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Crypto-Coins and Credit Risk: Modelling and Forecasting Their Probability of Death

Dean Fantazzini

Moscow School of Economics, Moscow State University, Leninskie Gory, 1, Building 61, 119992 Moscow, Russia; fantazzini@mse-msu.ru; Tel.: +7-4955105267; Fax: +7-4955105256

Abstract: This paper examined a set of over two thousand crypto-coins observed between 2015 and 2020 to estimate their credit risk by computing their probability of death. We employed different definitions of dead coins, ranging from academic literature to professional practice; alternative forecasting models, ranging from credit scoring models to machine learning and time-series-based models; and different forecasting horizons. We found that the choice of the coin-death definition affected the set of the best forecasting models to compute the probability of death. However, this choice was not critical, and the best models turned out to be the same in most cases. In general, we found that the *cauchit* and the zero-price-probability (ZPP) based on the random walk or the Markov Switching-GARCH(1,1) were the best models for newly established coins, whereas credit-scoring models and machine-learning methods using lagged trading volumes and online searches were better choices for older coins. These results also held after a set of robustness checks that considered different time samples and the coins' market capitalization.

Keywords: bitcoin; crypto-assets; crypto-currencies; credit risk; default probability; probability of death; ZPP; cauchit; logit; probit; random forests; google trends

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

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1. Introduction

Crypto-asset research has become a hot topic in the field of finance: for example (and to name just a few), Antonopoulos (2014) describes the technical foundations of bitcoin and other cryptographic currencies, from cryptography basics, such as keys and addresses, to the data structures, network protocols and the consensus mechanism, while Narayanan et al. (2016) provides a comprehensive introduction to digital currencies. Burniske and Tatar (2018) discuss a general framework for investigating and valuing cryptoassets, Brummer (2019) focuses on the legal, regulatory, and monetary issues of the whole crypto ecosystem, Fantazzini (2019) discusses, in detail, the instruments needed to analyze cryptocurrencies markets and prices, while Schar and Berentsen (2020) provides a general introduction to cryptocurrencies and blockchain technology for practitioners and students.

The increasing number of traded crypto-assets[1] and the repeated cases of hacks, scams, and projects' failures has made the topic of crypto-asset risk a compelling issue; see Fantazzini and Zimin (2020), and references therein. A cryptocurrency does not have debt and it cannot default in a classical sense[2], but its price can crash quickly due to a hack, a scam, or other problems that can make its further development no longer viable. Fantazzini and Zimin (2020) showed that this kind of risk is not a market one and proposed a new definition of credit risk for crypto-coins based on their "*death*", that is, a situation when their price drops significantly and a coin becomes illiquid.

We remark that there is not a unique definition for a dead coin, neither in the professional literature[3] nor in the academic literature, see Feder et al. (2018), Grobys and Sapkota (2020) and Schmitz and Hoffmann (2020). Moreover, even when a coin is considered dead, it may still show some minimal trading volumes, either due to the possibility to recover a small amount of the initial investment, or simply to bet on its possible revamp. In this regard, a coin can be easily revamped by writing new code or simply by updating the previous old code, thus involving much less time and resources than traditional bankrupt firms; see Sid (2018), for an example. Therefore, the "death" state for a coin may be only a temporary state rather than a permanent one.

Despite the presence of thousands of dead coins and a yearly increase in 2021 of more than 30% (Soni (2021)), this topic has been barely examined in the academic literature. Feder et al. (2018) were the first to propose a formal definition of dead coin, while Schmitz and Hoffmann (2020) suggested some simplified procedures to identify a dead coin for portfolio management. Fantazzini and Zimin (2020) and Grobys and Sapkota (2020) were the first (and so far only) to propose models to predict crypto-currency defaults/deaths[4].

This paper aims to forecast the probability of death of a crypto-coin using different definitions of dead coins, ranging from the academic literature to professional practice, and different forecasting horizons. To reach the paper's objective, we first employed a set of models to forecast the probability of death, including credit-scoring models, machine-learning models, and time-series methods based on the zero-price-probability (ZPP) model by Fantazzini et al. (2008), which is a methodology to compute the probabilities of default using only market prices. Recent papers by Su and Huang (2010), Li et al. (2016), Dalla Valle et al. (2016), and Fantazzini and Zimin (2020) showed that ZPP models often outperform the competing models in terms of default probability estimation.

The second contribution of this paper is a forecasting exercise using a unique set of 2003 crypto-coins that were active from the beginning of 2014 till the end of May of 2020. Our results show that the choice of the coin-death definition can significantly affect the set of the best forecasting models to compute the probability of death. However, this choice is not critical, and the best models turned out to be the same in most cases. In general, we found that the cauchit and the zero-price-probability (ZPP) based on the random walk or the Markov Switching-GARCH(1,1) were the best models for newly established coins, whereas credit-scoring models and machine-learning methods using trading volumes and online searches are better choices for older coins.

The third contribution of the paper is a set of robustness checks to verify that our results also hold when considering different time samples and the coins' market capitalization.

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

2. Literature Review

The financial literature dealing with the credit risk involved in crypto-coins is very limited and, at the time of writing this paper, only four papers examined the topic of dead coins, while only two of them proposed methods to forecast the probability of a coin death. We remark that, when investing in a crypto-coin, there are two types of credit risks: the possibility that the coin "dies" and the price goes to zero (or close to zero), and the possibility that the exchange closes, taking most of its investors' money with it. We focus here on the first type of risk, while the latter was examined in Fantazzini and Calabrese (2021), who considered a unique 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.

Currently, there is not a unique definition of dead coins, neither in the professional literature, nor in the academic literature: in the professional literature, some define dead coins as those whose value drops below 1 cent [5], yet others stress, on top of that, no trading volume, no nodes running, no active community, and de-listing from (almost) all exchanges[6].

Feder et al. (2018) were the first to propose a formal definition of dead coin in the academic literature: they first define a "candidate peak" as a day in which the seven-day rolling price average is greater than any value 30 days before or after. Moreover, to choose only those peaks with sudden jumps, they define a candidate as a peak only if it is greater than or equal 50% of the minimum value in the 30 days prior to the candidate peak, and if its value is at least 5% as large as the cryptocurrency's maximum peak. Given these peak data, Feder et al. (2018) consider a coin *abandoned (= dead)*, if the daily average volume for a given month is less than or equal to 1% of the peak volume. In addition, if the currency is currently considered dead/abandoned but the average daily trading volume for a month following a peak is greater than 10% of the peak value, then Feder et al. (2018) change the coin status to *resurrected*.

Schmitz and Hoffmann (2020) proposed a simplified version of the previous method by Feder et al. (2018), and they suggested that a crypto-currency can be classified as dead if its average daily trading volume for a given month is lower or equal to 1% of its past historical peak. Instead, a dead crypto-currencyis classified as "resurrected" if this average daily trading volume reaches a value of more or equal to 10% of its past historical peak again[7].

Grobys and Sapkota (2020) and Fantazzini and Zimin (2020) were the first (and so far only) to propose models to predict crypto-currency defaults/deaths. Grobys and Sapkota (2020) examined a dataset of 146 proof-of-work-based cryptocurrencies that started trading before 2015 and followed their performance until December 2018, finding that about 60% of those cryptocurrencies died. They employed a model based on linear discriminant analysis to predict these defaults and found that it could predict most of the crypto-currency bankruptcies, but it struggled to predict functioning crypto-currencies. Predicting well the first category and poorly the second one is a well-known problem when using binary classification models. For this reason, model selection is usually based on loss functions such as the Brier (1950) score or the area under the receiver operating characteristic curve (AUC or AUROC) proposed by Metz (1978), Metz and Kronman (1980), and Hanley and McNeil (1982), instead of using the forecasting accuracy for each binary class[8]. Another problematic issue with the analysis performed in Grobys and Sapkota (2020) is the need to use several coin-specific variable candidates that might serve as predictor variables: unfortunately, this kind of information is not available for most dead coins, and Grobys and Sapkota (2020) had to discard several variables to obtain a meaningful dataset. Moreover, considering the large number of scams and frauds regularly taking place among crypto-assets, it is not advisable to take publicly available coin information at face value becasue it may be false. In addition, Grobys and Sapkota (2020) only performed an in-sample forecasting analysis, and they did not predict crypto-currencies that were not used to estimate their model. Unfortunately, there may be major differences between in-sample and out-of-sample forecasting performances, see Hastie et al. (2009), Giudici and Figini (2009) and Hyndman and Athanasopoulos (2018) for a discussion at the textbook level.

