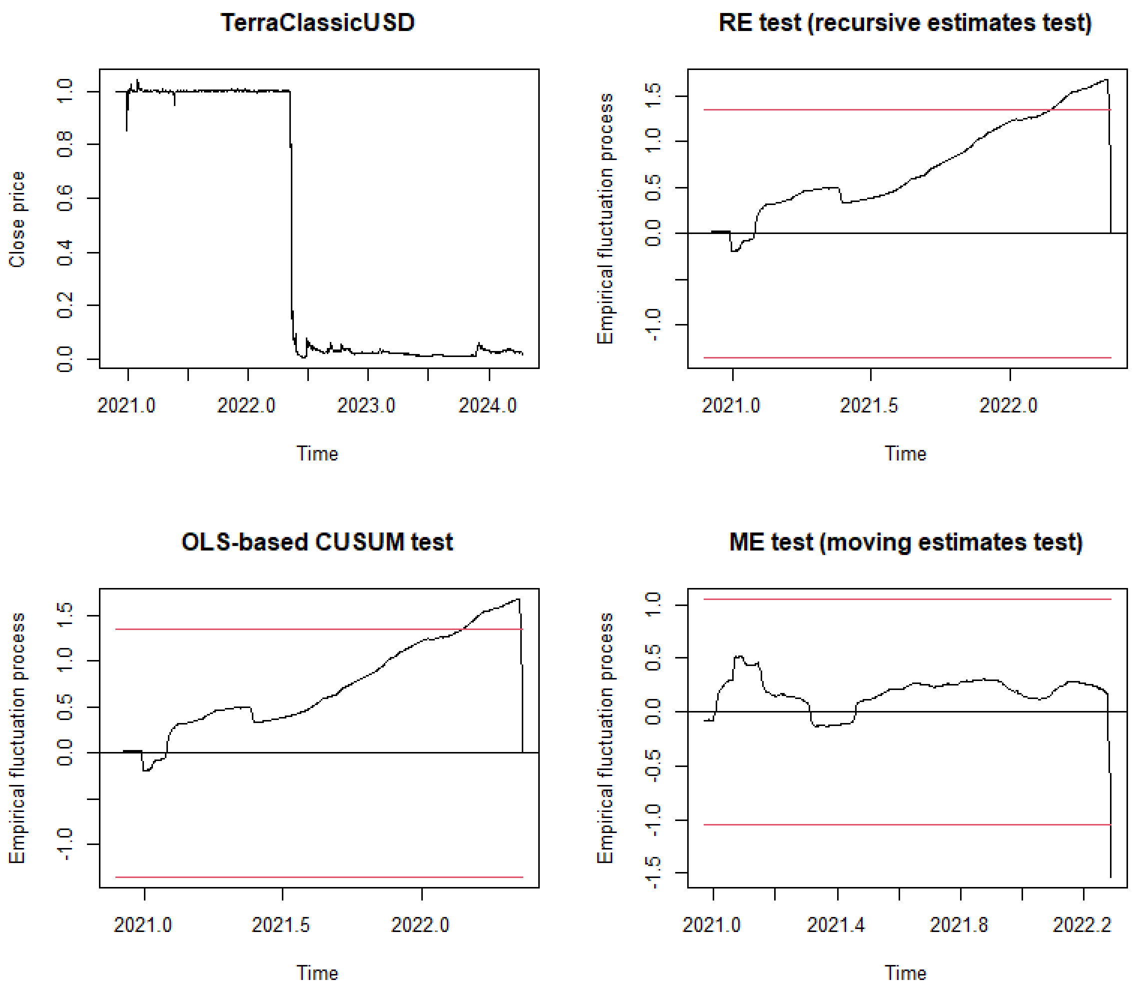

Figure 3: Prices behavior three empirical fluctuation processes for TerraClassicUSD (USTC)

We remark that if structural tests based on different processes yielded varying results, we primarily relied on the RE process rather than the ME process when assessing structural changes in stablecoin prices. The RE process is advantageous because it adapts to changes in the data over time by updating estimates recursively, making it more sensitive to structural breaks that occur gradually or intermittently. Unlike the ME tests, which depend on moving averages and may experience lag effects in detecting structural changes, the RE test operates without lag, providing more immediate insights into changes in stablecoin prices. This minimizes the risk of delayed responses to market developments.

