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Assessing the Credit Risk of Crypto-Assets Using Daily Range Volatility Models

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Abstract: In this paper, we analyzed a dataset of over 2000 crypto-assets to assess their credit risk by computing their probability of death using the daily range. Unlike conventional low-frequency volatility models that only utilize close-to-close prices, the daily range incorporates all the information provided in traditional daily datasets, including the open-high-low-close (OHLC) prices for each asset. We evaluated the accuracy of the probability of death estimated with the daily range against various forecasting models, including credit scoring models, machine learning models, and time-series-based models. Our study considered different definitions of "dead coins" and various forecasting horizons. Our results indicate that credit scoring models and machine learning methods incorporating lagged trading volumes and online searches were the best models for short-term horizons up to 30 days. Conversely, time-series models using the daily range were more appropriate for longer term forecasts, up to one year. Additionally, our analysis revealed that the models using the daily range signaled, far in advance, the weakened credit position of the crypto derivatives trading platform FTX, which filed for Chapter 11 bankruptcy protection in the United States on 11 November 2022.

Keywords: daily range; bitcoin; crypto-assets; cryptocurrencies; credit risk; default probability; probability of death; ZPP; cauchit; random forests

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

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1. Introduction

FTX was a Bahamas-based cryptocurrency exchange that at its peak in July 2021, had over one million users and was the third-largest cryptocurrency exchange by volume [1]. A revelation at the beginning of November 2022 that FTX's partner trading firm Alameda Research held a significant portion of its assets in FTX's native token FTT [2] prompted the rival exchange Binance to sell its holdings of this token. This event was immediately followed by customer withdrawals from FTX so large that FTX was unable to meet their demand [3]. On 11 November 2022, FTX, FTX.US (a separate associated exchange for US residents), Alameda Research, and more than 100 affiliates filed for bankruptcy in Delaware [4]. The price of the FTX token that reached a maximum of 80$ in September 2021 for a total market capitalization of almost 10 billion $ fell to single digits after the FTX bankruptcy and was *still* trading at the end of December 2022 close to 1$.

Aside from the significant financial losses incurred, the FTX bankruptcy is similar to numerous failed cryptocurrency projects in the past. These failures have been attributed to deficient corporate governance standards, inadequate cybersecurity measures, and inadequate management of credit and liquidity risks. It is noteworthy that Samuel Bankman-Fried, the former CEO of FTX, acknowledged that dedicating more time to risk management could have potentially prevented the collapse of the company, as stated on 30 November 2022 (see [5]).

Unfortunately, there is a lack of interest in credit risk management for crypto-assets, which is reflected in the scarce academic financial literature on the topic. This can be attributed to two main factors: the absence of sufficient financial and accounting data, and the need to use a different definition of credit risk. In this regard, in [6], a new definition of credit risk for crypto-assets was proposed based on their "*death*", which occurs when their price drops significantly and they become illiquid. It is worth noting that there is no unique definition for a dead asset, either in the professional or academic literature, as outlined in [7–11]. Furthermore, even when a crypto-asset is considered dead, it may still show some minimal trading volumes (as is the case with the current trading of the FTX token at the end of December 2022), either due to the possibility of recovering a small amount of the initial investment or simply to speculate on its possible revival. It is also worth noting that the "death" state of a crypto-asset may be temporary rather than permanent: indeed, in [10], it was demonstrated that some coins were abandoned and subsequently "resurrected" up to five times over several years.

This paper proposes for the first time to forecast the probability of death (PD) of a crypto-asset using the daily range, which employs all the information provided in traditional daily datasets such as open-high-low-close (OHLC) prices instead of only close-to-close prices that are used by low-frequency volatility models. Recent literature has revived the interest in range-based estimators that employ OHLC prices by showing that volatility models using high-frequency data outperformed low-frequency volatility models using range-based estimators only for short-term forecasts (usually for 1-day-ahead forecasts), while this was not the case for longer horizons (see [12,13]). This is particularly important for crypto-assets where the possibility to find long time series of high-frequency data is usually confined to a small number of well-established crypto-assets, such as Bitcoin and Ethereum.

The first contribution of this paper is a set of models to forecast the probability of death that combines the daily range with the zero-price-probability (ZPP) model byy [14], which is a methodology to compute the probabilities of default using only market prices. Recent literature has shown that the ZPP models tend to outperform the competing models in terms of default probability estimation over a 1-year horizon; see [6,15–18] for more details.

The second contribution of this paper is a large-scale forecasting exercise using a set of 2003 crypto coins that were active from the beginning of 2014 until the end of May 2020, which was first examined by [11]. We considered a large set of competing models ranging from credit scoring models to machine learning and time- series-based models, with different definitions of dead coins and different forecasting horizons. Our empirical evidence showed that credit-scoring models and machine-learning methods using lagged trading volumes and online searches were the best models for short-term horizons up to 30 days ahead. Meanwhile, time-series models using the daily range were better choices for longer-term forecasts up to 1-year ahead.

The third contribution of the paper is a robustness check to examine how the best forecasting models for the probability of death over a 1-year-ahead horizon behaved when modeling the token of the crypto trading platform FTX, which filed for the Chapter 11 bankruptcy protection in the United States on 11 November 2022.

The paper is organized as follows: Section 2 reviews the literature devoted to the credit risk of crypto-assets, crypto exchanges, and the daily range, while the methods proposed to model and forecast the probability of death of crypto-assets are discussed in Section 3. The empirical results are reported in Section 4, while robustness checks are discussed in Section 5. Section 6 concludes the paper.

2. Literature Review

2.1. Credit Risk of Crypto-Assets

The financial literature dealing with the credit risk involved in crypto-assets is very small, and, as of the time of writing this paper, only five papers have examined the topic of dead coins, while only three of these have proposed methods to forecast the probability of a coin death. In this regard, we remark that there is no unique definition of dead coins:

in the professional literature, some define dead coins as those whose value drops below 1 cent (https://www.investopedia.com/news/crypto-carnage-over-800-cryptocurrencies-are-dead/, accessed on 1 December 2022), while others consider a coin dead if there is no trading volume, no nodes running, and no active community and if the coin has been delisted from (almost) all exchanges (https://www.coinopsy.com/dead-coins/, accessed on 1 December 2022).

The work by [7] (the original workshop proceedings by [7] were later published as [10]) was the first to propose a formal definition of dead coins in the academic literature based on a complex formula involving price and volumes peaks and rolling time windows. Moreover, their approach allows a coin to be "resurrected" if there is a resurgence of trading volumes.

In Ref. [9], a simplified version of the previous method by [7] was proposed, where a crypto-currency can be considered as dead if its average daily trading volume for a given month is lower or equal to 1% of its past historical peak. dead crypto-currency is classified as "resurrected" if this average daily trading volume reaches a value of more or equal to 10% of its past historical peak again. We remark that [9] presented this method as the [7] approach when, in reality, the latter involves many more restrictions. The methodology used by [9] in their work is much simpler, and it assumes that a coin is (temporarily) dead if data gaps are present in its time series.

In [6,8,11], the first and only models to predict crypto-currency defaults/deaths were proposed. In [8], an in-sample analysis was performed using 146 proof-of-work-based cryptocurrencies that started trading before 2015 whose performance was followed until December 2018. It was found that about 60% of those cryptocurrencies died. The authors used linear discriminant analysis to forecast these defaults and found that their model could predict most of the crypto-currency bankruptcies but not the crypto-currencies that remained alive. Interestingly, the authors of [8] had to discard several variables to build a meaningful dataset because this information was not available for most dead coins.

Other authors [6] proposed a set of models to estimate the probability of death for a group of 42 crypto-currencies using the zero-price-probability (ZPP) model, as well as credit-scoring models and machine-learning methods. They found that credit-scoring models performed better in the training sample, whereas the models' performances were much closer in the validation sample.

The authors of [11] were the first to examine a very large dataset of over two thousand crypto-coins observed between 2015 and 2020 to estimate their credit risk by computing their probability of death using different definitions of dead coins, different forecasting models, and different horizons. They found that the choice of the coin-death definition affected the set of the best forecasting models to compute the probability of death, but this choice was not critical, and the best models were the same in most cases. They showed that the cauchit and the ZPP based on the random walk or the MS-GARCH(1,1) were the best models for newly established coins, while credit-scoring models and machine-learning methods performed better for older coins.

Finally, we remark that the dead coins collected in online repositories such as coinopsy.com or deadcoins.com are indeed dead, but they are not useful for credit risk management because their technical information and historical market data are no longer available for almost all of them. Therefore, it is better to use the methods proposed by [7,9] to detect dead crypto-assets or the professional rule that defines a crypto-asset as dead if its value drops below 1 cent: as highlighted by [11], even if there is still some trading for the assets defined as "dead" according to these methods, this is not a problem but an advantage because we can still analyze them when market data and other information are still available.

2.2. Credit Risk of Crypto Exchanges

Similar to crypto-assets, the financial literature dealing with the credit risk involved in crypto exchanges is very small and as of the writing of this paper, only five works have examined the main determinants that can lead to the closure/default of an exchange.

The authors of [19] used a dataset of 40 exchanges and found that exchanges that processed more transactions were less likely to shut down, whereas past security breaches and an antimoney laundering indicator were not statistically significant. The authors of [20] extended the work by [19] through considering data between 2010 and March 2015 and up to 80 exchanges, using a panel logit model with an expanded set of explanatory variables. They found that a security breach increases the odds that the exchange will close the same quarter, while an increase in the daily transaction volume significantly decreases the probability that the exchange will shut down that quarter. A significant negative time trend that decreases the probability of closure over time was also reported. Moreover, they showed that exchanges receive most of their transaction volume from fiat currencies traded by few other exchanges are 91% less likely to close than are other exchanges that trade fiat currencies with higher competition. Similarly to the findings in [19], an antimoney laundering indicator and two-factor authentication were found to not be significant.

The authors of [21] used the dataset first examined by [19] to propose several alternative approaches to forecast the probability of closure of a crypto exchange, ranging from credit scoring models to machine learning methods, but without any comprehensive forecasting analysis.

The authors of [22] considered a dataset of 144 exchanges active from the first quarter of 2018 to the first quarter of 2021 to analyze the determinants surrounding the decision to close an exchange using credit-scoring and machine-learning techniques. They found that having a public developer team is by far the most important determinant, followed by the CER cybersecurity grade, the age of the exchange, and the number of traded cryptocurrencies available on the exchange. Both in-sample and out-of-sample forecasting confirmed these findings.

The authors of [23] built a database containing eight publicly available characteristics for 238 cryptocurrency exchanges. They used four popular machine learning classifiers to predict which digital markets remained open and which faced closure. Their best model was the random forest classifier, while the most important variables in terms of feature importance across multiple algorithms were the exchange lifetime, the transacted volume, and cybersecurity measures such as security audit, cold storage, and bug bounty programs.

Finally, we remark that if an exchange issues tokens representing ownership and they are traded daily, or even if these tokens are simply utility tokens (such as is the FTX token), then the probability of default/closure of the exchange can be forecast using the methods for crypto-assets discussed in Section 2.1; see [21] for a discussion at the textbook level.

2.3. Daily Range

The price range has long been known in both the academic and professional literature. For example, the opening, highest, lowest, and closing (OHLC) prices of an asset have been used in Japanese candlestick charting techniques since the 19th century [24], while the first applications in the financial literature can be traced to Mandelbrot [25]. Several authors, starting from [26], then developed volatility measures based on the daily range that were more efficient than were return-based volatility estimators; see [27] for an extensive review and the references therein.

Recent literature has revived interest in range-based estimators that employ OHLC prices to estimate the daily volatility; see [27–30]. Interestingly, the authors of [12] found that high-frequency volatility models outperformed low-frequency volatility models using range-based estimators only for short-term forecasts (usually for 1-day-ahead forecasts). As the forecast horizon increased (up to one month), the difference in forecast accuracy became statistically indistinguishable for most market indices.

Similarly, in [13], the role of high-frequency data in multivariate volatility forecasting was examined for investors with different investment horizons. The authors found that that models using high-frequency data significantly outperformed models with low-frequency data over the daily forecasting horizon, but this evidence decreased when longer horizons were considered. Moreover, they showed that investors may not obtain significant economic benefits from using high-frequency data depending on the type of economic loss they employ.

This encouraging evidence about the daily range stimulated our work of using this volatility estimator to model and forecast the probability of death for crypto-assets, given that finding high-frequency data for all 2003 crypto coins in our dataset was impossible.

3. Materials and Methods

In the context of crypto-assets, credit risk refers to the potential for gains and losses on the value of an abandoned and deemed "dead" cryptocurrency that can potentially be revived; see [6] for more details. This scenario occurs when the price of the crypto-asset plummets close to or to zero, as evidenced by a lack of trading activity for an extended period. Despite being considered dead, crypto-assets may continue to be traded as investors attempt to recover a portion of their initial investment or bet on the potential revamp of the asset.

Three criteria have been employed in the literature to classify crypto-assets as dead or alive [11]: (1) This first is the restrictive approach by [7,10]. According to this approach, first a "candidate peak" is defined as a day where the 7-day rolling price average is greater than any value 30 days before or after. A candidate peak is considered valid only if it is at least 50% greater than the minimum value in the 30 days prior to the candidate peak and at least 5% of the cryptocurrency's maximum peak. Using this peak data, the authors of [7,10] classified a coin as abandoned or dead if the average daily volume for a given month is less than or equal to 1% of the peak volume. A coin's status is changed to "resurrected" if the average daily trading volume for the month following a peak is greater than 10% of the peak value and the coin is currently considered dead). (2) The simplified approach proposed by [9] classifies a cryptocurrency as dead if its average daily trading volume for a given month is lower than or equal to 1% of its historical peak, while it is considered "resurrected" if this average daily trading volume reaches a value of 10% or more of its historical peak. The third criterion (3) is the professional rule, which considers a coin dead if its value drops below 1 cent.