Fantazzini and Zimin (2020) 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 by Fantazzini et al. (2008), which is a methodology to compute the probabilities of default using only market prices, as well as credit-scoring models and machine-learning methods. Their empirical analysis showed that classical credit-scoring models performed better in the training sample, whereas the models' performances were much closer in the validation sample[9], with the simple ZPP computed using a random walk with drift performing remarkably well. The main limitation of the analysis performed by Fantazzini and Zimin (2020) is the very low number of coins used for backtesting (only 42), which can strongly limit the significance of their empirical evidence.

The past literature and professional practice highlighted that the dead coins collected in well-known online repositories such as *coinopsy.com* or *deadcoins.com* are indeed dead, but this fact represents (paradoxically) a problem. Unfortunately, the information set for the vast majority of these coins does not exist anymore because their technical information and historical market data are no longer available. In simple terms, when a coin name is inserted in these repositories, it is too late to gain any valuable information for credit risk modelling and forecasting. It is for this reason that Grobys and Sapkota (2020) and

Fantazzini and Zimin (2020) were forced to use small coin datasets in their analyses and to employ a limited set of variables to forecast these dead coins. Therefore, it makes more sense to employ the methods proposed by Feder et al. (2018) and Schmitz and Hoffmann (2020) to detect dead coins, or the simple professional rule that defines a coin as dead if its value drops below 1 cent. Even though there is still some marginal trading for the coins defined as dead according to these rules, this is not a problem but an advantage, because we can analyze them before they go into permanent (digital) oblivion.

Another issue that emerged from the literature review is the need to use indicators and methods that are robust to potential frauds and scams. As highlighted by Fantazzini and Zimin (2020), the lack of financial oversight for several crypto-based companies and exchanges means that coins' prices can be subject to manipulations, pump-and-dump schemes and market frauds of various types, see Gandal et al. (2018), Wei (2018), Griffin and Shams (2020), Hamrick et al. (2021), and Gandal et al. (2021) for more details about this unlawful conduct.

3. Materials And Methods

We consider three approaches to forecast the probability of death of a large set of crypto-coins: credit-scoring models, machine learning, and time-series methods. A review of the (large) literature on credit-scoring models can be found in Baesens and Van Gestel (2009) and Joseph (2013), while for machine-learning methods in finance we refer to James et al. (2013), De Prado (2018) and Dixon et al. (2020). Time-series methods based on market prices to compute the probability of default of quoted stocks and small and medium enterprises (SMEs) are discussed in Fantazzini et al. (2008), Su and Huang (2010), Li et al. (2016), Dalla Valle et al. (2016), and Jing et al. (2021), while their use with crypto-coins is explored in Fantazzini (2019) and Fantazzini and Zimin (2020).

We first briefly review the main aspects of credit risk for cryptocurrencies. Secondly, we discuss a set of credit-scoring and machine-learning models that will be used in the empirical analysis. Then, time-series methods based on the ZPP originally proposed by Fantazzini et al. (2008), as well as new variants, are presented. Thirdly, we review several metrics to evaluate the estimated death probabilities. Finally, we also present the data used in our empirical analysis.

3.1. Credit Risk for Crypto-Coins

In traditional finance, *credit risk* is defined as the gains and losses on a position or portfolio associated with the fulfillment (or not) of contractual obligations, while *market risk* is the gains and losses on the value of a position or portfolio that can take place due to the movements in market prices (such as exchange rates, commodity prices, interest rates, etc.), see Basel Committee on Banking Supervision (2009), Hartmann (2010) and references therein for more details. However, the Basel Committee on Banking Supervision (2009) highlighted that "*the securitization trend in the last decade has diminished the scope for differences in measuring market and credit risk, as securitization transforms the latter into the former*" (Basel Committee on Banking Supervision (2009), p. 14). In addition, a large amount of literature showed that market and credit risk are driven by the same economic factors; see the special issue on the interaction of market and credit risk in the *Journal of Banking and Finance* in 2010 for more details.

Fantazzini and Zimin (2020) highlighted that the separation between market and credit risk becomes even more blurred when dealing with crypto-currencies than in traditional finance. In simple terms, the credit risk for a crypto-coin is its "death", a situation when its price falls significantly and a coin becomes illiquid. More formally, Fantazzini and Zimin (2020) define the "*credit risk for cryptocurrencies as the gains and losses on the value of a position of a cryptocurrency that is abandoned and considered dead according to professional and/or academic criteria, but which can be potentially revived and revamped*".

Therefore, it follows that the differences between credit and market risk for crypto-currencies are of quantitative and temporal nature, not qualitative because, if the financial losses and the technical problems are small, then we have a market event whereas, if the financial losses are too big and the technical problems cannot be solved, then we have a credit event and the crypto-currency"dies" (Fantazzini and Zimin (2020)). In addition, the longer the time horizon is, the more probable are large losses and/or technical problems, so credit risk becomes more important [10]. Once a credit event takes place, the development of the crypto-coin stops, and its price falls close to zero, or even to zero (if the lack of trading for several days or weeks is considered evidence of a zero price). However, trading may continue afterward for the reasons discussed in the introduction, that is, for the possibility to recover a small amount of the initial investment, or simply to bet on its possible revamp.

More specifically, we employed three competing criteria to classify a coin as dead or alive in our work:

- The approach by Feder et al. (2018): first, a "candidate peak" is defined as a day in which the 7-day rolling price average is greater than any value 30 days before or after. Moreover, to choose only those peaks with sudden jumps, a candidate is defined as a peak only if it is greater than or equal 50% of the minimum value in the 30 days prior to the candidate peak, and if its value is at least 5% as large as the cryptocurrency's maximum peak. Given these peak data, Feder et al. (2018) consider a coin *abandoned (= dead)*, if the daily average volume for a given month is less than or equal to 1% of the peak volume. In addition, if the average daily trading volume for a month following a peak is greater than 10% of the peak value and that currency is currently abandoned, then Feder et al. (2018) change the coin status to *resurrected*.
- The simplified Feder et al. (2018) approach proposed by Schmitz and Hoffmann (2020): a crypto-currency can be classified as dead if its average daily trading volume for a given month is lower or equal to 1% of its past historical peak. Instead, a 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.
- The professional rule that defines a coin dead if its value drops below 1 cent, and alive if its value rises above 1 cent.

3.2. Credit-Scoring Models and Machine Learning

Scoring models merge different variables into a quantitative score, which can be either interpreted as a probability of default (PD), or used as a classification system, depending on the model used. In the former case, and considering our framework, a scoring model has the following form:

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

where $PD_{i,t+T}$ is the probability of death for coin i over a period of time $t+T$, given that it is alive at the time t, and $\mathbf{X}_{i,t}$ is a vector of regressors. If we use the *logit* model, or the *probit* model, or the *cauchit* model, $F(\beta' \mathbf{X}_{i,t})$ is given by the logistic, standard normal, standard Cauchy, respectively, cumulative distribution function,

$$\begin{aligned} F_{Logit}(\beta' \mathbf{X}_{i,t}) &= \frac{1}{1+e^{-(\beta' \mathbf{X}_{i,t})}} \\ F_{Probit}(\beta' \mathbf{X}_{i,t}) &= \Phi(\beta' \mathbf{X}_{i,t}) = \int_{-\infty}^{(\beta' \mathbf{X}_{i,t})} \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}z^2} dz \\ F_{Cauchit}(\beta' \mathbf{X}_{i,t}) &= \frac{1}{\pi}\left[\tan^{-1}(\beta' \mathbf{X}_{i,t}) + \frac{\pi}{2}\right] \end{aligned} \tag{1}$$

The maximum likelihood method is usually used to estimate the parameters vector β in the Equation (1), see McCullagh and Nelder (1989) for more details.