We applied these tests and then calculated the time period between the structural change and the stablecoin's collapse/recovery for the entire dataset of stablecoins. More specifically, for the dead stablecoins, we considered the period between the statistically significant structural break and the time when the price stabilized around a “new” lower value, while for resurrected stablecoins, we considered the period between the structural break and the time when the price recovered to their peg value. However, we remark that we had to exclude a certain number of stablecoins with extreme price volatility that were simply unable to maintain their peg throughout their existence, so the dataset for the second step of our analysis consisted of 50 stablecoins. Besides, if a stablecoin did not break its peg, we obviously did not compute the time between the peg break and the stablecoin’s collapse or stabilization. The average number of days for the stablecoins included in the analysis was approximately 10 days. The table with the test p-values (using the RE process), the date of the price peg break, and the final outcomes for each stablecoin considered in this analysis are presented in Table 3.

№	Abbreviation	Name	p-value	Structural change	End date	# of days	Outcome
1	AGEUR	Angel Protocol	0.045	yes	2023-03-16	3	Stabilization
2	ALUSD	Alchemix USD	0.010	yes	2023-06-08	10	Collapse
3	AUSD	Alpaca USD	0.330	no	2022-08-18	-	Stabilization
4	BAC	Basis Cash	0.000	yes	2021-01-16	9	Collapse
5	BIDR	BIDR	0.038	yes	2020-09-15	4	Collapse
6	BITCNY	bitCNY	0.000	yes	2018-09-19	1	Stabilization
7	BSD	Basis Dollar	0.293	no	2021-12-16	-	Stabilization
8	BUSD	Binance USD	0.000	yes	2024-03-17	10	Stabilization
9	cCUSD	Coin98 Dollar	0.000	yes	2023-04-18	8	Stabilization
10	CUSD	Celo Dollar	0.019	yes	2022-11-17	10	Stabilization
11	DAI	Dai	0.147	no	2024-04-27	-	Stabilization
12	DFUSD	DefiDollar	0.006	yes	2022-12-27	15	Stabilization
13	DOLA	DOLA	0.000	yes	2023-04-22	12	Stabilization
14	EOSDT	EOSDT	0.014	yes	2023-03-19	4	Collapse
15	FRAX	Frax	0.182	no	2021-09-27	-	Stabilization
16	fUSDT	Frapped USDT	0.474	no	2024-04-27	-	Stabilization
17	FUSDT	FEG Wrapped USDT	0.013	yes	2022-05-06	16	Stabilization
18	GUSD	Gemini Dollar	0.018	yes	2018-12-23	6	Stabilization
19	HUSD	HUSD	0.000	yes	2022-11-08	12	Collapse
20	IDRT	Rupiah Token	0.308	no	2019-12-08	-	Stabilization
21	IRON	Iron	0.035	yes	2022-12-23	7	Collapse
22	mCUSD	Moola Celo USD	0.000	yes	2022-11-01	14	Stabilization
23	MIM	Magic Internet Money	0.000	yes	2023-07-13	7	Stabilization
24	MIMATIC	MAI	0.000	yes	2023-07-27	15	Stabilization
25	MONEY	Moremoney USD	0.429	no	2024-04-27	-	Stabilization
26	MSUSD	mStable USD	0.152	no	2021-09-01	-	Stabilization
27	nUSD	nUSD (HotBit)	0.000	yes	2022-11-15	21	Stabilization
28	ONEICHI	ONEICHI	0.389	no	2024-04-27	-	Stabilization
29	OUSD	Origin Dollar	0.047	yes	2021-01-08	2	Collapse
30	PYUSD	PayPal USD	0.071	no	2024-04-27	-	Stabilization
31	RSV	Reserve	0.049	yes	2023-12-13	12	Stabilization
32	STATIK	Statik	0.011	yes	2022-08-10	4	Collapse
33	TOR	TOR	0.028	yes	2023-07-10	4	Collapse
34	USDEX	USDEX	0.002	yes	2023-05-20	13	Collapse
35	USDH	USDH	0.048	yes	2023-05-07	13	Stabilization
36	USDI	USDi	0.058	no	2024-04-27	-	Stabilization
37	USDJ	USDJ	0.000	yes	2022-11-16	6	Increase
38	USDPS	USDP Stablecoin	0.010	yes	2022-04-21	3	Collapse
39	USDQ	USDQ	0.001	yes	2020-04-26	16	Stabilization
40	USDR	Ratio Stable Coin	0.000	yes	2023-10-23	11	Collapse
41	USDS	Stably USD	0.315	no	2023-02-14	-	Stabilization
42	USDSC	Stably USD Classic	0.194	no	2023-02-14	-	Stabilization
43	USDT	Tether	0.000	yes	2017-04-30	21	Stabilization
44	USDZ	ZEDXION	0.015	yes	2023-03-13	5	Stabilization
45	USN	USN	0.273	no	2024-04-23	-	Stabilization
46	USTC	TerraClassicUSD	0.017	yes	2022-05-12	8	Collapse
47	xDAI	xDAI	0.198	no	2024-01-24	-	Stabilization
48	XIDR	XIDR	0.280	no	2023-09-18	-	Stabilization
49	XSTUSD	SORA Synthetic USD	0.009	yes	2022-09-11	20	Stabilization
50	xXUSD	xDollar Stablecoin	0.042	yes	2023-04-22	4	Stabilization