The aim of this work is to propose a new model to forecast the probability of death (PD) of a crypto-asset using the daily range computed with open-high-low-close (OHLC) prices, a departure from traditional models that use only close-to-close prices. A simple way to use the OHLC prices for the computation of the PD of crypto-assets is to combine the daily range with the zero-price-probability (ZPP) model by [14], which is a methodology to compute the probabilities of default using only market prices P_t. This method calculates the market-implied probability of the stock's or crypto-asset's price being less than or equal to zero $\mathcal{P}(P_\tau \leq 0)$ within a specified time horizon ($t < \tau \leq t + T$), considering that the price of a traded asset is a truncated variable that cannot fall below zero. The ZPP represents the probability of the price falling below the truncation level of zero, serving as a default indicator; see [14] for further details. For a univariate time series, the ZPP can be computed as follows:

1. Establish a conditional model for the price differences, $X_t = P_t - P_{t-1}$ without log transformation, $X_t = \mu_t + \sigma_t z_t$, where $z_t \sim i.i.d\ f(0,1)$, and μ_t and σ_t are the conditional mean and standard deviation, respectively.
2. Simulate a large number N of price trajectories up to time $t + T$, utilizing the estimated time-series model from step 1. We will consider the 1-day-ahead, 30-day-ahead, and 365-day0ahead probability of death for each crypto-asset, that is $T = \{1, 30, 365\}$, respectively.
3. The probability of default for a crypto-asset is computed as n/N, where n is the number of times among N simulations when the simulated price P^k_τ touches or crosses the zero barrier for a specified time interval $t < \tau \leq t + T$, and $k = 1, \ldots, N$.

In this study, we introduce, for the first time, the use of a price range estimator to model the conditional standard deviation of the price differences $X_t = P_t - P_{t-1}$ in the ZPP model. As we discussed in the literature review, there is an increasing amount of literature that has revived the interest in range-based estimators that employ OHLC prices to estimate the daily volatility; see [27–30].

We adopt the Garman–Klass [31] volatility estimator, which [29] found to be the best volatility estimator based on large-scale simulation studies. The authors of [29] showed that the Garman–Klass estimator is capable of producing standardized returns that are normally distributed and that the estimates obtained from daily data are comparable to those obtained from high-frequency data. This is important for crypto-assets, which have high-frequency data availability for only a limited number of assets. The Garman–Klass estimator assumes a Brownian motion with zero drift and no opening jumps, which is appropriate for crypto-assets since most of them eventually become worthless (see, e.g., [32,33]) and are traded 24/7. However, in the event of an opening jump (as may occur for illiquid assets), the jump-adjusted Garman–Klass volatility estimator described in [29] was used. In addition, we also evaluated the Yang and Zhang volatility estimator [34], which is unbiased, independent of drift, and consistent in the presence of opening price jumps. This estimator is interesting because it can be used to calculate the average daily volatility over multiple days, which could be more appropriate for crypto-assets used for trading strategies that involve dividing large orders over several days (these kind of strategies are often used by miners and "whales", where the latter are entities or people that hold enough crypto-assets to influence their market prices, see [35,36] for more details). Moreover, the author wants to thank three anonymous professional traders in crypto-assets for highlighting this issue). After evaluating different values of n, we found that $n = 2$ produced the best results.

The formulas for the jump-adjusted Garman–Klass (GK) volatility estimator and the Yang and Zhang (YZ) volatility estimator, to be used for the daily conditional variance σ_t^2 of the price differences $X_t = P_t - P_{t-1}$ without log transformation, are presented below.

$$
\begin{aligned}
\sigma^2_{GK,t} &= \left[(O_t - C_{t-1})^2 + \frac{1}{2}(H_t - L_t)^2 - (2 \times \log 2 - 1)(C_t - O_t)^2 \right] \\
\sigma^2_{YZ,t} &= \sigma^2_{o,t} + k\sigma^2_{c,t} + (1-k)\sigma^2_{RS,t}\,, \quad \text{where} \\
& \sigma^2_{o,t} = \frac{1}{n-1} \sum_{j=t-n}^{t} \Big((O_j - C_{j-1}) - \mu_o \Big)^2, \quad \mu_o = \frac{1}{n} \sum_{j=t-n}^{t} (O_j - C_{j-1}) \\
& \sigma^2_{c,t} = \frac{1}{n-1} \sum_{j=t-n}^{t} \Big((C_j - O_j) - \mu_c \Big)^2, \quad \mu_c = \frac{1}{n} \sum_{j=t-n}^{t} (C_j - O_{j-1}) \\
& \sigma^2_{RS,t} = \frac{1}{n} \sum_{j=t-n}^{t} \Big((H_j - C_j) \times (H_j - O_j) + (L_j - C_j) \times (L_j - O_j) \Big) \\
& k = \frac{1.34 - 1}{1.34 + \frac{n+1}{n-1}}
\end{aligned}
$$

We employed four competing models to forecast the dynamics of the range-based daily volatilities σ_t^2: the simple random walk model by [27], the HAR model by [37], the ARFIMA model by [38], and the CARR model by [39].

The random walk model by [27] simply assumes that the log of the daily volatility follows a random walk without drift, so the the best prediction of tomorrow's log-volatility is today's log-volatility. The "no-change" forecast is a traditional benchmark used in several fields of research; see [40] for a comprehensive survey.

The HAR model by [37] assumes that the daily volatility is influenced by the past volatility over different time periods and is represented as follows:

$$
\begin{aligned}
\sigma_t^2 &= \beta_0 + \beta_D \sigma^2_{t-1,D} + \beta_W \sigma^2_{t-1,W} + \beta_M \sigma^2_{t-1,M} + \epsilon_t, \quad \text{where} \\
& \sigma^2_{t-1,W} = \frac{1}{7} \sum_{j=1}^{7} \sigma^2_{t-j,D}, \quad \sigma^2_{t-1,M} = \frac{1}{30} \sum_{j=1}^{30} \sigma^2_{t-j,D}
\end{aligned}
$$

and σ_D^2, σ_W^2, and σ_M^2 stand for the daily, weekly, and monthly volatility components, respectively. We used 7 and 30 days for the weekly and monthly volatilities instead of the usual 5 and 22 days, as cryptocurrency exchanges operate continuously without weekends.

The auto-regressive fractional integrated moving average model, ARFIMA(p,d,q), was proposed by [38] to forecast the daily realized volatility, and it can be used to model the range-based volatility estimates as follows:

$$\Phi(L)(1-L)^d(\sigma_t^2-\mu)=\Theta(L)\varepsilon_t$$

where L is the lag operator, and $\Phi(L)=1-\varphi_1 L-\ldots-\varphi_p L^p$, $\Theta(L)=1+\theta_1 L+...+\theta_q L^q$, and $(1-L)^d$ form the fractional differencing operator defined by

$$(1-L)^d=\sum_{k=0}^{\infty}\frac{\Gamma(k-d)L^k}{\Gamma(-d)\Gamma(k+1)}$$

where $\Gamma(\cdot)$ is the gamma function. Given our large dataset, we employed the ARFIMA(1,d,1) model to keep the computational burden tractable and with consideration to its past empirical prowess; see [41] and the references therein.

The CARR(1,1) model by [39] can be used to model the conditional standard deviation σ_t computed using range-based estimators as follows:

$$\begin{aligned}\sigma_t &= \lambda_t\varepsilon_t, \quad \varepsilon_t\sim\exp(1,\cdot)\\ \lambda_t &= \omega+\alpha_1\sigma_{t-1}+\beta_1\lambda_{t-1}\end{aligned}$$

where λ_t is the conditional mean of σ_t, and ε_t is the error term which has an exponential density function with a unit mean. The exponential distribution is a common choice for the conditional distribution of ε_t because it takes positive values. Moreover, it allows the parameters of the CARR model to be estimated using the quasi-maximum likelihood method; see [39] for more details.

Finally, we remark that the conditional mean μ_t of the price difference X_t was set to zero when the Garman—Klass volatility estimator was used, while it was set to the sample mean of the price differences X_t when the Yang and Zhang volatility estimator was employed.

In this work, we will compare our novel models based on the daily range to the traditional models used in credit risk management such as credit-scoring models, machine learning, and time-series methods that rely on close-to-close prices for the ZPP model. A brief overview of these models is provided below.

Credit scoring models employ a set of variables to build a quantitative score, which is then used to estimate the probability of default/death. The standard form of a credit scoring model is represented as follows:

$$PD_{i,t+T}=\mathcal{P}(D_{i,t+T}=1|D_{i,t}=0;\mathbf{X}_{i,t})=F(\beta'\mathbf{X}_{i,t})$$

where $PD_{i,t+T}$ is the probability of death for the crypto-asset i over a time period of $t+T$ given that it is not dead at time t, and $\mathbf{X}_{i,t}$ is a vector of variables. Three popular models used in credit risk management are the logit model, the probit model, and the cauchit model, each obtained by using the logistic, standard normal, or standard Cauchy cumulative distribution function for $F(\beta'\mathbf{X}_{i,t})$, respectively. The parameters of these models can be estimated through maximum likelihood methods; see [42] for more details. The logit and probit models are commonly used in credit risk management (see [43–46]), while the cauchit model is favored under high levels of sparseness in the input space due to its ability to handle more extreme values; see [47,48].

In this study, we will also use machine learning (ML) techniques to analyze data and develop a system for modeling and forecasting complex patterns. Specifically, we will employ the random forest algorithm proposed by [49,50], which was found to be the best model for short-term forecasting of the PD for crypto-assets with a long time series in [11]. Moreover, it has an excellent past track record in forecasting binary variables; see [22,51–53] for more details. This algorithm aggregates multiple decision trees into a "forest", where each tree is constructed differently from the others to decrease the correlation among trees and prevent overfitting. The probability of death is then computed using a majority vote among the trees in the forest.

Finally, following [11], we will also consider zero price probability (ZPP) models that utilize only close-to-close prices. This includes a simple random walk with drift model with constant variance (i.e., $\sigma_t = \sigma$) and a GARCH(1,1) model with normal errors, both of which have closed-form solutions for ZPP computation, as described in [6]. Additionally, we will consider the case of a GARCH(1,1) model with Student's t errors, as introduced in [14]. We will also evaluate the ZPP using the GARCH(1,1) model with errors following the generalized hyperbolic skewed Student distribution, which has a polynomial behavior in one tail and exponential behavior in the other, as proposed in [54]. Finally, we will examine the ZPP computed using the two-regime Markov-switching GARCH model introduced in [55,56].

4. Results

4.1. Data

Our study analyzed a dataset consisting of 2003 crypto-assets that were either alive or dead (according to different criteria) between January 2014 and May 2020. This dataset was first used in [11]. The daily data, obtained from Coinmarketcap.com and Google Trends, included daily open, high, low, and close prices; volume; market capitalization; and the search volume index that shows the number of searches performed for a particular keyword or topic on Google within a specific time frame and region. The dataset was divided into two groups: "young coins" with fewer than 750 observations and "old coins" with more than 750 observations. The young coin group was used to forecast the 1-day and 30-day probabilities of death, while the old coin group was used to forecast the 1-day, 30-day, and 365-day probabilities of death. The dataset used in this paper is the same one introduced in [11] and is currently the largest dataset available on crypto-asset credit risk. It is unique in that the data for several crypto-assets are no longer available, and we had to reconstruct them through extensive online searches.

To assess the normality of the price differences X_t of each crypto-asset, the Jarque–Bera and Kolmogorov–Smirnov statistics were computed. The same tests were employed with the standardized price differences, which were obtained by dividing the price differences by the daily volatility estimated using range-based methods $X_t/\sqrt{\sigma_t^2}$. The results of the normality tests, represented as the percentage of p-values higher than 5%, are presented in Table 1 for both young and old coins.

The price differences of cryptocurrencies are not normally distributed. However, when standardized using the squared root of the Garman–Klass volatility estimator, the majority of cryptocurrencies display normality. Only a small fraction of price differences standardized with the Yang and Zhang volatility estimator seem to be normally distributed. This evidence supports the findings of [29], who demonstrated that the Garman–Klass estimator is the only one that can yield standardized returns that are normally distributed.

Table 1. Number of times (in percentage) when the p-values of the Jarque–Bera (J.B.) and the Kolmogorov–Smirnov (K.S.) tests were higher than 5% for the price differences X_t and for the price differences standardized with the squared root of the range-based daily volatility $X_t/\sqrt{\sigma_t^2}$. GK = Garman—Klass volatility estimator. YZ = Yang and Zhang volatility estimator.

YOUNG COINS (%)	
p-value J.B. $(X_t) > 0.05$	p-value K.S. $(X_t) > 0.05$
0.09	0.17
p-value J.B. $\left(X_t//\sqrt{\sigma^2_{GK,t}}\right) > 0.05$	p-value K.S. $\left(X_t//\sqrt{\sigma^2_{GK,t}}\right) > 0.05$
60.86	71.93
p-value J.B. $\left(X_t//\sqrt{\sigma^2_{YZ,t}}\right) > 0.05$	p-value K.S. $\left(X_t//\sqrt{\sigma^2_{YZ,t}}\right) > 0.05$
1.97	27.73
OLD COINS (%)	
p-value J.B. $(X_t) > 0.05$	p-value K.S. $(X_t) > 0.05$
0.00	0.00
p-value J.B. $\left(X_t//\sqrt{\sigma^2_{GK,t}}\right) > 0.05$	p-value K.S. $\left(X_t//\sqrt{\sigma^2_{GK,t}}\right) > 0.05$
53.70	68.85
p-value J.B. $\left(X_t//\sqrt{\sigma^2_{YZ,t}}\right) > 0.05$	p-value K.S. $\left(X_t//\sqrt{\sigma^2_{YZ,t}}\right) > 0.05$
0.12	16.47

To classify a cryptocurrency as "dead" or "alive," three criteria were employed as discussed in Section 3 and listed here:

- The approach proposed by [7];
- The approach proposed by [9];
- The professional rule that defines an asset as dead if its value drops below 1 cent and alive if its value rises above 1 cent.

The total number of coins available each day and the number of dead coins each day computed using these criteria are presented in Figures A1 and A2 in Appendix A. For convenience, the approach proposed by [7] will be referred to as "*restrictive*", the simplified approach proposed by [9] will be referred to as "*simple*", and the professional rule will be referred to as "*1 cent*".

The approach of [7] was found to be the most restrictive, as it identified fewer dead coins. On the other hand, the professional rule, which defines a coin as dead if its value drops below 1 cent, was found to be more lenient, leading to a higher number of identified dead coins. In [9], a simplified version of the [7] approach is proposed, which falls in between the two previously mentioned methods for young coins. However, for old coins, it was found to be the least restrictive approach. Moreover, the restrictive approach proposed by [7] is the most stable, whereas the professional rule is the most volatile.

In this study, credit scoring models and machine learning methods employed the lagged average monthly trading volume and the lagged average monthly search volume index obtained from Google Trends as predictors. The future probabilities of death were directly forecast by using 1-day-lagged predictors to forecast the 1-day-ahead probability of death, 30-day-lagged predictors to forecast the 30-day-ahead probability of death, and so on. To account for potential structural breaks, two types of estimation windows were considered: a rolling fixed window of 100,000 observations and an expanding window.