The logit and probit models are the widely used benchmarks for credit-risk management, see Fuertes and Kalotychou (2006), Rodriguez and Rodriguez (2006), Fantazzini and Figini (2008), Fantazzini and Figini (2009), and references therein. The Cauchy distribution has heavier tails than the normal and logistic distributions, thus allowing more extreme values. As discussed in detail by Koenker and Yoon (2009), the cauchit model can be used to model binary responses when observations occur for which the linear predictor is large in absolute value, indicating that the outcome is rather certain but the outcome is different. The cauchit model is more forgiving of these "outliers" than the logit or probit models. In addition, Gündüz and Fokoué (2017) shed some light on the theoretical reasons that explain the similar performance of four binary models (logit, probit, cauchit, and complementary log-log) in univariate settings. However, their simulation studies highlighted that the performance of the four models in high-dimensional spaces tends to depend on the internal structure of the input, with the cauchit being the model of choice under a high level of sparseness of the input space.

Machine learning (ML) deals with the development of systems able to recognize complex patterns and make correct choices using a dataset already analyzed. Among the many methods available, we will use the *random forest* algorithm proposed by Ho (1995) and Breiman (2001), given its excellent past performances in forecasting binary variables, see Hastie et al. (2009), Barboza et al. (2017), Moscatelli et al. (2020), and Fantazzini and Calabrese (2021) for more details. A random forest is an ensemble method consisting of a large number of decision trees, where a decision tree is similar to a reversed tree diagram with branches and leaves, where a choice is made at each step based on the value of a single variable, or a combination of several variables. In case of a classification problem, each leaf places an object either in one class or the other. A single decision tree can provide a poor classification and suffer from overfitting and model instability. *Random forests* solve these problems by aggregating several decision trees into a so-called "forest", where each tree is obtained by introducing a random component in their construction. More specifically, each decision tree in a forest is built using a bootstrap sample from the original data, where 2/3 of these data are used to build a tree, while the remaining 1/3 is used as a control set which is known as out-of-bag (OOB) data. In addition, m variables out of the original n variables are randomly selected at each node of the tree, and the best split based on these m variables is used to split the node. The random selection of variables at each node decreases the correlation among the trees in the forest, so that the algorithm can deal with redundant variables and avoid model overfitting. Moreover, each tree is grown up to its maximum size and not pruned to maximize its instability, which is neutralized by the high number of trees created to obtain the "forest". We remark that, for a given i-th crypto-coin in the OOB control set, the forecasts are computed using a majority vote, which means that the probability of death is given by the proportion of trees voting for the death of coin i. This procedure is repeated for all observations in the control set, which leads to the computation of the overall OOB classification error.

3.3. Time-Series Methods

The zero price probability (ZPP) was originally introduced in Fantazzini et al. (2008) to compute the probabilities of the default of traded stocks using only market prices P_t. This approach computes the market-implied probability $\mathcal{P}(P_\tau \leq 0)$ with $t < \tau \leq t+T$ using the fact that, for a traded stock (or a traded coin), the price P_τ is a truncated variable that cannot become less than zero. Therefore, the zero price probability is simply the probability that P_τ goes below the truncation level of zero. Fantazzini et al. (2008) discussed, in detail, why the null price can be used as a default barrier.

The general estimation procedure of the ZPP for univariate time series is reported below[11]:

1. Consider a generic conditional model for the differences in price levels $X_t = P_t - P_{t-1}$ without the log-transformation:

$$X_t = \mu_t + \sigma_t z_t, \quad z_t \sim i.i.d\ f(0,1) \tag{2}$$

where μ_t is the conditional mean, σ_t is the conditional standard deviation, while z_t represents the standardized error.

2. Simulate a high number N of price trajectories up to time $t+T$, using the estimated time-series model (2) at step 1. We will compute the 1-day ahead, 30-day ahead, and 365-day ahead probability of death for each coin, that is $T = \{1, 30, 365\}$, respectively.
3. The probability of default/death for a crypto-coin i is simply the ratio n/N, where n is the number of times out of N when the simulated price P_τ^k touched or crossed the zero barrier along the simulated trajectory:

$$PD_{i,t+T} = \frac{1}{N}\sum_{k=1}^{N} \mathbf{1}\left\{P_{\tau,i}^k \leq 0, \quad \text{for some} \quad t < \tau \leq t+T\right\}$$

The previously cited literature dealing with the ZPP showed that the modelling of the conditional standard deviation σ_t and the conditional distribution $f(\cdot)$ are the key elements affecting the estimated probability of default/death. We will consider the simple random walk with drift (where $\sigma_t = \sigma$) and the case where σ_t follows a GARCH(1,1) with normal errors because both of them allow for closed-form solutions for the ZPP, see Fantazzini and Zimin (2020) for details. We will also consider the case where σ_t follows a GARCH(1,1) with Student's t errors, as originally proposed in Fantazzini et al. (2008), and a GARCH(1,1) with errors following the generalized hyperbolic skew-Student distribution proposed by Aas and Haff (2006), which has one tail with polynomial and one with exponential behavior. More recently, Ardia et al. (2019) and Maciel (2021) found that a two-regime Markov-switching GARCH model showed the best in-sample performance when modelling crypto-coin log-returns, and outperformed standard single-regime GARCH models when forecasting the one-day ahead value at risk. Therefore, we will also use this model in our empirical analysis to compute the ZPP for the first time using a Markov-Switching model.

3.4. Model Evaluation

The main tool to compare the forecasting performances of models with binary data is the confusion matrix by Provost and Kohavi (1998), see Table 1.

Table 1. Theoretical confusion matrix. Number of: a true positive, b false positive, c false negative, d true negative.

Observed/Predicted	Dead Coins	Alive
Dead coins	a	b
Alive	c	d

In our specific case, the cells of the confusion matrix have the following meaning: a is the number of correct predictions that a coin is dead, b is the number of incorrect predictions that a coin is dead, c is the number of incorrect predictions that a coin is alive, while d is the number of correct predictions that a coin is alive. The confusion matrix is then used to compute the area under the receiver operating characteristic curve (AUC or AUROC) proposed by Metz (1978), Metz and Kronman (1980), and Hanley and McNeil (1982) for all forecasting models. The ROC curve is created by plotting, for any probability cut-off value between 0 and 1, the proportion of correctly predicted dead coins $a/(a+b)$ on the y axis, also known as sensitivity or hit rate, and the proportion of alive coins predicted as dead coins $c/(c+d)$ on the x axis, also known as false-positive rate or as 1–specificity, where the latter is $d/(d+c)$. The AUC lies between zero and one and the closer it is to one the more accurate the forecasting model is, see Sammut and Webb (2011), pp. 869–75, and references therein for more details.