Table 3: P-values for the structural change tests based on RE empirical fluctuation processes, date of the price peg break, and final outcomes for each stablecoin.

4.4 Key findings: computation of market-implied probabilities of default

We calculated market-implied probabilities of default (PDs) using the Zero Price Probability (ZPP) method by Fantazzini et al. (2008), incorporating stablecoins' market capitalization instead of prices. As previously mentioned, the rationale for using market capitalization is that it reflects both the price and circulating supply of stablecoins, thereby capturing the overall market sentiment. To illustrate the relationship between prices and market capitalization, we can examine the examples of two stablecoins: TerraClassicUSD (USTC) and Tether (USDT). The former broke its peg in May 2022, while the latter generally maintained its peg, as shown in Figure 4.

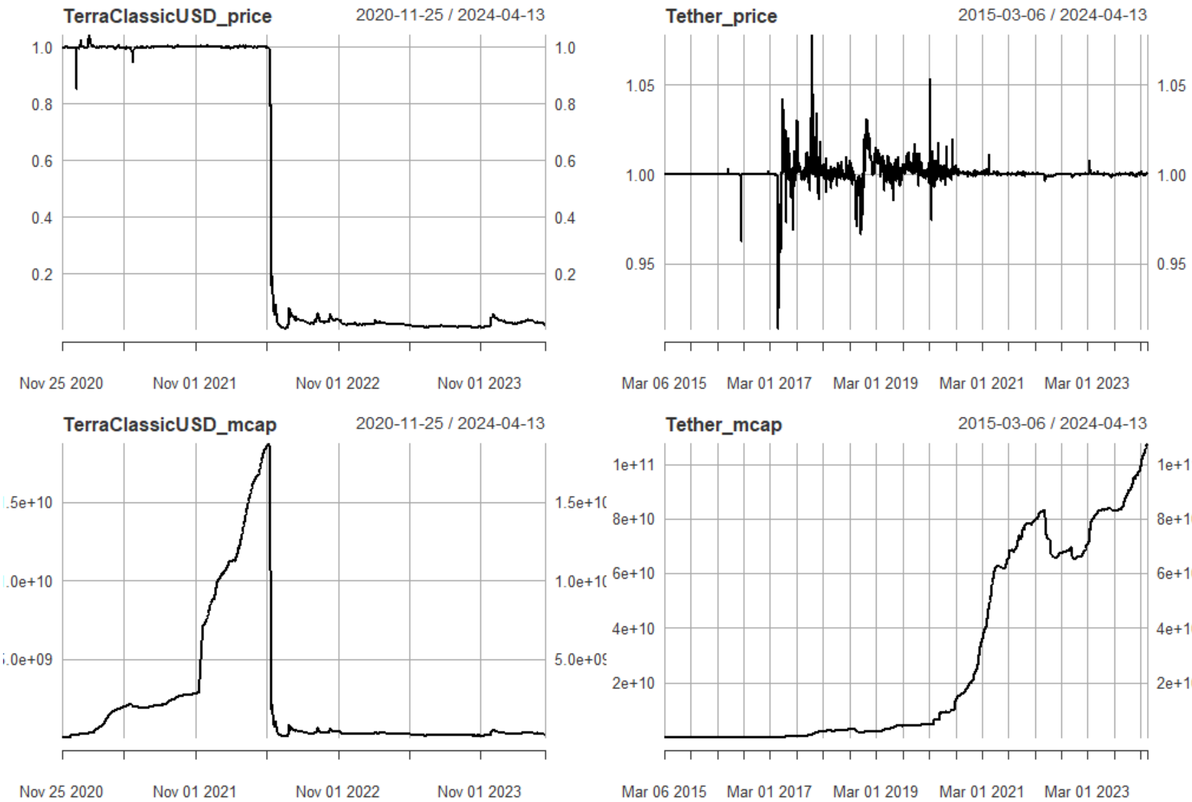

Figure 4: Market prices and market capitalization of TerraClassicUSD (USTC) and Tether (USDT).

As evident from Figure 4, when Terra broke its peg, its market capitalization also experienced a sharp decline. In contrast, Tether's market capitalization followed an upward trend while its price remained relatively stable.

We analyzed the entire dataset of stablecoins, but many stablecoins (especially those that collapsed) had missing market capitalization data, which led us to exclude them from the analysis. The final dataset for the third step of our analysis consisted of 47 stablecoins [2]. We computed different PDs for