The time-series models for each coin were estimated separately using zero-point progression (ZPP) with and without the daily range, based on an expanding window approach. The first estimation sample consisted of 30 observations, and full estimation details can be found in [11]. The probabilities of deaths for various forecast horizons were calculated by employing recursive forecasts. It should be noted that the datasets utilized for credit scoring and machine learning models were distinct from those used for the time-series models, which resulted in some dates for which forecasts from all models were not available. Although this did not have an impact on the calculation of the area under the curve (AUC) metrics, it did affect the estimation of the model confidence sets and Brier scores, as detailed in the following section. Therefore, only those dates that were common across all models were used to calculate these metrics.

4.2. Forecasting Analysis

In accordance with [11], two groups of crypto-assets were considered:

- A total of 1165 young coins with a total of 537,693 observations, listed in Tables A1–A3 in Appendix B, were used to forecast the 1-day- and 30-day-ahead probabilities of death.
- A total of 838 old coins with a total of 987,018 observations, listed in Tables A4 and A5 in Appendix B, were used to forecast the 1-day-, 30-day-, and 365-day-ahead probabilities of death.

The classification performance of the models was evaluated using the area under the receiver operating characteristic curve (AUC or AUROC), which measures the ability of the model to discriminate between alive and dead crypto-assets regardless of the discrimination threshold. A higher AUC score, close to 1, indicates a better performing model, as detailed in [57] pages869–875 and references therein. Due to limitations of the AUC, as discussed in [58], the model confidence set (MCS) proposed by [59] and extended by [60] was also used. This method selects the best forecasting models among a group of models based on a confidence level using an evaluation rule that is based on a loss function, in this case the Brier's score [61].

The `Rdata` file, which contains the forecasts of the probability of deaths across all horizons (1-, 30-, and 365-day ahead) for the three definitions of "dead coins" (*restricted* [7], *simple* [9], and *1 cent* [professional rule]) for both small young coins (SCs) and old big coins (BCs), along with the binary dependent variable, is now available on the author's website: https://drive.google.com/file/d/1hVZYt6W_nwvvTtqicsUJFoBzUJfX0kJH/view?usp=share_link, accessed on 28 February 2023. This dataset includes the merged forecasts that were used to compute the model confidence set and the Brier scores for all models. The ZPPs were computed using functions from the R package `bitcoinFinance` (https://github.com/deanfantazzini/bitcoinFinance, accessed on 1 December 2022) and straightforward modifications of these functions. The random forest model was computed using the R package `randomForest`, while the credit scoring models were computed using the *glm* function from the R package `stats`.

The results of the AUC scores, the models included in the MCS, the Brier scores, and the percentage of times when the models failed to reach numerical convergence are reported in Table 2 for young coins and in Tables 3 and 4 for old coins for all three criteria used to classify a crypto-asset as dead or alive.

In the case of young crypto-assets, the results confirm the findings of [11], in that the cauchit model is the best model for all forecast horizons and across most classification criteria. Additionally, the ZPP computed using an MS-GARCH(1,1) model remains the best model when using the professional rule that defines a dead coin as one whose value drops below 1 cent, while the ZPP computed with the simple random walk provides good forecasts for all horizons and classification criteria.

For old coins, the random forests model with an expanding estimation window remains the best model for forecasting the probability of death up to 30 days ahead, but differently from [11], the ZPP models computed with the range-based estimators are the best models for forecasting the 365-day-ahead probability of death. This horizon is crucial for risk management, as it is the horizon considered by national regulations and international agreements, such as the Basel 2 and Basel 3 agreements.

Table 2. Young coins: AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), models included in the MCS, and numerical convergence failures in percentage across three competing criteria to classify a coin as dead or alive. Ref. [7] approach = "*restrictive*"; simplified [7] approach = "*simple*"; professional rule = "*1 cent*"; D.R. = daily range-based estimator. Highest AUC, lowest Brier score and model included in the MCS are reported in bold font.

Young Coins: 1-Day-Ahead Probability of Death

Models	AUC (Restrictive)	AUC (Simple)	AUC (1 Cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1 Cent)	MCS (Restrictive)	MCS (Simple)	MCS (1 Cent)	*% Not Converged*
Logit (expanding window)	0.79	0.73	0.60	0.048	0.137	0.242	not included	not included	not included	0.00
Probit (expanding window)	0.75	0.70	0.59	0.049	0.140	0.244	not included	not included	not included	0.00
Cauchit (expanding window)	0.86	0.80	0.64	**0.044**	0.121	**0.235**	**included**	**included**	**included**	0.00
Random Forest (expanding window)	0.78	0.78	0.72	0.047	**0.120**	0.275	not included	**included**	not included	0.00
Logit (fixed window)	0.84	0.77	0.58	0.046	0.127	0.285	not included	not included	not included	0.00
Probit (fixed window)	0.83	0.74	0.58	0.047	0.133	0.286	not included	not included	not included	0.00
Cauchit (fixed window)	**0.86**	**0.80**	0.64	0.044	0.120	0.264	not included	**Included**	not included	0.00
Random Forest (fixed window)	0.74	0.75	0.65	0.056	0.147	0.354	not included	not included	not included	0.00
ZPP—Random walk	0.79	0.75	0.77	0.093	0.178	0.338	not included	not included	not included	0.00
ZPP—Normal GARCH(1,1)	0.74	0.69	0.65	0.068	0.184	0.387	not included	not included	not included	1.70
ZPP—Student'st GARCH(1,1)	0.60	0.57	0.66	0.057	0.182	0.398	not included	not included	not included	0.90
ZPP—GH Skew-Student GARCH(1,1)	0.62	0.59	0.44	0.057	0.187	0.407	not included	not included	not included	43.17
ZPP—MSGARCH(1,1)	0.73	0.70	**0.83**	0.054	0.182	0.379	not included	not included	not included	0.81
ZPP—D.R.(Garman and Klass)RW	0.58	0.55	0.59	0.056	0.197	0.416	not included	not included	not included	0.00
ZPP—D.R.(Garman and Klass)HAR	0.75	0.72	0.73	0.084	0.176	0.344	not included	not included	not included	7.40
ZPP—D.R.(Garman and Klass)ARFIMA	0.75	0.70	0.74	0.081	0.173	0.342	not included	not included	not included	67.62
ZPP—D.R.(Garman and Klass)CARR	0.70	0.66	0.64	0.058	0.188	0.397	not included	not included	not included	9.88
ZPP—D.R.(Yang and Zhang)RW	0.64	0.61	0.64	0.083	0.218	0.414	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)HAR	0.75	0.71	0.73	0.087	0.177	0.345	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)ARFIMA	0.76	0.69	0.74	0.084	0.176	0.347	not included	not included	not included	69.29
ZPP—D.R.(Yang and Zhang)CARR	0.72	0.66	0.66	0.080	0.204	0.396	not included	not included	not included	7.39

Young Coins: 30-Day-Ahead Probability of Death

Models	AUC (Restrictive)	AUC (Simple)	AUC (1 Cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1 Cent)	MCS (Restrictive)	MCS (Simple)	MCS (1 Cent)	*% Not Converged*
Logit (expanding window)	0.71	0.63	0.60	0.052	0.155	0.241	not included	not included	not included	0.00
Probit (expanding window)	0.69	0.61	0.59	0.052	0.157	0.243	not included	not included	not included	0.00
Cauchit (expanding window)	**0.82**	0.74	0.63	**0.048**	0.140	0.236	**included**	not included	not included	0.00
Random Forest (expanding window)	0.65	0.65	0.64	0.064	0.175	0.328	not included	not included	not included	0.00
Logit (fixed window)	0.71	0.66	0.57	0.055	0.150	0.284	not included	not included	not included	0.00
Probit (fixed window)	0.69	0.66	0.57	0.057	0.151	0.285	not included	not included	not included	0.00
Cauchit (fixed window)	0.82	**0.76**	0.60	0.049	**0.136**	0.272	not included	**included**	not included	0.00
Random Forest (fixed window)	0.64	0.65	0.61	0.068	0.180	0.368	not included	not included	not included	0.00

Table 2. *Cont.*

Young Coins: 30-Day-Ahead Probability of Death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1 Cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1 Cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1 Cent)**	*% Not Converged*
ZPP—Random walk	0.73	0.71	0.76	0.390	0.328	0.248	not included	not included	not included	0.00
ZPP—Normal GARCH(1,1)	0.69	0.66	0.65	0.281	0.290	0.332	not included	not included	not included	1.70
ZPP—Student'st GARCH(1,1)	0.67	0.63	0.55	0.189	0.233	0.387	not included	not included	not included	0.90
ZPP—GH Skewed Student GARCH(1,1)	0.69	0.64	0.50	0.154	0.211	0.373	not included	not included	not included	43.17
ZPP—MSGARCH(1,1)	0.72	0.70	**0.85**	0.150	0.178	**0.189**	not included	not included	**Included**	0.81
ZPP—D.R.(Garman and Klass)RW	0.59	0.56	0.60	0.095	0.194	0.347	not included	not included	not included	0.00
ZPP—D.R.(Garman and Klass)HAR	0.75	0.72	0.72	0.264	0.239	0.217	not included	not included	not included	7.40
ZPP—D.R.(Garman and Klass)ARFIMA	0.75	0.70	0.74	0.261	0.240	0.226	not included	not included	not included	67.62
ZPP—D.R.(Garman and Klass)CARR	0.68	0.65	0.56	0.196	0.217	0.307	not included	not included	not included	9.88
ZPP—D.R.(Yang and Zhang)RW	0.73	0.69	0.73	0.473	0.425	0.391	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)HAR	0.73	0.71	0.74	0.418	0.348	0.253	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)ARFIMA	0.72	0.69	0.76	0.414	0.344	0.253	not included	not included	not included	69.29
ZPP—D.R.(Yang and Zhang)CARR	0.74	0.70	0.69	0.470	0.404	0.360	not included	not included	not included	7.39

Table 3. Old coins: AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), models included in the MCS, and numerical convergence failures in percentage across three competing criteria to classify a coin as dead or alive. Ref. [7] approach = "*restrictive*"; simplified [7] approach = "*simple*"; professional rule = "*1 cent*"; D.R. = daily range-based estimator. Highest AUC, lowest Brier score and model included in the MCS are reported in bold font.

Old Coins: 1-Day-Ahead Probability of Death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1 Cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1 Cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1 Cent)**	*% Not Converged*
Logit (expanding window)	0.74	0.74	0.69	0.060	0.212	0.165	not included	not included	not included	0.00
Probit (expanding window)	0.73	0.71	0.67	0.073	0.232	0.171	not included	not included	not included	0.00
Cauchit (expanding window)	0.76	0.86	0.74	0.051	0.128	0.138	not included	not included	not included	0.00
Random Forest (expanding window)	**0.96**	**0.97**	**0.95**	**0.015**	**0.045**	**0.051**	**included**	**included**	**included**	0.00
Logit (fixed window)	0.77	0.75	0.75	0.049	0.198	0.156	not included	not included	not included	0.00
Probit (fixed window)	0.76	0.74	0.74	0.054	0.206	0.168	not included	not included	not included	0.00
Cauchit (fixed window)	0.77	0.85	0.76	0.050	0.131	0.125	not included	not included	not included	0.00
Random Forest (fixed window)	0.78	0.84	0.77	0.041	0.133	0.100	not included	not included	not included	0.00

Table 3. *Cont.*

Models	AUC (Restrictive)	AUC (Simple)	AUC (1 Cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1 Cent)	MCS (Restrictive)	MCS (Simple)	MCS (1 Cent)	*% Not Converged*
Old Coins: 1-Day-Ahead Probability of Death										
ZPP—Random walk	0.76	0.75	0.71	0.090	0.227	0.136	not included	not included	not included	0.00
ZPP—Normal GARCH(1,1)	0.64	0.59	0.64	0.062	0.294	0.140	not included	not included	not included	1.22
ZPP—Student'st GARCH(1,1)	0.57	0.54	0.63	0.056	0.284	0.145	not included	not included	not included	1.92
ZPP—GH Skewed Student GARCH(1,1)	0.57	0.55	0.42	0.057	0.290	0.147	not included	not included	not included	42.70
ZPP—MSGARCH(1,1)	0.69	0.68	0.70	0.053	0.282	0.139	not included	not included	not included	0.67
ZPP—D.R.(Garman and Klass)RW	0.51	0.50	0.58	0.057	0.311	0.152	not included	not included	not included	0.00
ZPP—D.R.(Garman and Klass)HAR	0.70	0.75	0.72	0.074	0.247	0.128	not included	not included	not included	12.06
ZPP—D.R.(Garman and Klass)ARFIMA	0.74	0.74	0.72	0.072	0.252	0.127	not included	not included	not included	74.30
ZPP—D.R.(Garman and Klass)CARR	0.64	0.60	0.66	0.056	0.305	0.148	not included	not included	not included	11.86
ZPP—D.R.(Yang and Zhang)RW	0.57	0.53	0.62	0.061	0.313	0.153	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)HAR	0.71	0.73	0.74	0.073	0.250	0.128	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)ARFIMA	0.76	0.73	0.75	0.073	0.254	0.127	not included	not included	not included	75.17
ZPP—D.R.(Yang and Zhang)CARR	0.64	0.59	0.67	0.060	0.307	0.148	not included	not included	not included	13.97
Old Coins: 30-Day-ahead Probability of Death										
Models	AUC (Restrictive)	AUC (Simple)	AUC (1 Cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1 Cent)	MCS (Restrictive)	MCS (Simple)	MCS (1 Cent)	*% Not Converged*
Logit (expanding window)	0.71	0.73	0.68	0.051	0.188	0.164	not included	not included	not included	0.00
Probit (expanding window)	0.70	0.68	0.67	0.051	0.199	0.170	not included	not included	not included	0.00
Cauchit (expanding window)	0.74	0.77	0.74	0.049	0.181	0.138	not included	not included	not included	0.00
Random Forest (expanding window)	0.76	**0.80**	**0.77**	**0.047**	**0.172**	**0.117**	**included**	**included**	**included**	0.00
Logit (fixed window)	0.74	0.77	0.74	0.049	0.181	0.158	not included	not included	not included	0.00
Probit (fixed window)	0.73	0.77	0.74	0.049	0.181	0.165	not included	not included	not included	0.00
Cauchit (fixed window)	0.75	0.79	0.75	0.049	0.176	0.127	not included	not included	not included	0.00
Random Forest (fixed window)	0.69	0.72	0.71	0.052	0.202	0.127	not included	not included	not included	0.00
ZPP—Random walk	0.75	0.69	0.68	0.321	0.246	0.301	not included	not included	not included	0.00
ZPP—Normal GARCH(1,1)	0.66	0.58	0.58	0.189	0.280	0.214	not included	not included	not included	1.22
ZPP—Student'st GARCH(1,1)	0.63	0.55	0.61	0.184	0.275	0.254	not included	not included	not included	1.92
ZPP—GH Skew-Student GARCH(1,1)	0.64	0.57	0.60	0.160	0.264	0.229	not included	not included	not included	42.70
ZPP—MSGARCH(1,1)	0.68	0.67	0.74	0.123	0.218	0.144	not included	not included	not included	0.67
ZPP—D.R.(Garman and Klass)RW	0.52	0.50	0.58	0.087	0.296	0.143	not included	not included	not included	0.00
ZPP—D.R.(Garman and Klass)HAR	0.70	0.74	0.70	0.276	0.214	0.260	not included	not included	not included	12.06
ZPP—D.R.(Garman and Klass)ARFIMA	0.75	0.75	0.71	0.273	0.213	0.257	not included	not included	not included	74.30
ZPP—D.R.(Garman and Klass)CARR	0.64	0.61	0.58	0.162	0.247	0.193	not included	not included	not included	11.86
ZPP—D.R.(Yang and Zhang)RW	0.70	0.57	0.68	0.273	0.382	0.257	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)HAR	0.74	0.69	0.73	0.346	0.254	0.315	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)ARFIMA	**0.77**	0.73	0.73	0.338	0.244	0.309	not included	not included	not included	75.17
ZPP—D.R.(Yang and Zhang)CARR	0.73	0.61	0.68	0.298	0.316	0.290	not included	not included	not included	13.97

Table 4. Old coins (continuation): AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), models included in the MCS, and numerical convergence failures in percentage across three competing criteria to classify a coin as dead or alive. Ref. [7] approach = "*restrictive*"; simplified [7] approach = "*simple*"; professional rule = "*1 cent*"; D.R. = daily range-based estimator. Highest AUC, lowest Brier score and model included in the MCS are reported in bold font.