Despite its widespread use, the AUC also has some limitations, as discussed in detail by Krzanowski and Hand (2009), p. 108. Therefore, we also employed the model confidence set (MCS) proposed by Hansen et al. (2011) and extended by Fantazzini and Maggi (2015) to binary models, to select the best forecasting models among a set of competing models with a specified confidence level. The MCS procedure picks the best forecasting model and computes the probability that the other models are statistically different from the best one using an evaluation rule based on a loss function that, in the case of binary models, is represented by the Brier (1950) score. Briefly, the MCS approach tests, at each iteration, that all models in the set of forecasting models $M = M_0$ have an equal forecasting accuracy using the following null hypothesis for a given confidence level $1 - \alpha$,

$$H_{0,M} = E(d_{ij}) = 0, \quad \forall i, j \in M, \quad vs \quad H_{A,M} = E(d_{ij}) \neq 0$$

where $d_{ij} = L_i - L_j$ is the sample loss differential between forecasting models i and j and L_i stands for the loss function of model i (in our case, the Brier score). If the null hypothesis cannot be rejected, then $\widehat{M}^*_{1-\alpha} = M$. If the null hypothesis is rejected, an elimination rule is used to remove the worst forecasting models from the set M. The procedure is repeated until the null hypothesis cannot be rejected, and the final set of models defines the so-called model-confidence set $\widehat{M}^*_{1-\alpha}$. We will employ the T-max statistic for the equivalence test in the MCS procedure. A brief description of this test is reported below, while we refer to Hansen et al. (2011), for more details. First, the following t-statistics are computed, $t_{i\cdot} = \bar{d}_{i\cdot}/\widehat{var}(\bar{d}_{i\cdot})$, for $i \in M$, where $\bar{d}_{i\cdot} = m^{-1}\sum_{j\in M}\bar{d}_{ij}$ is the simple loss of the ith model relative to the average losses across models in the set M, and $\bar{d}_{ij} = H^{-1}\sum_{h=1}^{H} d_{ij,h}$ measures the sample loss differential between model i and j, and H is the number of forecasts. The T-max statistic is then calculated as $T_{max} = \max_{i\in M}(t_{i\cdot})$. This statistic has a non-standard distribution that is estimated using bootstrapping methods with 1000 replications. If the null hypothesis is rejected, one model is eliminated using the following elimination rule: $e_{max,M} = \arg\max_{i\in M}\left(\bar{d}_{i\cdot}/\widehat{var}(\bar{d}_{i\cdot})\right)$.

3.5. Data

We collected the data examined in this paper using two sources of information:

- https://coinmarketcap.com, accessed on 1 June 2022: CoinMarketCap is the main aggregator of crypto-coin market data, and it has been owned by the crypto-exchange Binance since April 2020, see https://crypto.marketswiki.com/index.php?title=CoinMarketCap, accessed on 1 June 2022. It provides open-high-low-close price data, volume data, market capitalization, and a wide range of additional information.
- Google Trends: the *Search Volume Index* provided by Google Trends shows how many searches have been performed for a keyword or a topic on Google over a specific period and a specific region. See https://support.google.com/trends/?hl=en, (accessed on 1 June 2022) for more details.

The dataset consisted of 2003 crypto-coins that were alive or dead (according to different criteria) between January 2014 and May 2020. When collecting coin data, we noticed the presence of coins with short time series and coins with long time series. Therefore, we decided to separate coins with fewer than 750 observations (*young coins*) from the coins with more than 750 observations (*old coins*): we chose this type of grouping because we used the first set of coins to forecast the 1-day and 30-day ahead probabilities of death, while the second set to forecast the 1-day, 30-day, and 365-day ahead probabilities of death, respectively. The effects of different types of groupings are presented in the robustness checks.

As discussed in detail in Section 3.1, we employed three competing criteria to classify a coin as dead or alive:

- The approach proposed by Feder et al. (2018);
- The approach proposed by Schmitz and Hoffmann (2020);
- The professional rule that defines a coin dead if its value drops below 1 cent, and alive if its value rises above 1 cent.

The total number of "dead days", that is, the total number of days when the coins are deemed as "*dead*" according to the previous criteria, is reported in Table 2, both in absolute value and percentages.

Table 2. Number of dead days (in absolute value and %) for different criteria used to classify a coin as dead or alive.

Young coins					
Feder et al. (2018)		*Simplified Feder et al. (2018)*		*1 cent*	
N. of dead days	*%*	*N. of dead days*	*%*	*N. of dead days*	*%*
53,169	9.89	128,163	23.84	310,707	57.79
Old coins					
Feder et al. (2018)		*Simplified Feder et al. (2018)*		*1 cent*	
N. of dead days	*%*	*N. of dead days*	*%*	*N. of dead days*	*%*
114,790	11.63	428,288	43.39	379,226	38.42

As expected, the Feder et al. (2018) approach is the most restrictive with fewer identified dead coins, while the professional rule that defines a coin dead if its value drops below 1 cent is laxer, allowing for a much larger number of dead coins. The simplified Feder et al. (2018) approach proposed by Schmitz and Hoffmann (2020) stays in the middle between the previous two approaches in the case of young coins, whereas it is the least restrictive in the case of old coins[12].

The total number of coins available each day, and the total number of dead coins each day computed using the previous three criteria and the price and volume data from https://coinmarketcap.com, (accessed on 1 June 2022) are reported in Figure 1. The Feder et al. (2018) approach appears to be more stable than the other two methods, which show much more volatile numbers, instead.

The dataset of young coins ranges between August 2015 and May 2020, while the dataset of old coins ranges between January 2014 and May 2020. Following Fantazzini and Zimin (2020), in the case of young coins, we used the lagged average monthly trading volume and the lagged average monthly search volume index provided by Google Trends as regressors for the logit, probit, cauchit, and random forest models. We computed direct forecasts, so we used the 1-day lagged regressors to forecast the 1-day ahead probability of death, while the 30-day lagged regressors to forecast the 30-day ahead probability of death. In the case of old coins, we also added the lagged average yearly trading volume and the lagged average yearly search volume index, and we used the 365-day lagged regressors to forecast the 365-day ahead probability of death.

The first initialization sample used for the estimation of credit-scoring and ML models was August 2015–December 2018 for the young coins, and January 2014–December 2015 for the old coins. These time samples were chosen so that the first estimation windows had approximately 100.000 observations[13]. In simple terms, all coin data were pooled together up to time t (for example), and the credit-scoring and ML models were then fitted to this dataset and the required forecasted probabilities of deaths were computed. After that, the time window was increased by 1 day, and the previous procedure was repeated. A schematic example of a pooled coin dataset used for credit-scoring and ML models is reported in Table 3.