[2] The dataset used to test for a break in the peg includes 50 stablecoins, excluding those with extreme price volatility that were unable to maintain their peg throughout their lifespan. Although these coins are formally classified as stablecoins,

the stablecoins included in our study, based on varying time frames for the estimation windows (30 days, 365 days, and the entire available historical data before the forecast) and different forecasting horizons (1-day ahead, 30-day ahead, and 365-day ahead). As in our earlier method for testing structural change, we selected the end date as the period when the price began to deviate for at least a few days. For example, TerraClassicUSD (USTC) broke its peg in May 2022, so we analyzed the period up to the beginning of May 2022 (2022-05-12), considering three time frames: 1) from 2022-04-12 to 2022-05-12; 2) from 2021-05-12 to 2022-05-12; and 3) from its launch in September 2020 to 2022-05-12. The computed probabilities for all stablecoins are available from the authors upon request.

After calculating the PDs for different estimation windows and forecasting horizons, we treated the analysis as a classification problem and computed the AUC score for each model specification, as well as the Brier Score. Additionally, we also calculated accuracy, sensitivity, and specificity for each model, using two alternative thresholds for converting probabilities into binary variables: 1) a threshold of 50%; 2) a threshold equal to the proportion of dead stablecoins in the sample (i.e., the empirical prevalence). We remark that a 50% threshold is not advisable for our dataset due to the imbalance between the two classes. These forecasting metrics are reported in Table 4, together with the models included in the MCS at the 10% confidence level.