Old Coins: 365-Day-Ahead Probability of Death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1 Cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1 Cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1 Cent)**	*% Not Converged*
Logit (expanding window)	0.59	0.57	0.61	0.088	0.337	0.179	not included	not included	not included	0.00
Probit (expanding window)	0.58	0.55	0.61	**0.085**	0.331	0.182	**Included**	not included	not included	0.00
Cauchit (expanding window)	0.63	0.61	0.65	0.089	0.354	**0.172**	not included	not included	**included**	0.00
Random Forest (expanding window)	0.61	0.60	0.59	0.089	0.341	0.206	not included	not included	not included	0.00
Logit (fixed window)	0.60	0.58	0.65	0.103	0.366	0.188	not included	not included	not included	0.00
Probit (fixed window)	0.60	0.57	0.63	0.107	0.363	0.198	not included	not included	not included	0.00
Cauchit (fixed window)	0.63	0.60	0.65	0.096	0.381	0.177	not included	not included	not included	0.00
Random Forest (fixed window)	0.62	0.61	0.61	0.086	0.327	0.190	**Included**	not included	not included	0.00
ZPP—Random walk	0.69	0.50	0.63	0.697	0.503	0.584	not included	not included	not included	0.00
ZPP—Normal GARCH(1,1)	0.66	0.51	0.55	0.802	0.554	0.718	not included	not included	not included	1.22
ZPP—Student'st GARCH(1,1)	0.68	0.52	0.56	0.360	0.414	0.355	not included	not included	not included	1.92
ZPP—GH Skew-Student GARCH(1,1)	0.67	0.50	0.54	0.328	0.411	0.330	not included	not included	not included	42.70
ZPP—MSGARCH(1,1)	0.63	0.52	0.69	0.333	0.354	0.298	not included	not included	not included	0.67
ZPP—D.R.(Garman and Klass)RW	0.51	0.55	0.58	0.292	**0.286**	0.276	not included	**Included**	not included	0.00
ZPP—D.R.(Garman and Klass)HAR	0.64	**0.62**	0.66	0.544	0.301	0.467	not included	not included	not included	12.06
ZPP—D.R.(Garman and Klass)ARFIMA	0.69	0.60	**0.70**	0.543	0.296	0.467	not included	not included	not included	74.30
ZPP—D.R.(Garman and Klass)CARR	0.60	0.55	0.51	0.513	0.312	0.477	not included	not included	not included	11.86
ZPP—D.R.(Yang and Zhang)RW	**0.70**	0.47	0.64	0.914	0.702	0.771	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)HAR	0.69	0.52	0.66	0.766	0.495	0.639	not included	not included	not included	0.00
ZPP—D.R.(Yang and Zhang)ARFIMA	0.68	0.54	0.69	0.686	0.443	0.575	not included	not included	not included	75.17
ZPP—D.R.(Yang and Zhang)CARR	0.70	0.51	0.65	0.756	0.509	0.660	not included	not included	not included	13.97

The estimated AUCs for the models without the daily range in Tables 2–4 are consistent with the findings reported in [11] (using the same dataset). However, this is not the case for the model confidence sets (MCS) and the Brier scores, which now incorporate models using range-based volatility estimators. Due to significant numerical convergence failures of some models, such as the GARCH model with the generalized hyperbolic skewed Student distribution and ARFIMA models, the number of forecasts used to calculate the MCS and the Brier scores is significantly lower than those used to calculate the AUC. The former metrics require common data for all models, whereas the latter can be calculated individually. Therefore, for our dataset, the AUC is probably a more appropriate evaluation metric than are the MCS and the Brier score. However, we also provide the latter for completeness and interest.

Our results suggest that ZPP models utilizing range-based volatility estimators are generally more effective for long-term forecasts, supporting the evidence presented in [12], which found that high-frequency volatility models outperformed low-frequency models using range-based estimators only for short-term forecasts but not for longer horizons. In [12], it is posited that volatility exhibits long memory and changes gradually over time, so an accurate estimate of current day's volatility is useful in predicting the following day's volatility but less so for forecasts several weeks ahead. A similar dynamic may apply here: lagged trading volumes and online search data utilized by credit scoring models and ML methods are useful for short-term PD forecasts up to 30 days ahead but less so for 1-year-ahead forecasts, which are the standard in credit risk management. In this case, range-based estimators with long-memory models or the simple random walk may be sufficient. Furthermore, given the lack of a single ZPP model that is best across all classification criteria, this empirical evidence supports the possibility of improved forecasts through forecast combinations methods, which we leave as a topic for future research.

Regarding the differences between range-based estimators, we observe that the Yang–Zhang estimator produces better AUC forecasts than does the Garman–Klass estimator, particularly for long-term forecasts. However, this is not universally true for all forecasting models, and the Yang–Zhang estimator has significantly worse Brier scores than does the Garman–Klass estimator. This highlights the potential for improved forecasts through forecast combinations methods, and we leave this as an interesting topic for future research.

Finally, we wish to emphasize the poor numerical performance of the ARFIMA models, which failed to converge in almost 70% of cases. It is well established in the literature that the estimation of the fractional parameter d in ARFIMA(p, d, q) models is challenging, as documented in large simulation studies; see [62–66]. We used the exact maximum likelihood procedure with normal errors proposed in [67], which is theoretically efficient and has quasi-maximum likelihood properties. Unfortunately, the noisy nature and short time series of most crypto-assets had a significant impact on the numerical performance of this model. To keep the computational time within reasonable limits, we did not attempt alternative model estimators, leaving this as an interesting avenue for future research.

5. A Robustness Check: Forecasting the 1-Year-Ahead PD of the Crypto Trading Platform FTX

We evaluated the performance of the best forecasting models for the probability of death (PD) over the one-year horizon in modeling the token of the crypto trading platform FTX (symbol: FTT), which filed for Chapter 11 bankruptcy protection in the United States. on 11 November 2022. FTT, the native cryptocurrency token of FTX, was launched on 8 May 2019 and initially served as a reward for exchange transactions. However, over time, the list of functions for the FTT token expanded, and it became mainly used for reducing trading fees and securing futures positions. Further details can be found in a comprehensive summary available at coinmarketcap.com/currencies/ftx-token (accessed on 1 December 2022). Figure 1 displays the price in US dollars of the FTX token over the time sample from 1 August 2019 to 11 November 2022.

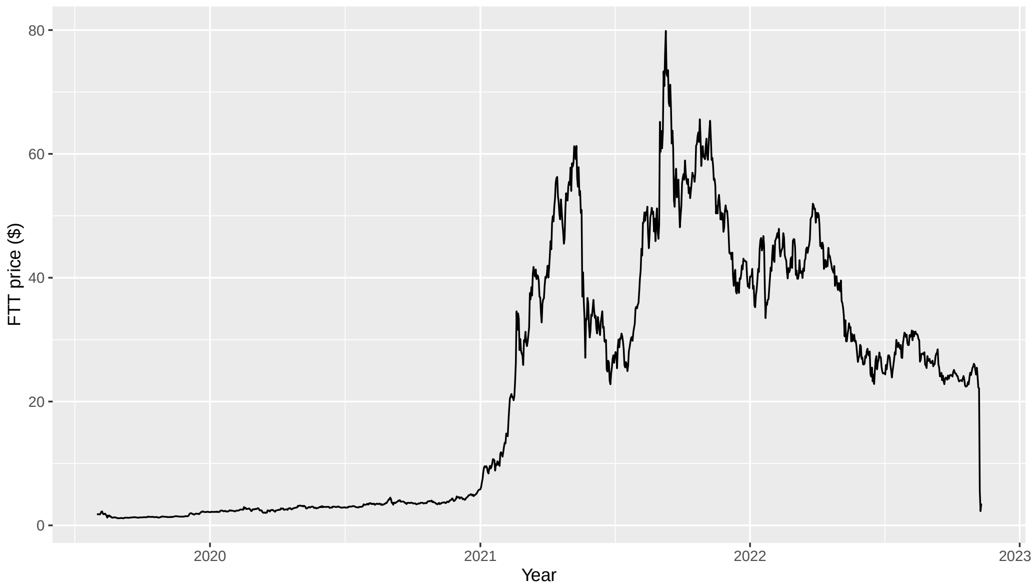

Figure 1. Price in USD of the FTX token over the time sample 1 August 2019/11 November 2022.

We computed the 1-year-ahead PD using the ZPP with all the range-based estimators, as well as the ZPP based on the random walk or the Markov-switching GARCH(1,1), which were found to be the best models for long-term PD forecasts in [11]. All models were estimated using an expanding window with the first estimation sample consisting of 365 observations. The estimated probabilities of death for all models are reported in Figures 2 and 3 from July 2020 until the end of October 2022, which is 11 days prior to the official bankruptcy of FTX.

The 1-year-ahead probabilities of death computed with range-based volatility estimators reached their highest values approximately one year prior to the official bankruptcy of FTX, thereby indirectly confirming why they were the best models for forecasting the 1-year-ahead PD in the baseline case. However, both the HAR models with the daily range and the models using close-to-close prices showed steadily increasing probabilities of death from the end of 2021 until just before the bankruptcy.

In general, it is noted that models using range-based estimators resulted in much noisier signals compared to models using close-to-close prices. Furthermore, the HAR models experienced numerical instability at the beginning of the sample due to the small sample size, while ARFIMA models with daily range were not reported because they failed to converge several times in the sample, thereby confirming the estimation problems discussed in Section 4.2.

This empirical evidence leads to two conclusions: first, the market was pricing a potential credit event related to FTX well in advance of the official bankruptcy. Second, this evidence supports the potential for forecasting gains by combining the estimates of the PD obtained from different methods. We leave this topic as an interesting avenue for future research.

Finally, we would like to note that, in line with the methodology outlined in [11], we tested the robustness of our findings using different data samples, including data prior to and after 2017, and by stratifying crypto-assets based on their market capitalization. Specifically, the authors of [11] separated their dataset into two subsamples consisting of data before and after 10 December 2017 to investigate how their models' forecasting performances would change in these two subsamples. This date was chosen because it marked the introduction of the first bitcoin futures on the CBOE, and there is a significant body of literature demonstrating that there was a financial bubble in bitcoin prices in 2016–2017 that burst at the end of 2017, potentially triggered by the introduction of these new bitcoin futures (see [11] and references therein for more details). We conducted the same robustness check using range-based volatility estimators and found no significant differences between the two subsamples. Additionally, as per [11], we conducted a second robustness check where we separated the 100 crypto coins with the largest market capitalization from all other coins with a smaller market capitalization. We did not identify any qualitative differences from the baseline case. While the tables containing the results of these robustness checks were quite extensive, they did not contribute anything new to our findings and are not reported here. However, they are available on the author's webpage at https://docs.google.com/spreadsheets/d/1pqM0HdBPPyZAzBKsgiarkisCoQhmbCae/edit?usp=share_link&ouid=103750598646225124705&rtpof=true&sd=true, accessed on 28 February 2023.