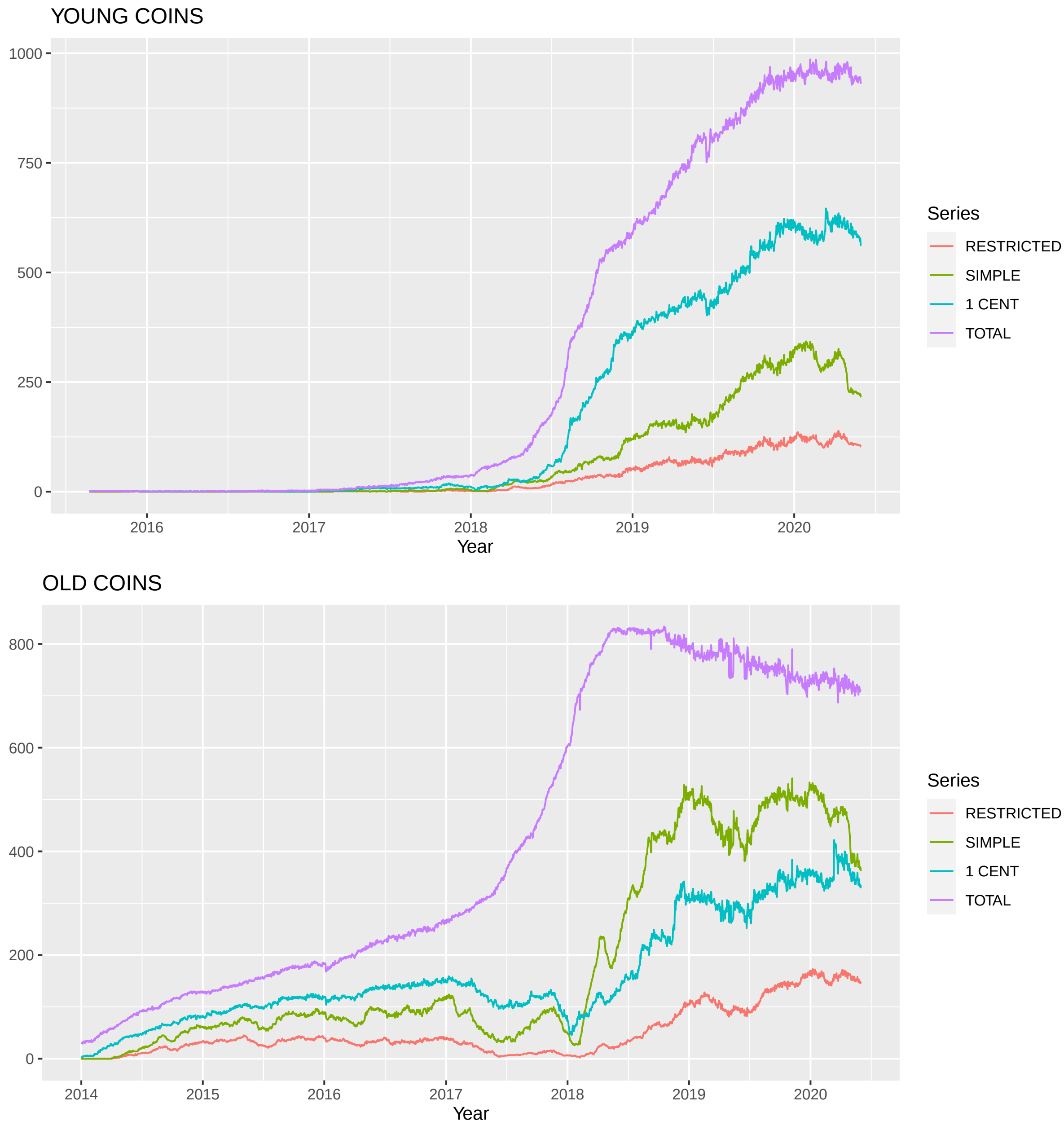

Figure 1. Daily number of total available coins, and the daily number of dead coins computed using the previous three criteria and the price and volume data from https://coinmarketcap.com, accessed on 1 June 2022.

To deal with potential structural breaks, we considered two types of estimation windows: a rolling fixed window of 100.000 observations and the traditional expanding window.

Time-series models using the ZPP were instead estimated separately for each coin. Given that the time series of historical market prices were relatively short (particularly for young coins), we employed only an expanding window scheme with the first estimation sample consisting of 30 observations[14].

Table 3. Schematic example of a pooled coin dataset used for credit-scoring and ML models.

Coins	*Time*	**Alive (dep. Variable)**	**Regressor 1**	**...**	**Regressor *n***
	t_1	0	...	...	...
	t_2	0	...	...	...
COIN 1	t_3	1	...	...	...
	t_4	0			
	t_5	0	...	...	...
	t_1	0	...	...	...
	t_2	0	...	...	...
COIN 2	t_3	0	...	...	...
	t_4	0			
	t_5	0	...	...	...
	t_3	0	...	...	...
COIN 3	t_4	1			
	t_5	0	...	...	...
	t_2	0	...	...	...
COIN 4	t_3	0	...	...	...
	t_4	0			
	t_5	1	...	...	...

4. Results

We computed the probability of death for the following two sets of coins:

- A total of 1165 young coins for a total of 537,693 observations, whose names are reported in Table A1–A3 in Appendix A. We used this set of coins to forecast the 1-day and 30-day ahead probabilities of death.
- A total of 838 old coins for a total of 987,018 observations, whose names are reported in Table A4–A5 in Appendix A. We used this set of coins to forecast the 1-day, 30-day, and 365-day ahead probabilities of death.

For the sake of space and interest, given the very large dataset at our disposal, we focused exclusively on out-of-sample forecasting, whereas the in-sample analysis dealing with the models' residuals was not considered[15].

We computed direct forecasts for the credit-scoring and ML models so, at a given time t, we estimated these models as many times as the number of forecast horizons and with regressors lagged as many days as the length of the forecast horizons (1-day lagged regressors to forecast the 1-day ahead probability of death, and so on). Instead, the time-series models using the ZPP were estimated only once, and the probabilities of deaths for different forecast horizons were computed using recursive forecasts[16].

The AUC scores, the Brier scores, the models included in the model confidence set (MCS), and how many times (in %) the models did not reach numerical convergence, across the three competing criteria to classify a coin as dead or alive, are reported in Table 4 for the young coins, and in Table 5 for the old coins.

Table 4. 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. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

Young coins: 1-day ahead probability of death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**	*% Not Converged*
Logit (expanding window)	0.79	0.73	0.60	0.089	0.182	0.238	not included	not included	not included	0.00
Probit (expanding window)	0.75	0.70	0.59	0.091	0.186	0.240	not included	not included	not included	0.00
Cauchit (expanding window)	0.86	0.80	0.64	0.077	0.161	**0.233**	not included	not included	**INCLUDED**	0.00
Random Forest (expanding window)	0.78	0.78	0.72	0.080	0.158	0.240	not included	**INCLUDED**	not included	0.00
Logit (fixed window)	0.84	0.77	0.58	0.081	0.170	0.250	not included	not included	not included	0.00
Probit (fixed window)	0.83	0.74	0.58	0.083	0.175	0.250	not included	not included	not included	0.00
Cauchit (fixed window)	**0.86**	**0.80**	0.64	**0.077**	**0.157**	0.241	**INCLUDED**	**INCLUDED**	not included	0.00
Random Forest (fixed window)	0.74	0.75	0.65	0.089	0.180	0.291	not included	not included	not included	0.00
ZPP - Random walk	0.79	0.75	0.77	0.152	0.199	0.384	not included	not included	not included	0.00
ZPP - Normal GARCH(1,1)	0.74	0.69	0.65	0.107	0.248	0.512	not included	not included	not included	1.70
ZPP - Student'st GARCH(1,1)	0.60	0.57	0.66	0.098	0.244	0.532	not included	not included	not included	0.90
ZPP - GH Skew-Student GARCH(1,1)	0.62	0.59	0.44	0.099	0.250	0.540	not included	not included	not included	43.17
ZPP - MSGARCH(1,1)	0.73	0.70	**0.83**	0.101	0.241	0.469	not included	not included	not included	0.81
Young coins: 30-day ahead probability of death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**	*% Not Converged*
Logit (expanding window)	0.71	0.63	0.60	0.091	0.201	0.238	not included	not included	not included	0.00
Probit (expanding window)	0.69	0.61	0.59	0.092	0.203	0.239	not included	not included	not included	0.00
Cauchit (expanding window)	0.82	0.74	0.63	0.081	0.182	0.234	not included	not included	not included	0.00
Random Forest (expanding window)	0.65	0.65	0.64	0.102	0.218	0.290	not included	not included	not included	0.00
Logit (fixed window)	0.71	0.66	0.57	0.090	0.190	0.249	not included	not included	not included	0.00
Probit (fixed window)	0.69	0.66	0.57	0.091	0.191	0.250	not included	not included	not included	0.00
Cauchit (fixed window)	**0.82**	**0.76**	0.60	**0.081**	**0.174**	0.244	**INCLUDED**	**INCLUDED**	not included	0.00
Random Forest (fixed window)	0.64	0.65	0.61	0.107	0.221	0.305	not included	not included	not included	0.00
ZPP - Random walk	0.73	0.71	0.76	0.615	0.471	0.305	not included	not included	not included	0.00
ZPP - Normal GARCH(1,1)	0.69	0.66	0.65	0.360	0.358	0.385	not included	not included	not included	1.70
ZPP - Student'st GARCH(1,1)	0.67	0.63	0.55	0.213	0.253	0.448	not included	not included	not included	0.90
ZPP - GH Skew-Student GARCH(1,1)	0.69	0.64	0.50	0.183	0.243	0.437	not included	not included	not included	43.17
ZPP - MSGARCH(1,1)	0.72	0.70	**0.85**	0.228	0.233	**0.197**	not included	not included	**INCLUDED**	0.81