Model	AUC	Brier-S.	MCS	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
				Binary	*threshold:*	50%	*Binary*	*threshold:*	*e. prevalence*
zpp_1 exp 30	0.56	0.15	Included	0.83	0.00	0.97	0.76	0.00	0.90
zpp_30 exp 30	0.77	0.16	Included	0.80	0.57	0.85	0.76	0.85	0.75
zpp_365 exp 30	0.83	0.32	NO	0.63	1.00	0.57	0.59	1.00	0.52
zpp_1 exp 365	0.61	0.13	Included	0.85	0.00	1.00	0.85	0.14	0.97
zpp_30 exp 365	0.77	0.13	Included	0.83	0.28	0.92	0.87	0.57	0.92
zpp_365 exp 365	0.74	0.19	Included	0.78	0.71	0.80	0.72	0.71	0.72
zpp_1 exp all	0.58	0.14	Included	0.83	0.00	0.97	0.83	0.14	0.95
zpp_30 exp all	0.73	0.15	Included	0.78	0.28	0.87	0.78	0.57	0.82
zpp_365 exp all	0.69	0.19	Included	0.78	0.71	0.80	0.70	0.71	0.70

Table 4: AUC, Brier scores, models included in the MCS, and evaluation metrics for different ZPP models (with different estimation windows and forecasting horizons), using two alternative thresholds for converting probabilities into binary variables. Abbreviations meaning: the first number is the number of days for the forecasting window, while second number is the size of the estimation window. For example, *zpp_1 exp* 30 refers to the PD computed with the ZPP model for 1-day ahead forecasts, using an estimation window of 30 days

The ZPP models with 365-day estimation windows seem to offer the best balance in terms of forecasting metrics, while models with 30-day estimation windows appear to be less stable, particularly regarding Brier scores and sensitivity. However, it is important to emphasize that more robust results would require

their behavior resembled that of cryptocurrencies with large price fluctuations, making it meaningless to test for a break in their peg. Market capitalization data were not required for this analysis. Conversely, the dataset used to compute market-implied probabilities of default (PDs) consists of 47 stablecoins for which market capitalization data were available. Unlike the first dataset, the criterion of maintaining the peg was not applied. Instead, the analysis focused on whether a stablecoin was classified as "dead" or "alive" (a binary classification problem). The similar sizes of these two groups (50 and 47 stable-coins, respectively) are purely coincidental and unrelated to the selection criteria a much larger dataset, especially with respect to stablecoins that have collapsed. This highlights a key limitation of our study: the small size of our dataset. This is not a new challenge when working with credit risk for crypto-assets. For example, the seminal work by Moore et al. (2013), which addressed credit risk for crypto-exchanges, also dealt with a dataset of only 40 exchanges.

We then used the Cox Proportional Hazards Model (CPHM) to calculate the probability of death for each stablecoin following a break in the peg, with lagged market capitalization levels as the regressors. Our analysis considered lagged market capitalization data up to seven days. In this context, a deviation from the peg was treated as an event. Since the hazard model produces time-dependent survival probabilities, we calculated the default probabilities (the complement of survival probabilities) over time for each stablecoin. As in the ZPP method, we considered three forecasting horizons: 1-day ahead, 30-days ahead, and 365-days ahead. The calculated probabilities for the CPHM are available from the authors upon request. After obtaining the PDs, we computed the AUC and Brier scores for all considered models, as well as the usual evaluation metrics (accuracy, sensitivity, and specificity) for the previously discussed probability thresholds, and we also found which models were included into the MCS, as shown in Table 5.