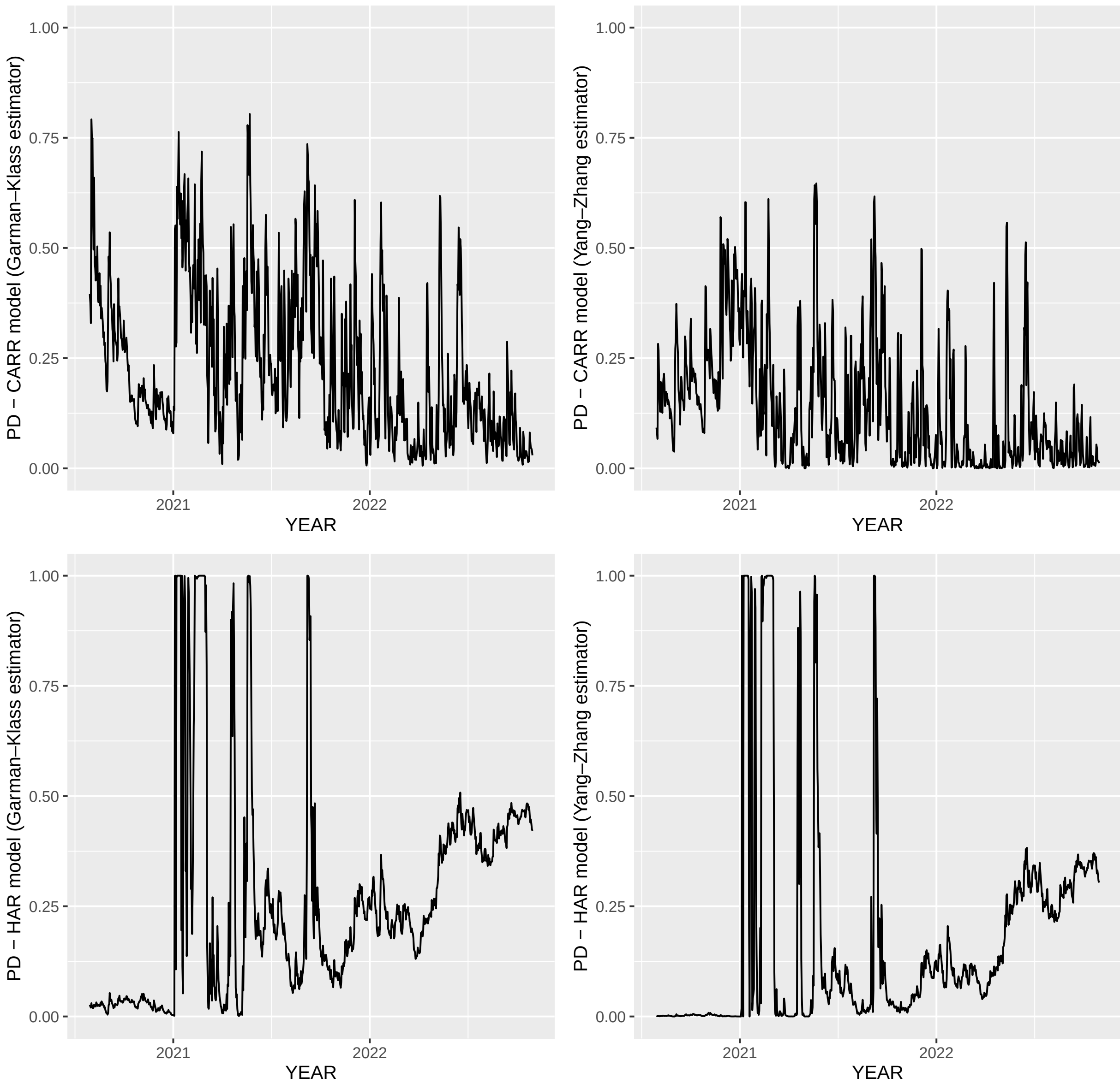

Figure 2. One-year-ahead probability of death (PD) estimated over the time sample 30 July 2020/30 October 2022 using an expanding window with the first estimation sample consisting of 365 observations for these ZPP models: CARR model with the Garman—Klass estimator, CARR model with the Yang—Zhang estimator, HAR model with the Garman—Klass estimator, and HAR model with the Yang—Zhang estimator.

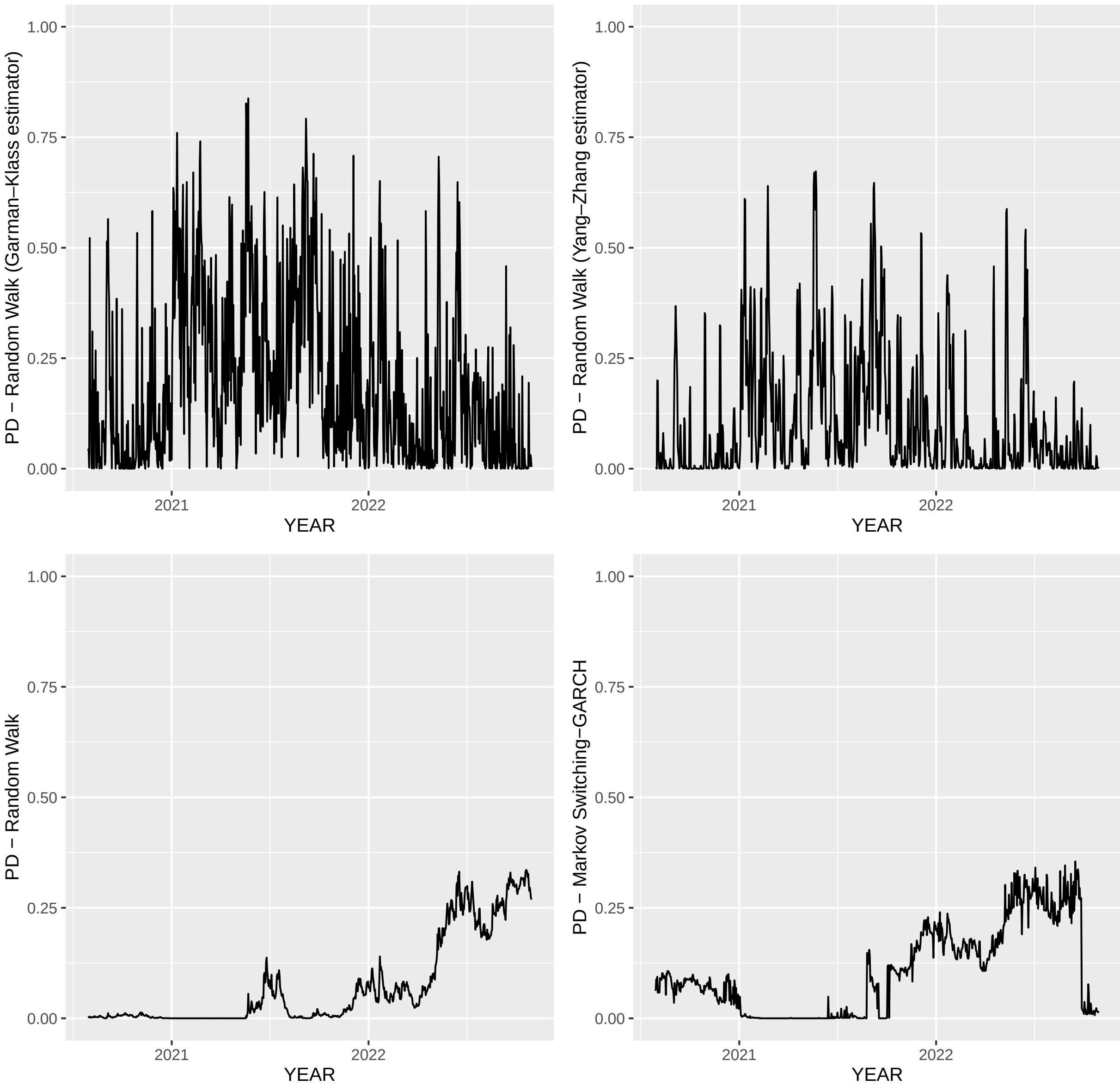

Figure 3. One-year-ahead probability of death (PD) estimated over the time sample 30 July 2020/30 October 2022 using an expanding window with the first estimation sample consisting of 365 observations for these ZPP models: random walk with Garman—Klass estimator), random walk with Yang—Zhang estimator, random walk, and Markov-switching GARCH.

6. Discussion and Conclusions

This paper aimed to estimate the credit risk of crypto-assets by computing their probability of death using the daily range data, which incorporate all the information available in traditional daily datasets, such as the open-high-low-close prices.

To achieve this aim, we first proposed a set of models to forecast the probability of death that combines the daily range with the zero-price probability (ZPP) model, which is an approach to compute these probabilities using only market prices. Then, we conducted a comprehensive forecasting exercise using a sample of 2003 crypto coins active from 2014 to 2020, as previously examined by [11]. We employed a wide range of competing models, including credit-scoring models, machine-learning models, and time-series-based models, with various definitions of dead coins and forecasting horizons. The results showed that credit-scoring models and machine-learning methods using lagged trading volumes and online searches were the most effective models for short-term forecasts, up to 30 days ahead, whereas time-series models using the daily range were better suited for longer-term forecasts, up to 1 year ahead. Furthermore, we conducted a robustness check and found that our best models for forecasting the 1-year-ahead probability of death indicated that the market was anticipating a potential credit event related to FTX well before its official bankruptcy, which occurred on 11 November 2022.

The main recommendation for investors is to use credit-scoring and machine-learning models for short-term forecasting up to 30 days ahead, particularly the cauchit and the random forest models first suggested by [11]. Meanwhile, ZPP-based models using range-based volatility estimators are a better choice for long-term forecasts up to 1 year ahead, which is the traditional horizon for credit risk management. This evidence is consistent with the results reported in [12,13], which found that high-frequency volatility models outperformed low-frequency models using range-based estimators only for short-term forecasts but not for longer horizons.The authors of [12] argued that volatility exhibits long memory and changes gradually over time, so an accurate estimate of the current day's volatility is useful in predicting the following day's volatility but less so for forecasts several weeks ahead. A similar dynamic may apply in our case, where lagged trading volumes and online search data utilized by credit scoring models and ML methods are useful for short-term PD forecasts up to 30 days ahead but less so for 1-year-ahead forecasts, which is the standard horizon in credit risk management. In this case, range-based estimators with long-memory models or the simple random walk can be sufficient.

Our research findings strongly support the notion of improving credit risk reporting for crypto-assets. Our stance aligns with similar proposals made by [6,11,21]. We recommend that crypto exchanges be mandated to publish daily death probability estimates for their traded crypto-assets, utilizing either one of the models discussed in this paper or any other methodology that regulators deem appropriate. Such information would facilitate more informed investment decisions for investors interested in crypto-assets. Furthermore, the collapse of FTX and its associated trading firm, Alameda Research, highlights the need for more stringent regulations regarding reserve assets for crypto exchanges. National and international regulators should consider including fiat currencies, precious metals, or tangible assets, such as power plants, in the list of potential capital reserves. Conversely, digitally generated tokens that function as discount cards should not be used as reserve assets.

It is important to also highlight the limitations of this study. Firstly, we did not attempt to model the returns of crypto-assets. Modeling the volatility of assets is generally more important for risk modeling purposes than is modeling the returns, as discussed in [68] and the references therein. However, recent advances in time series forecasting and nonlinear modeling may aid in producing more accurate risk estimates; see [69–73] for more details. Moreover, we focused on end-of-day data due to its availability for all crypto-assets. However, exploring how our results may differ when using high-frequency data would be of interest. We leave these matters as future research possibilities.

Our work leaves a number of other issues for future research: the computational problems that emerged in this work seem to suggest Bayesian methods as a possible solution for smoothing noisy data and improving the model's computation in the case of small-time series. Moreover, several instances in our empirical analysis highlighted the possibility of forecasting gains by combining the estimated PDs obtained from different methods. We leave all these issues as avenues of future work.

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Conflicts of Interest: The author declares no conflict of interest.

Appendix A. Daily Number of Total Available Coins and of Dead Coins

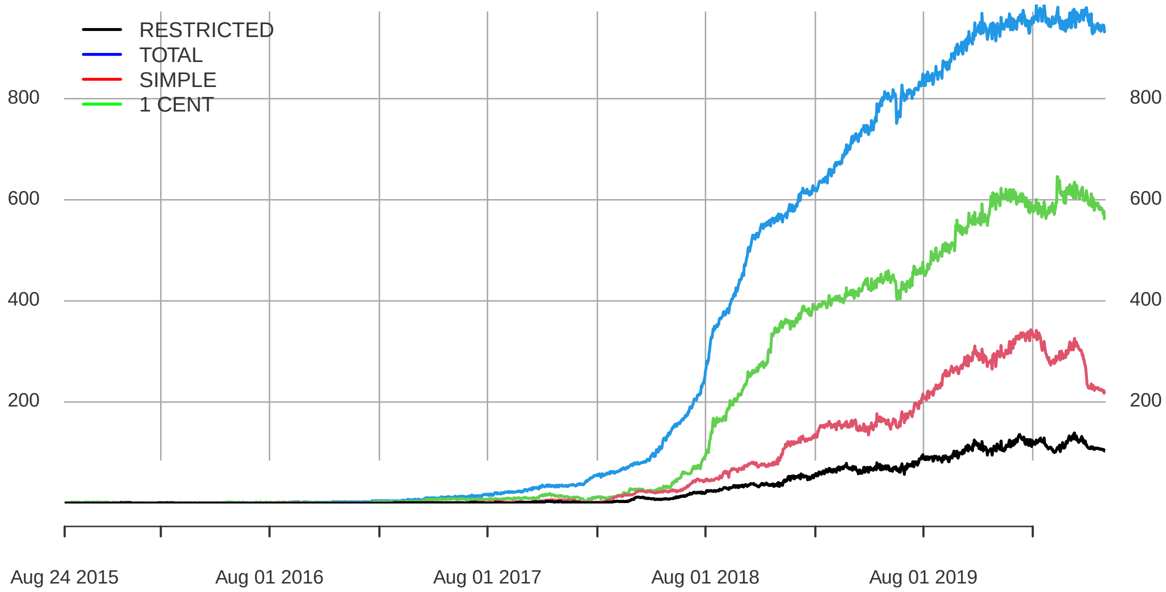

Figure A1. Young coins: Daily number of total available coins and the daily number of dead coins computed using the previous three criteria. The data are from [11]. For convenience, the approach proposed by [7] is referred to as "*restrictive*", the simplified approach proposed by [9] as "*simple*", and the professional rule as "*1 cent*".

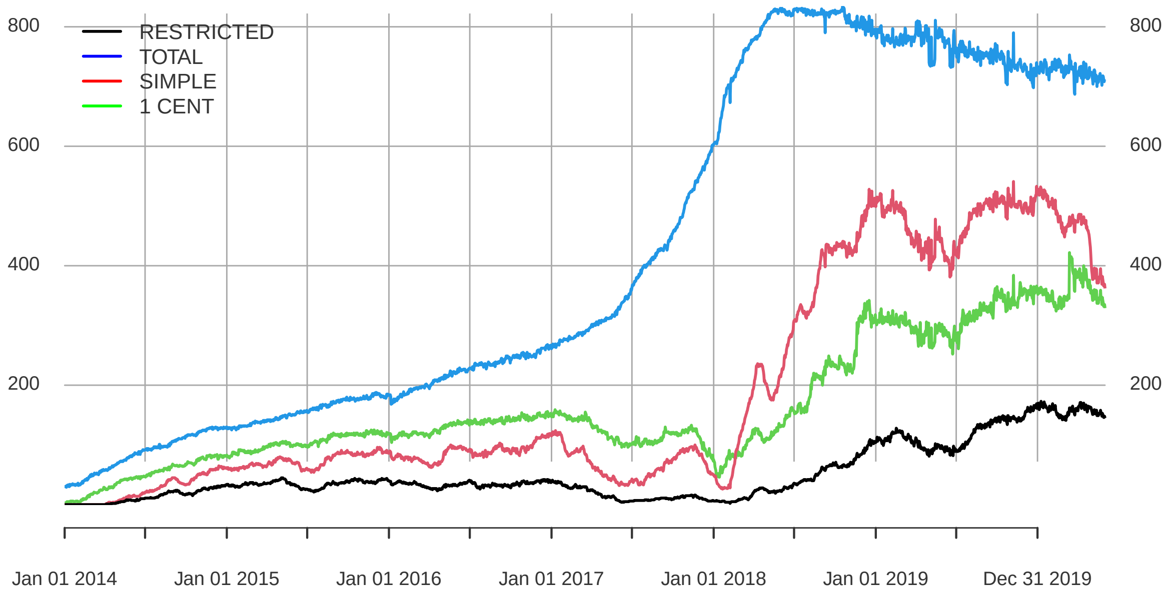

Figure A2. Old coins: Daily number of total available coins and the daily number of dead coins computed using the previous three criteria. The data are from [11]. For convenience, the approach proposed by [7] is referred to as "*restrictive*", the simplified approach proposed by [9] as "*simple*", and the professional rule as "*1 cent*".