Table 5. 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. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

Old coins: 1-day ahead probability of death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**	***% Not Converged***
Logit (expanding window)	0.74	0.74	0.69	0.109	0.227	0.194	not included	not included	not included	0.00
Probit (expanding window)	0.73	0.71	0.67	0.117	0.241	0.197	not included	not included	not included	0.00
Cauchit (expanding window)	0.76	0.86	0.74	0.103	0.167	0.181	not included	not included	not included	0.00
Random Forest (expanding window)	**0.96**	**0.97**	**0.95**	**0.034**	**0.065**	**0.069**	**INCLUDED**	**INCLUDED**	**INCLUDED**	0.00
Logit (fixed window)	0.77	0.75	0.75	0.103	0.224	0.196	not included	not included	not included	0.00
Probit (fixed window)	0.76	0.74	0.74	0.106	0.228	0.202	not included	not included	not included	0.00
Cauchit (fixed window)	0.77	0.85	0.76	0.104	0.183	0.193	not included	not included	not included	0.00
Random Forest (fixed window)	0.78	0.84	0.77	0.087	0.191	0.167	not included	not included	not included	0.00
ZPP - Random walk	0.76	0.75	0.71	0.182	0.257	0.216	not included	not included	not included	0.00
ZPP - Normal GARCH(1,1)	0.64	0.59	0.64	0.125	0.402	0.243	not included	not included	not included	1.22
ZPP - Student'st GARCH(1,1)	0.57	0.54	0.63	0.117	0.387	0.248	not included	not included	not included	1.92
ZPP - GH Skew-Student GARCH(1,1)	0.57	0.55	0.42	0.120	0.396	0.251	not included	not included	not included	42.70
ZPP - MSGARCH(1,1)	0.69	0.68	0.70	0.111	0.374	0.229	not included	not included	not included	0.67
Old coins: 30-day ahead probability of death										
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**	***% Not Converged***
Logit (expanding window)	0.71	0.73	0.68	0.104	0.220	0.194	not included	not included	not included	0.00
Probit (expanding window)	0.70	0.68	0.67	0.104	0.240	0.197	not included	not included	not included	0.00
Cauchit (expanding window)	0.74	0.77	0.74	0.102	0.211	0.181	not included	not included	not included	0.00
Random Forest (expanding window)	**0.76**	**0.80**	**0.77**	**0.096**	0.210	**0.170**	**INCLUDED**	not included	**INCLUDED**	0.00
Logit (fixed window)	0.74	0.77	0.74	0.103	**0.205**	0.197	not included	**INCLUDED**	not included	0.00
Probit (fixed window)	0.73	0.77	0.74	0.103	0.207	0.200	not included	**INCLUDED**	not included	0.00
Cauchit (fixed window)	0.75	0.79	0.75	0.103	0.207	0.194	not included	**INCLUDED**	not included	0.00
Random Forest (fixed window)	0.69	0.72	0.71	0.107	0.247	0.193	not included	not included	not included	0.00
ZPP - Random walk	0.75	0.69	0.68	0.514	0.331	0.440	not included	not included	not included	0.00
ZPP - Normal GARCH(1,1)	0.66	0.58	0.58	0.222	0.325	0.269	not included	not included	not included	1.22
ZPP - Student'st GARCH(1,1)	0.63	0.55	0.61	0.209	0.301	0.313	not included	not included	not included	1.92
ZPP - GH Skew-Student GARCH(1,1)	0.64	0.57	0.60	0.191	0.309	0.294	not included	not included	not included	42.70
ZPP - MSGARCH(1,1)	0.68	0.67	0.74	0.178	0.261	0.193	not included	not included	not included	0.67

Table 5. *Cont.*

Models	AUC (Restrictive)	AUC (Simple)	AUC (1cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1cent)	MCS (Restrictive)	MCS (Simple)	MCS (1cent)	*% Not Converged*
Old coins: 365-day ahead probability of death										
Logit (expanding window)	0.59	0.57	0.61	0.121	0.323	**0.210**	not included	not included	**INCLUDED**	0.00
Probit (expanding window)	0.58	0.55	0.61	**0.119**	**0.319**	0.211	**INCLUDED**	**INCLUDED**	not included	0.00
Cauchit (expanding window)	0.63	**0.61**	0.65	0.124	0.337	0.212	not included	not included	not included	0.00
Random Forest (expanding window)	0.61	0.60	0.59	0.131	0.338	0.237	not included	not included	not included	0.00
Logit (fixed window)	0.60	0.58	0.65	0.135	0.347	0.223	not included	not included	not included	0.00
Probit (fixed window)	0.60	0.57	0.63	0.138	0.345	0.246	not included	not included	not included	0.00
Cauchit (fixed window)	0.63	0.60	0.65	0.132	0.368	0.231	not included	not included	not included	0.00
Random Forest (fixed window)	0.62	0.61	0.61	0.129	0.318	0.227	not included	**INCLUDED**	not included	0.00
ZPP - Random walk	**0.69**	0.50	0.63	0.998	0.707	0.828	not included	not included	not included	0.00
ZPP - Normal GARCH(1,1)	0.66	0.51	0.55	0.929	0.668	0.806	not included	not included	not included	1.22
ZPP - Student'st GARCH(1,1)	0.68	0.52	0.56	0.390	0.400	0.368	not included	not included	not included	1.92
ZPP - GH Skew-Student GARCH(1,1)	0.67	0.50	0.54	0.362	0.395	0.351	not included	not included	not included	42.70
ZPP - MSGARCH(1,1)	0.63	0.52	**0.70**	0.366	0.354	0.304	not included	not included	not included	0.67

The forecasting metrics for the young coins show that the cauchit model with a fixed estimation window of 100,000 observations is generally the best model for all forecast horizons considered and across most criteria to classify a coin as dead or alive. This result confirms the simulation evidence reported in Gündüz and Fokoué (2017), who showed that the cauchit is the model of choice under a high level of sparseness of the input space: this is definitely the case for the dataset of young coins, whose trading volumes and Google searches are mostly very low and close to zero. However, we remark that the ZPP computed using a MS-GARCH(1,1) model is the best model when using the professional rule that defines a coin dead if its value drops below 1 cent, thus indirectly confirming the good empirical performances reported in Ardia et al. (2019) and Maciel (2021). Similarly, according to the AUCs, the ZPP computed using the simple random walk provides good forecasts across all horizons and classifying criteria, which is in-line with all the past literature dealing with the ZPP.

In the case of old coins, the random forests model with an expanding estimation window is the best model for forecasting the probability of death up to 30 days ahead. Instead, credit-scoring models and the ZPP models computed with the random walk and the MS-GARCH(1,1) are the best for the 365-day ahead horizon, according to loss functions and AUCs, respectively. The latter horizon is arguably the most important for credit-risk management purposes, because this is the time interval that is usually considered by national rules and international agreements, such as the Basel 2 and Basel 3 agreements.

In general, our empirical evidence shows that ZPP-based models tend to show better AUCs for long-term forecasts of the probability of death, whereas credit-scoring and ML models have better loss functions. This result was expected because the latter models tend to provide smoothed forecasts by construction, while this is not the case for time-series-based models. An important advantage of credit-scoring and ML models is the greater ease of estimation than the other models. The ZPP computed with the random walk model share the same numerical efficiency, whereas the GARCH(1,1) with errors following the generalized hyperbolic skew-Student distribution had (by far) the worst numerical performance across all datasets: this was not a surprise given that the high complexity of this model is poorly suited for (extremely) noisy data such as crypto-coins data.

Given that ZPP-based models seem to better distinguish between future dead and alive coins, while credit-scoring and ML models provide smaller loss functions, this evidence strongly suggests the possibility of forecasting gains using forecast combinations methods. We leave this topic as an avenue for future research.