Model	AUC	Brier-S.	MCS	Accuracy	Sensitivity	Specificity	Accuracy	Sensitivity	Specificity
				Binary	*threshold:*	50%	*Binary*	*threshold:*	*e. prevalence*
hz_1	0.69	0.13	Included	0.85	0.14	0.97	0.87	0.28	0.97
hz_30	0.82	0.12	Included	0.85	0.28	0.95	0.89	0.57	0.95
hz_365	0.87	0.11	Included	0.80	0.57	0.85	0.80	1.00	0.77

Table 5: AUC, Brier scores, models included in the MCS, and evaluation metrics for different CPHMs (with different forecasting horizons), using two alternative thresholds for converting probabilities into binary variables.

High AUC values and respectable accuracy indicate that the Cox Proportional Hazards Model can be considered a good option for assessing the risk of default for stablecoins. However, we note again that when using different thresholds for obtaining binary variables in predicting models, it is better in our case to rely on the empirical prevalence rather than the more common threshold of 50%. This is due to the unbalanced nature of our dataset between defaulted and surviving stablecoins.

If we compare the ZPP and CPHM models' performance, we observe that the most accurate models were those that used the "1-year-ahead" forecasting horizon. While both the ZPP and hazard models performed well in predicting the probability of stablecoin default, the hazard model was slightly superior according to the AUC and Brier scores. This may be because hazard models are specifically designed to model event occurrence over time, making them well-suited for survival analysis tasks, such as predicting stablecoins deaths. Their formulation accounts for censoring and time-to-event data, providing a more robust framework for modeling the likelihood of stablecoin death. However, all models except one (the

ZPP with 365-day ahead forecasts and a 30-day estimation window) were included in the MCS at the 10% confidence level (see Tables 4-5), indicating that the models' forecasts are generally not statistically different. In this context, it is worth noting that large-scale simulation evidence reported by Hansen et al. (2011) suggests that "*it takes about 500 observations to remove all the poor models*" (Hansen et al., 2011, p. 479). Given that our forecasting sample consists of fewer than 50 observations, it is expected that most models would be included in the MCS.

Overall, these models complement each other due to their distinct strengths and capabilities. The ZPP model excels in estimating the probability of default based solely on market capitalization, offering valuable insights into market sentiment and investor behavior. On the other hand, the hazard model provides a robust framework for survival analysis. By combining insights from both models, researchers and investors can gain a comprehensive understanding of stablecoin default probabilities, enabling more effective risk management and investment strategies. Combining these two approaches can be an interesting avenue for further research.

5 Robustness check: key factors behind stablecoins' collapse

To further understand the underlying factors that contribute to stablecoin instability and potential collapse, we conducted a robustness analysis using the Cox Proportional Hazards Model. Inspired by the approach of Gatabazi et al. (2022), who employed this model to explore the determinants of coin and token survival, we extend our analysis to stablecoins specifically, examining the following regressors: 1) the type of stablecoin (asset-backed, crypto-backed, or algorithmic, where the first one represent the base category), 2) the year the stablecoin was launched ("Year launch"), 3) whether the stablecoin was built on the Ethereum blockchain ("Ethereum"), 4) the average stablecoin market capitalization and 5) the stablecoin's final status –whether it collapsed or not ("Status"), which served as the dependent variable.

Given the limited size of our dataset, we considered four possible model specifications: a full model with all variables, a model where the variables were selected by stepwise selection (single p-values < 0.10 and p-value for the joint LR test < 0.05), a model where the variables were selected using LASSO regularization via 10-fold cross-validation following the procedure outlined in James et al. (2023), and a model with LASSO where the variable "Year launch" was substituted with yearly dummy variables from 2018 till 2023. The estimated coefficients of these models are reported in Table 6, along with the p-value for the likelihood ratio test for the null hypothesis that all coefficients are zero, the p-value for the global test of the proportional hazards (PH) assumption of the Cox regression using the scaled Schoenfeld residuals (see Grambsch and Therneau (1994) for more details), and the concordance statistic, which computes the agreement between the observed responses and the predicted responses from the Cox model (closely related to Kendall's tau-a and tau-b, Goodman's gamma, and Somers' d), see Harrell et al. (1982) and Uno et al. (2011) for more details.