Appendix B. Lists of Young and Old Coins

Table A1. Names of the 1165 young coins: coins 1–400.

1	Bitcoin SV	101	Band Protocol	201	TROY	301	ETERNAL TOKEN
2	Crypto.com Coin	102	PLATINCOIN	202	Anchor	302	Pirate Chain
3	Acash Coin	103	UNI COIN	203	ShareToken	303	USDQ
4	UNUS SED LEO	104	Qubitica	204	QuarkChain	304	Electronic Energy Coin
5	USD Coin	105	MX Token	205	Content Value Network	305	VNDC
6	HEX	106	Ocean Protocol	206	Gemini Dollar	306	Egretia
7	Cosmos	107	BitMax Token	207	FLETA	307	Bitcoin Rhodium
8	VeChain	108	Origin Protocol	208	Cred	308	IPChain
9	HedgeTrade	109	XeniosCoin	209	Metadium	309	Digital Asset Guarantee Token
10	INO COIN	110	Project Pai	210	Cocos-BCX	310	BQT
11	OKB	111	WINk	211	MEXC Token	311	LINKA
12	FTX Token	112	Function X	212	Sport and Leisure	312	UGAS
13	VestChain	113	Fetch.ai	213	Nectar	313	Pundi X NEM
14	Paxos Standard	114	1irstcoin	214	Morpheus.Network	314	Yap Stone
15	MimbleWimbleCoin	115	Wirex Token	215	Dimension Chain	315	Ondori
16	PlayFuel	116	Grin	216	Kleros	316	Lykke
17	Hedera Hashgraph	117	Aurora	217	Hxro	317	BOX Token
18	Algorand	118	Karatgold Coin	218	StakeCubeCoin	318	Sense
19	Largo Coin	119	SynchroBitcoin	219	Dusk Network	319	Newscrypto
20	Binance USD	120	DAD	220	Wixlar	320	CUTcoin
21	Hyperion	121	Ecoreal Estate	221	Diamond Platform Token	321	1SG
22	The Midas Touch Gold	122	AgaveCoin	222	Aencoin	322	Global Social Chain
23	Insight Chain	123	Folgory Coin	223	Aladdin	323	Agrocoin
24	ThoreCoin	124	BOSAGORA	224	VITE	324	MVL
25	TAGZ5	125	Tachyon Protocol	225	VNX Exchange	325	Robotina
26	Elamachain	126	Ultiledger	226	AMO Coin	326	Nyzo
27	MINDOL	127	Nash Exchange	227	XMax	327	Akropolis
28	Dai	128	NEXT	228	FNB Protocol	328	Trade Token X
29	Baer Chain	129	Loki	229	Aergo	329	VeriDocGlobal
30	HUSD	130	BigONE Token	230	CoinEx Token	330	Verasity
31	Flexacoin	131	WOM Protocol	231	QuickX Protocol	331	BitCapitalVendor
32	Velas	132	BitKan	232	Moss Coin	332	Kryll
33	Metaverse Dualchain Network Architecture	133	CONTRACOIN	233	Safe	333	EURBASE
34	ZB Token	134	Rocket Pool	234	Perlin	334	Cryptocean
35	GlitzKoin	135	IDEX	235	LiquidApps	335	GoCrypto Token
36	botXcoin	136	Egoras	236	OTOCASH	336	Sentivate
37	Divi	137	LuckySevenToken	237	Sentinel Protocol	337	Ternio
38	Terra	138	Jewel	238	LCX	338	CryptoVerificationCoin
39	DxChain Token	139	Celer Network	239	Tellor	339	VeriBlock
40	Quant	140	Bonorum	240	MixMarvel	340	VINchain
41	Seele-N	141	Kusama	241	CoinMetro Token	341	PCHAIN
42	Counos Coin	142	General Attention Currency	242	Levolution	342	Cardstack
43	Nervos Network	143	Everipedia	243	Endor Protocol	343	Tokoin
44	Matic Network	144	CryptalDash	244	IONChain	344	AmonD
45	Blockstack	145	Bitcoin 2	245	HyperDAO	345	MargiX
46	Energi	146	Apollo Currency	246	#MetaHash	346	S4FE
47	Chiliz	147	BORA	247	Digix Gold Token	347	SnapCoin
48	QCash	148	Cryptoindex.com 100	248	Effect.AI	348	EOSDT
49	BitTorrent	149	GoChain	249	Darico Ecosystem Coin	349	ZVCHAIN
50	ABBC Coin	150	MovieBloc	250	GreenPower	350	FansTime
51	Unibright	151	TOP	251	PlayChip	351	EOS Force
52	NewYork Exchange	152	Bit-Z Token	252	Cosmo Coin	352	ContentBox
53	Beldex	153	IRISnet	253	Atomic Wallet Coin	353	Maincoin
54	ExtStock Token	154	Machine Xchange Coin	254	IQeon	354	BaaSid
55	Celsius	155	CWV Chain	255	HYCON	355	Constant
56	Bitbook Gambling	156	NKN	256	LNX Protocol	356	USDx stablecoin
57	SOLVE	157	ZEON	257	Prometeus	357	PumaPay
58	Sologenic	158	Neutrino Dollar	258	V-ID	358	NIX
59	Tratin	159	WazirX	259	suterusu	359	JD Coin
60	RSK Infrastructure Framework	160	Nimiq	260	T.OS	360	FarmaTrust
61	v.systems	161	BHPCoin	261	XYO	361	Futurepia
62	PAX Gold	162	Fantom	262	ChronoCoin	362	Themis
63	BitcoinHD	163	Newton	263	YOU COIN	363	IntelliShare
64	Elrond	164	The Force Protocol	264	Telos	364	Content Neutrality Network
65	Bloomzed Token	165	COTI	265	Contents Protocol	365	BitMart Token
66	THORChain	166	ILCoin	266	EveryCoin	366	Vipstar Coin
67	Joule	167	Ethereum Meta	267	Ferrum Network	367	Humanscape
68	Xensor	168	TrustVerse	268	LINA	368	CanonChain
69	CRYPTOBUCKS	169	sUSD	269	Origo	369	Litex
70	STEM CELL COIN	170	VideoCoin	270	Atlas Protocol	370	Waves Enterprise
71	APIX	171	Ankr	271	VIDY	371	Spectre.ai Utility Token
72	Tap	172	Chimpion	272	Ampleforth	372	Esportbits
73	Bankera	173	Rakon	273	GNY	373	Beaxy
74	Breezecoin	174	Travala.com	274	ChainX	374	SINOVATE
75	FABRK	175	ThoreNext	275	DAPS Coin	375	SIX
76	Bitball Treasure	176	BitForex Token	276	Zano	376	Phantasma
77	BHEX Token	177	Wrapped Bitcoin	277	0Chain	377	BetProtocol
78	Theta Fuel	178	ZBG Token	278	GAPS	378	pEOS
79	Gatechain Token	179	Orchid	279	DigitalBits	379	MIR COIN

Table A1. *Cont.*

80	STASIS EURO	180	TTC	280	HitChain	380	Winding Tree
81	Kava	181	LTO Network	281	WeShow Token	381	Grid+
82	BTU Protocol	182	MicroBitcoin	282	apM Coin	382	BlockStamp
83	Thunder Token	183	Contentos	283	Sakura Bloom	383	BOLT
84	Beam	184	Lambda	284	Clipper Coin	384	INLOCK
85	Swipe	185	Constellation	285	FOAM	385	CEEK VR
86	Reserve Rights	186	Ultra	286	qiibee	386	Nuggets
87	Digitex Futures	187	FIBOS	287	Nestree	387	Lition
88	Orbs	188	DREP	288	SymVerse	388	Rublix
89	Buggyra Coin Zero	189	Invictus Hyperion Fund	289	ROOBEE	389	Spendcoin
90	IoTeX	190	CONUN	290	CryptoFranc	390	Bitrue Coin
91	inSure	191	Standard Tokenization Protocol	291	DDKoin	391	HoryouToken
92	Davinci Coin	192	Mainframe	292	Zel	392	RealTract
93	USDK	193	Chromia	293	Metronome	393	BidiPass
94	Super Zero Protocol	194	ARPA Chain	294	NPCoin	394	PlayCoin [ERC20]
95	Huobi Pool Token	195	REPO	295	ProximaX	395	MultiVAC
96	Harmony	196	Carry	296	NOIA Network	396	Artfinity
97	Poseidon Network	197	Valor Token	297	Eminer	397	EXMO Coin
98	Handshake	198	Zenon	298	Observer	398	Credit Tag Chain
99	12Ships	199	Elitium	299	Baz Token	399	Wowbit
100	Vitae	200	Emirex Token	300	KARMA	400	RSK Smart Bitcoin

Table A2. Names of the 1165 young coins: coins 401–800.

401	PegNet	501	ZeuxCoin	601	SPINDLE	701	Raise
402	Trias	502	TurtleCoin	602	Proton Token	702	Arbidex
403	PIBBLE	503	WPP TOKEN	603	Swap	703	W Green Pay
404	PLANET	504	Linkey	604	Olive	704	Digital Insurance Token
405	Snetwork	505	Noku	605	ImageCoin	705	Essentia
406	Cryptaur	506	Coineal Token	606	Infinitus Token	706	BioCoin
407	Aryacoin	507	Hashgard	607	ATMChain	707	Zen Protocol
408	Safe Haven	508	Fast Access Blockchain	608	WinStars.live	708	ZUM TOKEN
409	Rotharium	509	MEET.ONE	609	Alpha Token	709	Celeum
410	Traceability Chain	510	DACSEE	610	Grimm	710	MTC Mesh Network
411	Abyss Token	511	Kambria	611	TouchCon	711	TrueFeedBack
412	Naka Bodhi Token	512	ADAMANT Messenger	612	Lobstex	712	ZCore
413	Eterbase Coin	513	Merculet	613	Bitblocks	713	Agrolot
414	CashBet Coin	514	SBank	614	Sapien	714	Jobchain
415	Azbit	515	QChi	615	NOW Token	715	Global Awards Token
416	ZumCoin	516	YGGDRASH	616	GAMB	716	FidentiaX
417	MenaPay	517	Ouroboros	617	Xriba	717	Nerva
418	Fatcoin	518	Insureum	618	Alphacat	718	Scorum Coins
419	Netbox Coin	519	Sparkpoint	619	BitNewChain	719	Patron
420	VNT Chain	520	LHT	620	FLIP	720	TCASH
421	Cajutel	521	MassGrid	621	Nebula AI	721	ALL BEST ICO
422	Vexanium	522	QuadrantProtocol	622	OVCODE	722	wave edu coin
423	Callisto Network	523	KuboCoin	623	Plair	723	Membrana
424	Smartlands	524	Hashshare	624	Auxilium	724	PlayGame
425	TERA	525	Ivy	625	RED	725	Rapidz
426	GoWithMi	526	Banano	626	EUNO	726	Eristica
427	Egoras Dollar	527	DABANKING	627	NeuroChain	727	CryptoPing
428	Tolar	528	Ubex	628	Rivetz	728	x42 Protocol
429	Vetri	529	Bitsdaq	629	Coinsuper Ecosystem Network	729	Cubiex
430	WinCash	530	VegaWallet Token	630	BZEdge	730	OSA Token
431	1World	531	Ecobit	631	Bancacy	731	EvenCoin
432	Airbloc	532	Liquidity Network	632	CrypticCoin	732	CREDIT
433	Pigeoncoin	533	Eden	633	Evedo	733	Coinlancer
434	OneLedger	534	Beetle Coin	634	Niobium Coin	734	EXMR FDN
435	DEX	535	Merebel	635	LocalCoinSwap	735	TrueDeck
436	Pivot Token	536	Open Platform	636	EBCoin	736	AC3
437	Kuai Token	537	Locus Chain	637	Moneytoken	737	DAV Coin
438	Mcashchain	538	TEAM (TokenStars)	638	CoinUs	738	Jarvis+
439	Leverj	539	Proxeus	639	Enecuum	739	3DCoin
440	Databroker	540	BonusCloud	640	Noir	740	Silent Notary
441	Unification	541	Business Credit Substitute	641	BeatzCoin	741	IP Exchange
442	Blue Whale EXchange	542	MalwareChain	642	Quasarcoin	742	Moneynet
443	Color Platform	543	IQ.cash	643	Graviocoin	743	OWNDATA
444	Flowchain	544	Digital Gold	644	Max Property Group	744	uPlexa
445	CoinDeal Token	545	Brickblock	645	Ethereum Gold	745	StarCoin
446	PlatonCoin	546	MARK.SPACE	646	TigerCash	746	Mithril Ore
447	Krios	547	Conceal	647	DPRating	747	Ryo Currency
448	Nasdacoin	548	SafeCoin	648	Almeela	748	StarterCoin
449	LikeCoin	549	Spiking	649	Nexxo	749	CryptoBonusMiles
450	Okschain	550	COVA	650	smARTOFGIVING	750	MMOCoin
451	Bitex Global XBX Coin	551	PUBLISH	651	On.Live	751	FSBT API Token
452	Colu Local Network	552	Sessia	652	XcelToken Plus	752	PAL Network
453	Caspian	553	DOS Network	653	0xcert	753	Shadow Token
454	BOOM	554	NeoWorld Cash	654	Block-Logic	754	Scanetchain
455	Raven Protocol	555	ESBC	655	Actinium	755	BlitzPredict