The intuition behind these results is that the additional information provided by trading volumes and Google searches does indeed help to improve the forecasting of the probabilities of deaths, particularly for short-term horizons. We also tried to add these regressors to time-series-based models, but the estimation of the models turned out to be either poor or not viable due to the short time series available for estimation, and for this reason, we did not consider such models[17]. It is well-known, since the work by Fiorentini et al. (1996), that the estimation of GARCH models is complex and requires large samples. Moreover, the large simulation studies of GARCH processes in Hwang and Valls Pereira (2006), Fantazzini (2009) and Bianchi et al. (2011) showed that a sample of at least 250–500 observations is needed to have good model estimates and, in case of complex data-generating processes, even larger samples are required.

5. Robustness Checks

We wanted to verify that our previous results also held with different data samples. Therefore, we performed a series of robustness checks considering the models' forecasting performances before and after the burst of the bitcoin bubble at the end of 2017, and when separating crypto-coins with large market capitalization from coins with small market capitalization.

5.1. Forecasting the Probability of Death Before and after the 2017 Bubble

There is increasing literature showing that there was a financial bubble in bitcoin prices in 2016-2017 that burst at the end of 2017, see Fry (2018), Corbet et al. (2018), Gerlach et al. (2019), and Xiong et al. (2020). In addition, there is also a debate on whether the introduction of bitcoin futures in December 2017 crashed the market prices, see Köchling et al. (2019), Liu et al. (2020), Baig et al. (2020), Jalan et al. (2021), and Hattori and Ishida (2021). Fantazzini and Kolodin (2020) used several unit root tests allowing for an endogenous break and found a significant structural break located at the end of 2017, so they fixed a break date on 10 December 2017, which is the day when the first bitcoin futures were introduced on the CBOE.

Following this literature, we divided our dataset into two sub-samples consisting of data before and after 10 December 2017, and we examined the models' forecasting performances in these two sub-samples. Given the very small number of young coins available before the end of 2017, we only considered old coins for this robustness check (that is, coins with at least 750 observations).

The AUC scores, the Brier scores, and the models included in the model confidence set (MCS) across the three competing criteria to classify a coin as dead or alive are reported in Table 6 for the sub-sample ending on 10 December 2017, and in Table 7 for the sub-sample starting after that date.

Table 6 and 7 do not highlight any major differences between the two sub-samples. However, we can notice that the general levels of the AUCs for the 30-day and 365-days forecast horizons slightly decreased in the second sub-sample after the burst of the 2017 bubble. Moreover, in the latter sub-sample, credit-scoring models (particularly the cauchit) showed better results compared to the random forest and ZPP models than in the first sub-sample, that is, before the bubble burst. Probably, the fall in trading volumes and Google searches after 2017 increased the sparseness of the input space, thus favoring models such as the cauchit, as shown by Gündüz and Fokoué (2017) and discussed in the previous pages.

Table 6. Old coins: years 2016–2017. AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), and models included in the MCS across three competing criteria to classify a coin as dead or alive. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

Old coins: 1-day ahead probability of death (2016 –2017)									
Models	**AUC (restrictive)**	**AUC (simple)**	**AUC (1cent)**	**Brier Score (restrictive)**	**Brier Score (simple)**	**Brier Score (1cent)**	**MCS (restrictive)**	**MCS (simple)**	**MCS (1cent)**
Logit (expanding window)	0.76	0.72	0.76	0.087	0.197	0.232	not included	not included	not included
Probit (expanding window)	0.71	0.69	0.76	0.103	0.215	0.238	not included	not included	not included
Cauchit (expanding window)	0.80	0.83	0.81	0.079	0.142	0.195	not included	not included	not included
Random Forest (expanding window)	**0.97**	**0.96**	**0.96**	**0.025**	**0.052**	**0.066**	**INCLUDED**	**INCLUDED**	**INCLUDED**
Logit (fixed window)	0.77	0.81	0.80	0.086	0.147	0.198	not included	not included	not included
Probit (fixed window)	0.71	0.69	0.79	0.100	0.219	0.204	not included	not included	not included
Cauchit (fixed window)	0.81	0.84	0.82	0.079	0.137	0.184	not included	not included	not included
Random Forest (fixed window)	0.93	0.92	0.90	0.039	0.083	0.117	not included	not included	not included
ZPP - Random walk	0.81	0.76	0.72	0.105	0.202	0.292	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.60	0.60	0.65	0.118	0.249	0.307	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.56	0.51	0.37	0.097	0.236	0.312	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.55	0.51	0.43	0.098	0.240	0.315	not included	not included	not included
ZPP - MSGARCH(1,1)	0.71	0.71	0.83	0.092	0.232	0.289	not included	not included	not included
Old coins: 30-day ahead probability of death (2016–2017)									
Models	**AUC (restrictive)**	**AUC (simple)**	**AUC (1cent)**	**Brier Score (restrictive)**	**Brier Score (simple)**	**Brier Score (1cent)**	**MCS (restrictive)**	**MCS (simple)**	**MCS (1cent)**
Logit (expanding window)	0.76	0.73	0.76	0.083	0.174	0.236	not included	not included	not included
Probit (expanding window)	0.76	0.72	0.75	0.084	0.177	0.242	not included	not included	not included
Cauchit (expanding window)	0.77	0.74	0.81	0.081	0.165	0.202	not included	not included	not included
Random Forest (expanding window)	**0.81**	**0.78**	0.84	**0.078**	**0.160**	**0.170**	**INCLUDED**	**INCLUDED**	**INCLUDED**
Logit (fixed window)	0.76	0.73	0.78	0.081	0.170	0.207	not included	not included	not included
Probit (fixed window)	0.76	0.73	0.77	0.081	0.172	0.213	not included	not included	not included
Cauchit (fixed window)	0.77	0.75	0.81	0.080	0.163	0.190	not included	not included	not included
Random Forest (fixed window)	0.78	0.74	0.82	0.084	0.177	0.181	not included	not included	not included
ZPP - Random walk	0.80	0.74	0.70	0.288	0.257	0.328	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.66	0.62	0.58	0.170	0.239	0.303	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.65	0.55	0.63	0.133	0.225	0.343	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.66	0.57	0.63	0.128	0.230	0.338	not included	not included	not included
ZPP - MSGARCH(1,1)	0.69	0.69	**0.86**	0.135	0.206	0.171	not included	not included	**INCLUDED**

Table 6. *Cont.*

Models	AUC (Restrictive)	AUC (Simple)	AUC (1cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1cent)	MCS (Restrictive)	MCS (Simple)	MCS (1cent)
Old coins: 365-day ahead probability of death (2016–2017)									
Logit (expanding window)	0.67	0.61	0.68	0.071	0.189	0.299	**INCLUDED**	not included	not included
Probit (expanding window)	0.67	0.60	0.67	**0.071**	0.189	0.300	**INCLUDED**	not included	not included
Cauchit (expanding window)	0.64	0.64	0.70	0.072	**0.186**	0.282	not included	**INCLUDED**	not included
Random Forest (expanding window)	0.65	0.61	0.69	0.130	0.273	0.300	not included	not included	not included
Logit (fixed window)	0.66	0.60	0.65	0.073	0.191	0.282	not included	not included	not included
Probit (fixed window)	0.66	0.60	0.64	0.073	0.191	0.285	not included	not included	not included
Cauchit (fixed window)	0.65	0.62	0.69	0.073	0.206	0.271	not included	not included	not included
Random Forest (fixed window)	0.64	0.59	0.72	0.129	0.285	**0.267**	not included	not included	**INCLUDED**
ZPP - Random walk	**0.67**	**0.64**	0.60	1.106	0.881	0.878	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.65	0.58	0.54	0.764	0.647	0.682	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.62	0.58	0.53	0.358	0.328	0.394	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.66	0.61	0.49	0.302	0.285	0.358	not included	not included	not included
ZPP - MSGARCH(1,1)	0.59	0.64	**0.84**	0.443	0.377	0.300	not included	not included	not included