	CPH (full model)	CPH (stepwise selection)	CPH+LASSO (†)	CPH+LASSO (†) with separate years
Ethereum	–0.74	–0.92 (*)	–0.69	–0.81
Year launch	0.38	0.45 (*)	0.37	/
Algo_backed	0.58		0.72	0.57
Crypto_backed	–0.15			
Market_Cap	0.00		0.00	
Year 2018	/	/	/	–19.45
Year 2021	/	/	/	–0.38
Year 2022	/	/	/	0.76
P-value LR test	0.09	0.02	0.05	0.02
P-value test for PH assumption	NA (‡)	0.14	NA (‡)	0.28
Concordance	0.67	0.66	0.67	0.71

* Significance at the 10% level. (†) T-statistics not available for LASSO. (‡) The test could not be computed numerically.

Table 6: Coefficient estimates, hazard ratios and misspecification tests for the Cox Proportional Hazards Model (CPHM), under four specifications.

The estimated coefficients for the full model indicated that none of the variables were statistically significant, although the signs of the coefficients aligned with expectations. For example, stablecoins built on the Ethereum blockchain showed a lower likelihood of collapse, older stablecoins exhibited reduced risk, and algorithmic stablecoins were more prone to failure compared to asset-backed ones (which served as the baseline category). The lack of parameter significance was likely due to the limited sample size, prompting us to consider three additional model specifications. Notably, the results for these alternative models were qualitatively similar, confirming the importance of being built on the Ethereum blockchain, using older stablecoins, and avoiding algorithmic stablecoins. The fact that the test of the proportional hazards assumption could not be numerically computed for the full model and for the model estimated using LASSO highlights some numerical instability problems. However, the model estimated with LASSO where the variable "Year launch" was replaced with yearly dummy variables appears to be the best, according to post-estimation statistics.

These findings suggest that the resilience of stablecoins built on Ethereum may stem from the blockchain's established reputation, extensive adoption, and the fast and reliable operations it offers. Additionally, Ethereum's advanced smart contract functionality allows for the implementation of sophisticated stabilization mechanisms, which are crucial for maintaining the price stability of many stablecoins. These factors likely contribute to Ethereum-based stablecoins being less susceptible to collapse.

Our results are largely consistent with those of Gatabazi et al. (2022), who found that cryptocurrencies built on the Ethereum blockchain are less vulnerable to failure and that newer cryptocurrencies face a higher risk of collapse. However, it is also important to recognize the limitations of our analysis. The lack of statistical significance of most covariates and the numerical issues for some models' specifications are partly due to the small and imbalanced nature of our dataset, with only a limited number of stablecoins classified as "dead." These two factors reduce the statistical power of our models and makes it difficult to draw definitive conclusions regarding the impact of the covariates on stablecoin survival.

In summary, while our findings offer some insights into the factors influencing stablecoin stability, they should be interpreted with caution due to the constraints imposed by the dataset size and composition. Future research with a larger and more balanced dataset is needed to verify these results and provide more robust evidence on the determinants of stablecoin collapse.

6 Conclusions

Stablecoins represent a significant development within decentralized finance (DeFi) and are a highly debated topic given the growing interest in digital assets among researchers, investors, and crypto-enthusiasts. Designed to provide stability in the volatile cryptocurrency market, stablecoins aim to address key challenges in both traditional financial systems and DeFi, offering a solution to price volatility while providing more transparency, faster transactions, and lower costs compared to conventional banking. Their potential to reshape the future of finance highlights the importance of understanding the risks and factors influencing stablecoin stability.