Table A2. *Cont.*

456	DECOIN	556	BitBall	656	MineBee	756	Truegame
457	Gleec	557	Gold Bits Coin	657	eXPerience Chain	757	EurocoinToken
458	Amoveo	558	CoTrader	658	TurtleNetwork	758	Typerium
459	Teloscoin	559	Coinsbit Token	659	HashCoin	759	Ether-1
460	Zipper	560	Lisk Machine Learning	660	VeriSafe	760	TrakInvest
461	Quanta Utility Token	561	USDX	661	ZENZO	761	GoNetwork
462	IG Gold	562	SureRemit	662	Paytomat	762	Blockparty (BOXX Token)
463	ROAD	563	SnowGem	663	Seal Network	763	OptiToken
464	Midas	564	0xBitcoin	664	SnodeCoin	764	Bigbom
465	Cloudbric	565	Rate3	665	Bittwatt	765	Bethereum
466	Stronghold Token	566	Faceter	666	SpectrumCash	766	Sharpay
467	X-CASH	567	FREE Coin	667	WebDollar	767	Amino Network
468	Iconiq Lab Token	568	Qwertycoin	668	TV-TWO	768	PTON
469	Blockchain Certified Data Token	569	Gene Source Code Chain	669	Master Contract Token	769	MFCoin
470	Fountain	570	Golos Blockchain	670	BetterBetting	770	DeVault
471	MB8 Coin	571	ICE ROCK MINING	671	BitScreener Token	771	GoldFund
472	Origin Sport	572	REAL	672	Smartshare	772	Leadcoin
473	Tixl	573	PAYCENT	673	Vodi X	773	Carboneum [C8] Token
474	ParkinGo	574	StableUSD	674	Naviaddress	774	iDealCash
475	Ether Zero	575	NEXT.coin	675	FortKnoxster	775	Alt.Estate token
476	Asian Fintech	576	UpToken	676	HorusPay	776	EnergiToken
477	Bitcoin Confidential	577	SafeInsure	677	Ulord	777	MorCrypto Coin
478	DreamTeam Token	578	Eureka Coin	678	Q DAO Governance token v1.0	778	Hyper Speed Network
479	nOS	579	DEEX	679	ODUWA	779	eSDChain
480	HashBX	580	ZPER	680	RedFOX Labs	780	DogeCash
481	TEMCO	581	Bob's Repair	681	XPA	781	Daneel
482	Axe	582	Tarush	682	Birake	782	Gravity
483	BOMB	583	Mallcoin	683	savedroid	783	Kuende
484	HyperExchange	584	MIB Coin	684	TOKPIE	784	Kuverit
485	AIDUS TOKEN	585	Skychain	685	Halo Platform	785	Decentralized Machine Learning
486	Amon	586	Qredit	686	DeltaChain	786	Winco
487	Education Ecosystem	587	Project WITH	687	Mindexcoin	787	Monarch
488	X8X Token	588	Zippie	688	View	788	DOWCOIN
489	TRONCLASSIC	589	FYDcoin	689	Swace	789	Relex
490	Footballcoin	590	Howdoo	690	Ubcoin Market	790	Bitcoin CZ
491	Block-Chain.com	591	MidasProtocol	691	OLXA	791	Omnitude
492	SafeCapital	592	Shivom	692	Maximine Coin	792	Bee Token
493	POPCHAIN	593	Cashbery Coin	693	Webflix Token	793	RightMesh
494	Vision Industry Token	594	Lunes	694	Trittium	794	Catex Token
495	Opacity	595	Bitcoin Free Cash	695	Thrive Token	795	Bridge Protocol
496	Titan Coin	596	Honest	696	Bitcoin Incognito	796	Birdchain
497	Blocktrade Token	597	Safex Cash	697	Bitfex	797	BLOC.MONEY
498	Semux	598	GMB	698	FNKOS	798	Business Credit Alliance Chain
499	Uptrennd	599	PIXEL	699	Rapids	799	Alchemint Standards
500	Veil	600	Vezt	700	ebakus	800	Dynamite

Table A3. Names of the 1165 young coins: coins 801–1165.

801	Mainstream For The Underground	901	Blockburn	1001	BitRent	1101	Dash Green
802	WandX	902	LOCIcoin	1002	Decentralized Asset Trading Platform	1102	Joint Ventures
803	Blockpass	903	OPCoinX	1003	ROIyal Coin	1103	WXCOINS
804	ZMINE	904	BitCoen	1004	ShareX	1104	e-Chat
805	CryptoAds Marketplace	905	FUZE Token	1005	RefToken	1105	iBTC
806	CROAT	906	Commercium	1006	SHPING	1106	VikkyToken
807	BoatPilot Token	907	Hurify	1007	ETHplode	1107	CPUchain
808	Storiqa	908	Impleum	1008	Bitcoin Classic	1108	MiloCoin
809	Rupiah Token	909	Transcodium	1009	Bitcoin Adult	1109	BunnyToken
810	Ifoods Chain	910	Knekted	1010	GenesisX	1110	Electrum Dark
811	AiLink Token	911	No BS Crypto	1011	Intelligent Trading Foundation	1111	Playgroundz
812	Parachute	912	BlockMesh	1012	Zenswap Network Token	1112	Kora Network Token
813	Swapcoinz	913	PluraCoin	1013	Signatum	1113	Ragnarok
814	ONOToken	914	Aigang	1014	MetaMorph	1114	Escroco Emerald
815	Helium Chain	915	Arqma	1015	ShowHand	1115	Helper Search Token
816	Fire Lotto	916	Regalcoin	1016	4NEW	1116	Fivebalance
817	The Currency Analytics	917	Thar Token	1017	GoldenPyrex	1117	1X2 COIN
818	Matrexcoin	918	Mobile Crypto Pay Coin	1018	RPICoin	1118	Crystal Clear
819	BitClave	919	XMCT	1019	EOS TRUST	1119	Xenoverse
820	Zennies	920	Xuez	1020	Gold Poker	1120	VectorAI
821	BBSCoin	921	Ethouse	1021	Neural Protocol	1121	Bitcoinus
822	Civitas	922	Kind Ads Token	1022	EtherInc	1122	PAXEX
823	Aston	923	CommunityGeneration	1023	Sola Token	1123	MNPCoin
824	Bitnation	924	Agora	1024	SkyHub Coin	1124	Apollon
825	SRCOIN	925	nDEX	1025	Global Crypto Alliance	1125	Project Coin
826	PYRO Network	926	BTC Lite	1026	Level Up Coin	1126	Crystal Token
827	Veles	927	PUBLYTO Token	1027	Havy	1127	Veltor
828	BEAT	928	EtherSportz	1028	QUINADS	1128	Decentralized Crypto Token

Table A3. *Cont.*

829	Streamit Coin	929	Freyrchain	1029	EUNOMIA	1129	Fintab
830	Oxycoin	930	NetKoin	1030	EagleX	1130	Flit Token
831	HeartBout	931	REBL	1031	Asura Coin	1131	MoX
832	Atonomi	932	Vivid Coin	1032	Castle	1132	LiteCoin Ultra
833	SwiftCash	933	EveriToken	1033	Tourist Token	1133	Qbic
834	PDATA	934	UChain	1034	Gexan	1134	PAWS Fund
835	Artis Turba	935	Bitsum	1035	UOS Network	1135	Bitvolt
836	Rentberry	936	Cheesecoin	1036	Authorship	1136	Cannation
837	Plus-Coin	937	APR Coin	1037	WITChain	1137	BROTHER
838	Bitcoin Token	938	Soverain	1038	Netrum	1138	Silverway
839	ProxyNode	939	HyperQuant	1039	Eva Cash	1139	Staker
840	Signals Network	940	Bitcoin Zero	1040	YoloCash	1140	Cointorox
841	Giant	941	Narrative	1041	Cyber Movie Chain	1141	Secrets of Zurich
842	RoBET	942	HOLD	1042	TRAXIA	1142	Zoomba
843	XDNA	943	Italo	1043	Beacon	1143	Orbis Token
844	TENA	944	Gossip Coin	1044	KWHCoin	1144	Dinero
845	EtherGem	945	BLAST	1045	InterCrone	1145	Helpico
846	Vanta Network	946	ZeusNetwork	1046	ALAX	1146	X12 Coin
847	Linfinity	947	Japan Content Token	1047	Phonecoin	1147	Concoin
848	StrongHands Masternode	948	HYPNOXYS	1048	GINcoin	1148	LitecoinToken
849	Voise	949	Biotron	1049	Spectrum	1149	Xchange
850	Kalkulus	950	UNICORN Token	1050	Octoin Coin	1150	iBank
851	CryptoSoul	951	BUDDY	1051	Save Environment Token	1151	Benz
852	WOLLO	952	Guider	1052	Magic Cube Coin	1152	Abulaba
853	Cashpayz Token	953	InternationalCryptoX	1053	AceD	1153	Dystem
854	InterValue	954	InvestFeed	1054	CustomContractNetwork	1154	Storeum
855	WIZBL	955	BitStash	1055	ConnectJob	1155	QYNO
856	Ethereum Gold Project	956	IOTW	1056	Stakinglab	1156	Coin-999
857	Asgard	957	Stipend	1057	wys Token	1157	Posscoin
858	VULCANO	958	CyberMusic	1058	Bulleon	1158	LRM Coin
859	Wavesbet	959	Herbalist Token	1059	GoPower	1159	Elliot Coin
860	HeroNode	960	Thingschain	1060	SONDER	1160	UltraNote Coin
861	Gentarium	961	Arion	1061	Provoco Token	1161	Newton Coin Project
862	Webcoin	962	WABnetwork	1062	Cryptrust	1162	HarmonyCoin
863	SignatureChain	963	EZOOW	1063	Atheios	1163	TerraKRW
864	Bitcoin Fast	964	Arepacoin	1064	ArbitrageCT	1164	Bitpanda Ecosystem Token
865	Fiii	965	Waletoken	1065	INDINODE	1165	EmberCoin
866	CrowdWiz	966	Datarius Credit	1066	TokenDesk		
867	Fox Trading	967	TrustNote	1067	EnterCoin		
868	Verify	968	Data Transaction Token	1068	P2P Global Network		
869	Klimatas	969	CYBR Token	1069	FidexToken		
870	PRASM	970	FantasyGold	1070	ICOBID		
871	MODEL-X-coin	971	IGToken	1071	Fantasy Sports		
872	Menlo One	972	Coinchase Token	1072	Simmitri		
873	Arionum	973	Micromines	1073	CryptoFlow		
874	BlockCAT	974	Exosis	1074	JavaScript Token		
875	Version	975	SteepCoin	1075	ARAW		
876	KAASO	976	TOKYO	1076	EthereumX		
877	CyberFM	977	Galilel	1077	FUTURAX		
878	Ethersocial	978	MesChain	1078	Nyerium		
879	Neutral Dollar	979	Bitcoiin	1079	Natmin Pure Escrow		
880	Paymon	980	PRiVCY	1080	BitMoney		
881	Taklimakan Network	981	CFun	1081	Quantis Network		
882	HashNet BitEco	982	Zealium	1082	onLEXpa		
883	Netko	983	Connect Coin	1083	Akroma		
884	ZINC	984	GoHelpFund	1084	Carebit		
885	Asian Dragon	985	xEURO	1085	TravelNote		
886	IFX24	986	BitStation	1086	CCUniverse		
887	KanadeCoin	987	Italian Lira	1087	Alpha Coin		
888	Elementeum	988	Iungo	1088	TrueVett		
889	LALA World	989	MESG	1089	Couchain		
890	SiaCashCoin	990	Parkgene	1090	Absolute		
891	CYCLEAN	991	BitNautic Token	1091	MASTERNET		
892	Bitether	992	SCRIV NETWORK	1092	Luna Coin		
893	INMAX	993	FundRequest	1093	BitGuild PLAT		
894	Thore Cash	994	JSECOIN	1094	XOVBank		
895	Guaranteed Ethurance Token Extra	995	AirWire	1095	Peerguess		
896	Niobio Cash	996	Kabberry Coin	1096	EVOS		
897	Social Activity Token	997	Digiwage	1097	Eurocoin		
898	Iridium	998	Ether Kingdoms Token	1098	ICOCalendar.Today		
899	SF Capital	999	BitRewards	1099	Dragon Option		
900	Elysian	1000	BitcoiNote	1100	Crowdholding		

Table A4. Names of the 838 old coins: coins 1–420.

1	Bitcoin	106	DeviantCoin	211	Peercoin	316	Insights Network
2	Ethereum	107	Storj	212	Namecoin	317	Sentinel
3	Tether	108	Polymath	213	Quark	318	Aeron
4	XRP	109	Fusion	214	MOAC	319	ChatCoin
5	Bitcoin Cash	110	Waltonchain	215	Quantum Resistant Ledger	320	Red Pulse Phoenix
6	Litecoin	111	PIVX	216	Stakenet	321	Blockmason Credit Protocol
7	Binance Coin	112	Cortex	217	Steem Dollars	322	Hydro Protocol
8	EOS	113	Storm	218	Kcash	323	Tidex Token
9	Cardano	114	FunFair	219	United Traders Token	324	Litecoin Cash
10	Tezos	115	Enigma	220	All Sports	325	Refereum
11	Chainlink	116	CasinoCoin	221	EDUCare	326	Counterparty
12	Stellar	117	Dent	222	CargoX	327	MintCoin
13	Monero	118	XinFin Network	223	Genesis Vision	328	MediShares
14	TRON	119	Hellenic Coin	224	BnkToTheFuture	329	Incent
15	Huobi Token	120	TrueChain	225	Neumark	330	PolySwarm
16	Ethereum Classic	121	Loom Network	226	SIRIN LABS Token	331	Nucleus Vision
17	Neo	122	Metal	227	Tokenomy	332	Blackmoon
18	Dash	123	Acute Angle Cloud	228	TE-FOOD	333	NAGA
19	IOTA	124	Civic	229	ALQO	334	Lamden
20	Maker	125	Syscoin	230	PressOne	335	Global Cryptocurrency
21	Zcash	126	Aidos Kuneen	231	Mithril	336	Lympo
22	NEM	127	Dynamic Trading Rights	232	Ambrosus	337	Spectrecoin
23	Ontology	128	Populous	233	Dero	338	Penta
24	Basic Attention Token	129	Nebulas	234	Everex	339	Emercoin
25	Dogecoin	130	Ignis	235	SALT	340	Feathercoin
26	Synthetix Network Token	131	OriginTrail	236	Lightning Bitcoin	341	BOScoin
27	DigiByte	132	CRYPTO20	237	UnlimitedIP	342	Lunyr
28	0x	133	Gas	238	Molecular Future	343	Switcheo
29	Kyber Network	134	Groestlcoin	239	Wings	344	ColossusXT
30	OMG Network	135	SingularityNET	240	Pillar	345	NaPoleonX
31	Zilliqa	136	Uquid Coin	241	Ruff	346	BitGreen
32	THETA	137	Tierion	242	WePower	347	Blockport
33	BitBay	138	Vertcoin	243	U Network	348	DeepBrain Chain
34	Augur	139	Obyte	244	Revain	349	LinkEye
35	Decred	140	Melon	245	High Performance Blockchain	350	BitTube
36	ICON	141	Factom	246	INT Chain	351	Hydro
37	Aave	142	Dragon Coins	247	Ergo	352	Boolberry
38	Qtum	143	Cindicator	248	Wagerr	353	Mobius
39	Nano	144	Request	249	Metrix Coin	354	Skrumble Network
40	Siacoin	145	Envion	250	YOYOW	355	Odyssey
41	Lisk	146	Nexus	251	Blox	356	Myriad
42	Bitcoin Gold	147	Telcoin	252	SmartMesh	357	PotCoin
43	Enjin Coin	148	Voyager Token	253	Gulden	358	FintruX Network
44	Ravencoin	149	Utrust	254	ECC	359	Cube
45	TrueUSD	150	LBRY Credits	255	HTMLCOIN	360	Apex
46	Verge	151	Einsteinium	256	BABB	361	carVertical
47	Waves	152	Unobtanium	257	Viacoin	362	Paypex
48	MonaCoin	153	Quantstamp	258	Dock	363	YEE
49	Bitcoin Diamond	154	QASH	259	district0x	364	CanYaCoin
50	Advanced Internet Blocks	155	Tael	260	TokenClub	365	BlackCoin
51	Ren	156	Bread	261	AppCoins	366	Radium
52	Nexo	157	Nxt	262	Polybius	367	Loopring [NEO]
53	Loopring	158	Raiden Network Token	263	Ubiq	368	OKCash
54	Holo	159	Arcblock	264	doc.com Token	369	Cryptopay
55	SwissBorg	160	B2BX	265	Peculium	370	GridCoin
56	Cryptonex	161	Spectre.ai Dividend Token	266	SmartCash	371	Scry.info
57	IOST	162	Electra	267	OneRoot Network	372	Pluton
58	Status	163	MediBloc	268	GameCredits	373	AI Doctor
59	Komodo	164	NavCoin	269	Dentacoin	374	Crown
60	Mixin	165	PeepCoin	270	LockTrip	375	TokenPay
61	Steem	166	Haven Protocol	271	FLO	376	Change
62	MCO	167	AdEx	272	GET Protocol	377	bitUSD
63	Bytom	168	Asch	273	SwftCoin	378	Bloom
64	KuCoin Shares	169	RChain	274	bitCNY	379	Ixcoin
65	Centrality	170	Burst	275	SyncFab	380	Sumokoin
66	Horizen	171	Aeon	276	Universa	381	Unikoin Gold
67	WAX	172	Safex Token	277	Cashaa	382	Curecoin
68	BitShares	173	CyberMiles	278	Genaro Network	383	DAOBet
69	Numeraire	174	Time New Bank	279	DAOstack	384	WeOwn
70	Electroneum	175	ShipChain	280	Bitcoin Atom	385	Chrono.tech
71	Decentraland	176	Bibox Token	281	POA	386	THEKEY
72	Bancor	177	DMarket	282	Matrix AI Network	387	Mysterium
73	aelf	178	IoT Chain	283	QLC Chain	388	Stealth
74	Golem	179	Neblio	284	BLOCKv	389	Restart Energy MWAT
75	Ardor	180	SaluS	285	SONM	390	AMLT
76	Stratis	181	Moeda Loyalty Points	286	Etherparty	391	VeriCoin
77	HyperCash	182	Skycoin	287	Jibrel Network	392	ZClassic
78	iExec RLC	183	Santiment Network Token	288	Auctus	393	Denarius
79	MaidSafeCoin	184	DigixDAO	289	ZrCoin	394	Primas
80	ERC20	185	FirstBlood	290	Covesting	395	Bean Cash
81	Aion	186	Kin	291	Agrello	396	Banca

Table A4. *Cont.*

82	Aeternity	187	LATOKEN	292	OAX	397	DAEX
83	Zcoin	188	Bezant	293	Presearch	398	CoinPoker
84	WhiteCoin	189	Veritaseum	294	Hi Mutual Society	399	PayBX
85	CyberVein	190	Metaverse ETP	295	Morpheus Labs	400	Peerplays
86	Bytecoin	191	Propy	296	Etheroll	401	I/O Coin
87	Power Ledger	192	Gifto	297	VIBE	402	Bismuth
88	WaykiChain	193	AirSwap	298	Measurable Data Token	403	e-Gulden
89	Aragon	194	Mooncoin	299	Selfkey	404	Remme
90	NULS	195	Bluzelle	300	DigitalNote	405	Diamond
91	Streamr	196	Blocknet	301	Hiveterminal Token	406	SpaceChain
92	ReddCoin	197	Achain	302	SunContract	407	ATC Coin
93	Ripio Credit Network	198	ODEM	303	TrueFlip	408	indaHash
94	Crypterium	199	OST	304	Edge	409	Clams
95	Dragonchain	200	Polis	305	Viberate	410	ATLANT
96	GXChain	201	SingularDTV	306	Everus	411	Rise
97	Ark	202	Monolith	307	Bitcore	412	Pascal
98	Pundi X	203	Credits	308	Xaurum	413	Rubycoin
99	Insolar	204	EDC Blockchain	309	Monetha	414	COS
100	PRIZM	205	Po.et	310	Phore	415	GoldMint
101	Gnosis	206	TenX	311	QunQun	416	Substratum
102	TomoChain	207	Game.com	312	DATA	417	Swarm
103	Eidoo	208	TaaS	313	Tripio	418	NewYorkCoin
104	Elastos	209	Particl	314	Credo	419	Adshares
105	Wanchain	210	Monero Classic	315	Flash	420	Flixxo

Table A5. Names of the 838 old coins: coins 421–838.

421	Bottos	526	DECENT	631	Dether	736	BERNcash
422	CommerceBlock	527	ION	632	Primalbase Token	737	VoteCoin
423	Dynamic	528	Waves Community Token	633	PiplCoin	738	Aricoin
424	AquariusCoin	529	Playkey	634	Bitcloud	739	GuccioneCoin
425	IHT Real Estate Protocol	530	Sentient Coin	635	Ties.DB	740	Zurcoin
426	Dinastycoin	531	Karbo	636	bitEUR	741	PureVidz
427	CPChain	532	Internet of People	637	Indorse Token	742	Adzcoin
428	Nexty	533	Neutron	638	Energo	743	ELTCOIN
429	Aventus	534	Minereum	639	RealChain	744	SmartCoin
430	Sharder	535	Ink Protocol	640	Tokenbox	745	Bela
431	HalalChain	536	CryCash	641	Chronologic	746	EDRCoin
432	BANKEX	537	BUZZCoin	642	Limitless VIP	747	Blocklancer
433	42-coin	538	SIBCoin	643	Maxcoin	748	MarteXcoin
434	Pandacoin	539	DecentBet	644	Emerald Crypto	749	SparksPay
435	Omni	540	TraDove B2BCoin	645	Lampix	750	PayCoin
436	NuBits	541	AllSafe	646	PutinCoin	751	ClearPoll
437	Primecoin	542	XEL	647	AdHive	752	Ellaism
438	Ormeus Coin	543	AudioCoin	648	Pesetacoin	753	Digital Money Bits
439	MonetaryUnit	544	Pirl	649	Dropil	754	Acoin
440	Hush	545	Trinity Network Credit	650	Emphy	755	Theresa May Coin
441	Medicalchain	546	ProChain	651	KZ Cash	756	BTCtalkcoin
442	Hubii Network	547	Sentinel Chain	652	BitBar	757	GeyserCoin
443	Datum	548	Zeepin	653	BitSend	758	Nitro
444	Humaniq	549	GlobalBoost-Y	654	LEOcoin	759	Citadel
445	Lendingblock	550	The ChampCoin	655	Bonpay	760	YENTEN
446	KickToken	551	Zap	656	ACE (TokenStars)	761	STRAKS
447	PAC Global	552	Trollcoin	657	Gems	762	MojoCoin
448	EXRNchain	553	Datawallet	658	Bata	763	Blakecoin
449	PetroDollar	554	Espers	659	Rupee	764	Coin2.1
450	Nework	555	BitDegree	660	Adelphoi	765	Elementrem
451	NativeCoin	556	Qbao	661	PWR Coin	766	MedicCoin
452	Zero	557	OBITS	662	Carboncoin	767	ICO OpenLedger
453	SoMee.Social	558	Patientory	663	Unify	768	GoldBlocks
454	ToaCoin	559	Freicoin	664	InsaneCoin	769	FuzzBalls
455	SolarCoin	560	DATx	665	Bitradio	770	Titcoin
456	GeoCoin	561	adToken	666	Energycoin	771	Jupiter
457	Upfiring	562	Starbase	667	Profile Utility Token	772	Dreamcoin
458	Cappasity	563	HEROcoin	668	Digitalcoin	773	NevaCoin
459	DeepOnion	564	HOQU	669	TrumpCoin	774	Ratecoin
460	Edgeless	565	LIFE	670	Aditus	775	ParkByte
461	eosDAC	566	Electrify.Asia	671	Bitcoin Interest	776	Dalecoin
462	Snovian.Space	567	HempCoin	672	Cobinhood	777	Spectiv
463	NoLimitCoin	568	ExclusiveCoin	673	Litecoin Plus	778	Datacoin
464	Matryx	569	Zilla	674	Elcoin	779	BoostCoin
465	CloakCoin	570	Memetic / PepeCoin	675	Photon	780	Open Trading Network
466	Terracoin	571	Solaris	676	Lethean	781	Desire
467	SpankChain	572	VouchForMe	677	Zetacoin	782	X-Coin
468	Bitswift	573	Friendz	678	Synergy	783	PostCoin
469	Experty	574	Zeitcoin	679	Kobocoin	784	Galactrum
470	iEthereum	575	Swarm City	680	MicroMoney	785	bitJob

Table A5. *Cont.*

471	PayPie	576	LanaCoin	681	Global Currency Reserve	786	Ccore
472	SHIELD	577	Sociall	682	Eroscoin	787	Quebecoin
473	UNIVERSAL CASH	578	EverGreenCoin	683	Capricoin	788	BriaCoin
474	CannabisCoin	579	IDEX Membership	684	MktCoin	789	SpreadCoin
475	NuShares	580	Zeusshield	685	PoSW Coin	790	Centurion
476	DomRaider	581	DopeCoin	686	Cryptonite	791	Zayedcoin
477	Neurotoken	582	FujiCoin	687	Opal	792	Independent Money System
478	STK	583	EncryptoTel [WAVES]	688	SounDAC	793	ARbit
479	Delphy	584	KekCoin	689	Universe	794	Litecred
480	Sphere	585	IXT	690	CDX Network	795	Nekonium
481	MobileGo	586	CoinFi	691	Paragon	796	Rupaya
482	Pinkcoin	587	VeriumReserve	692	Bitstar	797	Bitcoin 21
483	Zebi Token	588	Motocoin	693	ATBCoin	798	Californium
484	Infinitecoin	589	Ignition	694	Kurrent	799	Comet
485	LUXCoin	590	FedoraCoin	695	Deutsche eMark	800	Phantomx
486	Manna	591	FlypMe	696	Suretly	801	AmsterdamCoin
487	BitCrystals	592	JET8	697	bitBTC	802	High Voltage
488	HEAT	593	CaixaPay	698	Rimbit	803	MustangCoin
489	Internxt	594	Ultimate Secure Cash	699	GCN Coin	804	Dollar International
490	Pylon Network	595	Pakcoin	700	BlueCoin	805	Dollarcoin
491	Dovu	596	Devery	701	FirstCoin	806	CrevaCoin
492	BitcoinZ	597	Bitzeny	702	Evil Coin	807	BowsCoin
493	StrongHands	598	Swing	703	ParallelCoin	808	Coinonat
494	Dimecoin	599	MinexCoin	704	BitWhite	809	DNotes
495	WeTrust	600	Masari	705	Autonio	810	LiteBitcoin
496	Bitcoin Plus	601	EventChain	706	TransferCoin	811	BitCoal
497	adbank	602	Bounty0x	707	TajCoin	812	SONO
498	EchoLink	603	NANJCOIN	708	2GIVE	813	SpeedCash
499	ATN	604	DIMCOIN	709	Golos	814	PlatinumBAR
500	Megacoin	605	Monkey Project	710	GlobalToken	815	Experience Points
501	Auroracoin	606	Veros	711	TagCoin	816	HollyWoodCoin
502	EncrypGen	607	Maverick Chain	712	SkinCoin	817	Prime-XI
503	Phoenixcoin	608	GoByte	713	Anoncoin	818	Cabbage
504	FuzeX	609	HelloGold	714	DraftCoin	819	BenjiRolls
505	Ink	610	GravityCoin	715	Cryptojacks	820	PosEx
506	PHI Token	611	Goldcoin	716	vSlice	821	Wild Beast Block
507	Bitcoin Private	612	Jetcoin	717	Bitcoin Red	822	Iconic
508	AICHAIN	613	MyWish	718	Advanced Technology Coin	823	PLNcoin
509	Scala	614	Crowd Machine	719	SuperCoin	824	SocialCoin
510	Stox	615	Startcoin	720	XGOX	825	SportyCo
511	Maecenas	616	LiteDoge	721	Blocktix	826	Project-X
512	Bulwark	617	Bezop	722	Worldcore	827	PonziCoin
513	SmileyCoin	618	InvestDigital	723	More Coin	828	Save and Gain
514	OracleChain	619	Bolivarcoin	724	iTicoin	829	Argus
515	AidCoin	620	Graft	725	Garlicoin	830	SongCoin
516	eBitcoin	621	MyBit	726	InflationCoin	831	CoinMeet
517	BiblePay	622	Equal	727	SophiaTX	832	Agoras Tokens
518	Shift	623	Privatix	728	SelfSell	833	Sexcoin
519	Orbitcoin	624	Matchpool	729	ChessCoin	834	RabbitCoin
520	Novacoin	625	eBoost	730	Eternity	835	Quotient
521	Expanse	626	Utrum	731	Moin	836	Bubble
522	CVCoin	627	imbrex	732	PopularCoin	837	Axiom
523	Blue Protocol	628	Yocoin	733	Payfair	838	Francs
524	TrezarCoin	629	BoutsPro	734	Rubies		
525	HiCoin	630	CryptoCarbon	735	bitGold		

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