This study contributes to the existing literature by focusing specifically on the credit risks associated with stablecoins, unlike previous research that tends to generalize findings across digital assets. Our results confirm that a significant proportion of stablecoins have already failed, consistent with previous studies dealing with crypto-assets as a whole. By applying the methodology proposed by Feder et al. (2018), we found that approximately 21% of stablecoins were "abandoned" at least once, with only 36% being "resurrected." However, the majority of these "resurrected" stablecoins were later abandoned again, and only 11% maintained their "resurrected" status over time. These findings align with the hypothesis that once a stablecoin loses its peg, regaining user confidence is challenging, often leading to further decline and eventual failure. This difficulty in recovery is intuitive, given that a broken peg typically signals underlying technical issues or market distrust, making it hard for the issuer to restore stability.

We also computed the time between a structural break in a stablecoin's price and its eventual collapse (or stabilization), and we found it to be relatively short, typically ranging from a few days to a couple of weeks. On average, this period was approximately equal to ten days. Testing for structural changes in the price peg is critical for several reasons. First, it enables the identification of breakpoints, allowing us to determine the precise moment when a stablecoin's peg begins to fail. This information is invaluable for investors and market participants seeking to make timely and well-informed decisions. Early detection of structural changes can also function as an early warning system, enabling investors to take proactive measures to manage risks, mitigate potential losses, and adjust their strategies accordingly. Additionally, analyzing these structural shifts offers researchers valuable insights into the market dynamics that contribute to stablecoin instability. Such understanding not only aids in regulatory efforts to stabilize the stablecoin market but also informs improvements in stablecoin design.

We then estimated stablecoin probabilities of death/default (PDs) based on market capitalization, considering different historical data windows and forecasting horizons. Our analysis showed that the Zero Price Probability (ZPP) models with a 365-day estimation window provided the best balance in forecasting performance, while models with a 30-day estimation window were less stable, particularly in terms of Brier scores and sensitivity. In addition to the ZPP approach, we also applied the Cox Proportional Hazards Model (CPHM) to estimate default probabilities, using lagged market capitalization as regressors. When comparing the performance of the ZPP and CPHM models, we found that the most accurate predictions came from models using a 1-year-ahead forecasting horizon. Moreover, while both models performed well, the hazard model had a slight edge, likely due to its design for survival analysis and time-to-event modeling, which makes it particularly suitable for predicting stablecoin deaths. The complementary nature of these models suggests that using both can provide a more comprehensive understanding of stablecoin credit risks. The ZPP model offers insights into market sentiment based on market capitalization, while the hazard model provides a robust framework for survival analysis. Together, these tools can guide better risk management and investment strategies in the stablecoin market, an avenue we leave for future research.

To further explore the factors driving stablecoin collapse, we conducted a robustness check using the Cox Proportional Hazards Model and four model specifications. The analysis revealed that stablecoins based on the Ethereum blockchain are less prone to failure, older stablecoins exhibit reduced risk, and algorithmic stablecoins are more prone to failure compared to asset-backed ones. The robustness of Ethereum's ecosystem, coupled with its strong security features and established reputation, likely contributes to the lower risk of stablecoin collapse when built on this blockchain.

However, several limitations of this study must be acknowledged. First, the dataset was limited to only 121 stablecoins, a relatively small number compared to similar studies that often analyze thousands of cryptocurrencies. Furthermore, this dataset was constrained by missing market capitalization data and several volatile stablecoins unable to maintain their pegs, reducing the sample size even further. Additionally, the sample was imbalanced, with a low proportion of failed stablecoins, which impacted the reliability of the statistical analysis. As a result, while our findings provide valuable insights, they should be interpreted with caution. Future research should aim to validate these results using a larger, more balanced dataset to provide more robust evidence on the factors driving stablecoin collapse.

Despite these limitations, we believe our study offers useful insights for investors and traders interested in maximizing returns, managing risks, and optimizing their portfolios in the stablecoin market. The data and models presented here can serve as tools to evaluate the credit risks associated with stablecoins, offering a deeper understanding of their nature and the dynamics influencing their stability.

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