Table 7. Old coins: years 2018–2020. AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), and models included in the MCS across three competing criteria to classify a coin as dead or alive. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

Models	AUC (Restrictive)	AUC (Simple)	AUC (1cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1cent)	MCS (Restrictive)	MCS (Simple)	MCS (1cent)
Old coins: 1-day ahead probability of death (2018 –2020)									
Logit (expanding window)	0.78	0.75	0.68	0.115	0.235	0.184	not included	not included	not included
Probit (expanding window)	0.76	0.73	0.66	0.120	0.247	0.187	not included	not included	not included
Cauchit (expanding window)	0.78	0.87	0.72	0.110	0.173	0.177	not included	not included	not included
Random Forest (expanding window)	**0.96**	**0.97**	**0.95**	**0.037**	**0.068**	**0.070**	**INCLUDED**	**INCLUDED**	**INCLUDED**
Logit (fixed window)	0.79	0.74	0.73	0.108	0.244	0.195	not included	not included	not included
Probit (fixed window)	0.79	0.76	0.72	0.108	0.230	0.202	not included	not included	not included
Cauchit (fixed window)	0.79	0.86	0.73	0.111	0.195	0.196	not included	not included	not included
Random Forest (fixed window)	0.74	0.82	0.72	0.100	0.220	0.181	not included	not included	not included
ZPP - Random walk	0.76	0.73	0.75	0.203	0.272	0.196	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.64	0.59	0.64	0.127	0.442	0.227	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.57	0.53	0.63	0.122	0.426	0.231	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.57	0.54	0.42	0.125	0.437	0.234	not included	not included	not included

Table 7. *Cont.*

Old coins: 1-day ahead probability of death (2018 –2020)									
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
ZPP - MSGARCH(1,1)	0.68	0.67	0.67	0.116	0.411	0.213	not included	not included	not included
Old coins: 30-day ahead probability of death (2018–2020)									
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
Logit (expanding window)	0.76	0.75	0.67	0.109	0.231	0.183	not included	not included	not included
Probit (expanding window)	0.75	0.70	0.66	0.109	0.255	0.186	not included	not included	not included
Cauchit (expanding window)	0.77	0.79	0.72	0.107	0.223	0.176	not included	not included	not included
Random Forest (expanding window)	0.75	**0.81**	**0.75**	**0.101**	0.223	**0.169**	**INCLUDED**	not included	**INCLUDED**
Logit (fixed window)	0.77	0.78	0.72	0.108	**0.214**	0.195	not included	**INCLUDED**	not included
Probit (fixed window)	0.77	0.77	0.72	0.108	0.215	0.197	not included	not included	not included
Cauchit (fixed window)	**0.78**	0.80	0.73	0.109	0.218	0.195	not included	not included	not included
Random Forest (fixed window)	0.68	0.73	0.67	0.113	0.264	0.196	not included	not included	not included
ZPP - Random walk	0.75	0.65	0.72	0.571	0.349	0.468	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.65	0.56	0.58	0.235	0.346	0.260	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.62	0.53	0.59	0.228	0.320	0.305	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.63	0.55	0.57	0.207	0.329	0.283	not included	not included	not included
ZPP - MSGARCH(1,1)	0.68	0.65	0.70	0.189	0.274	0.199	not included	not included	not included
Old coins: 365-day ahead probability of death (2018–2020)									
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
Logit (expanding window)	0.62	0.62	0.63	0.128	0.342	**0.198**	not included	not included	**INCLUDED**
Probit (expanding window)	0.61	0.61	0.62	**0.126**	0.336	0.199	**INCLUDED**	not included	not included
Cauchit (expanding window)	0.66	**0.66**	0.66	0.131	0.357	0.202	not included	not included	not included
Random Forest (expanding window)	0.62	0.63	0.58	0.131	0.346	0.229	not included	not included	not included
Logit (fixed window)	0.64	0.62	0.66	0.144	0.368	0.215	not included	not included	not included
Probit (fixed window)	0.63	0.60	0.63	0.147	0.365	0.241	not included	not included	not included
Cauchit (fixed window)	0.67	0.63	0.66	0.140	0.390	0.225	not included	not included	not included
Random Forest (fixed window)	0.63	0.63	0.59	0.129	**0.323**	0.222	not included	**INCLUDED**	not included
ZPP - Random walk	**0.69**	0.51	0.63	0.984	0.684	0.821	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.66	0.53	0.55	0.952	0.671	0.823	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.68	0.54	0.56	0.394	0.409	0.364	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.67	0.52	0.55	0.370	0.410	0.350	not included	not included	not included
ZPP - MSGARCH(1,1)	0.64	0.53	**0.68**	0.356	0.351	0.305	not included	not included	not included

5.2. Large Cap And Small Cap: Does It Matter?

In the baseline case, we separated our coins data based on the length of their time series for forecasting purposes. Moreover, before starting our analysis, we tried different clustering methods to group coins with similar attributes, and most methods proposed groupings quite close to our simple baseline approach[18]. However, we also noticed that some methods separated the 50–100 coins with the largest market capitalizations from all others. Therefore, we separated the 100 crypto-coins with the largest market capitalization from all other coins with a smaller market capitalization, and we examined how the models' forecasting performances changed.

The AUC scores, the Brier scores, and the models included in the model confidence set (MCS) across the three competing criteria to classify a coin as dead or alive are reported in Table 8 for the 100 coins with the largest market capitalization, and in Table 9 for all other coins.

Table 8 and 9 show that the separation of coins based on their market capitalization did not produce any major changes compared to the baseline case. However, there are some differences: in the case of big-cap coins, the random forests model remained the best model only for 1-day ahead forecasts, whereas the cauchit was the best model for both the 30-day and 365-day ahead forecast horizons. A similar picture also emerged for small-cap coins, where credit-scoring models and the ZPP computed with the MS-GARCH(1,1) were the best models for the 30-day and 365-day ahead forecast horizons. Interestingly, the success of credit-scoring and ZPP-based models for the long-term forecasts of the probability of death of small-cap coins are qualitatively similar to the evidence reported by Fantazzini and Zimin (2020), who used only 42 coins (most of them small cap).

Table 8. Big-cap coins: AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), and models included in the MCS across three competing criteria to classify a coin as dead or alive. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

				Big-cap coins: 1-day ahead probability of death					
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
Logit (expanding window)	0.88	0.87	0.75	0.012	0.089	0.083	not included	not included	not included
Probit (expanding window)	0.86	0.86	0.75	0.020	0.101	0.086	not included	not included	not included
Cauchit (expanding window)	0.90	0.90	0.74	0.007	0.072	0.093	**INCLUDED**	not included	not included
Random Forest (expanding window)	**0.96**	**0.97**	**0.96**	**0.003**	**0.027**	**0.032**	**INCLUDED**	**INCLUDED**	**INCLUDED**
Logit (fixed window)	0.82	0.66	0.66	0.006	0.084	0.106	**INCLUDED**	not included	not included
Probit (fixed window)	0.83	0.66	0.63	0.010	0.087	0.106	not included	not included	not included
Cauchit (fixed window)	0.89	0.85	0.75	0.005	0.078	0.104	**INCLUDED**	not included	not included
Random Forest (fixed window)	0.66	0.63	0.62	0.006	0.093	0.106	**INCLUDED**	not included	not included
ZPP - Random walk	0.83	0.83	0.49	0.036	0.079	0.126	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.64	0.54	0.60	0.006	0.100	0.097	**INCLUDED**	not included	not included
ZPP - Student'st GARCH(1,1)	0.73	0.56	0.29	0.006	0.097	0.098	**INCLUDED**	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.65	0.58	0.39	0.006	0.098	0.098	**INCLUDED**	not included	not included
ZPP - MSGARCH(1,1)	0.76	0.69	0.62	0.006	0.093	0.091	**INCLUDED**	not included	not included
				Big-cap coins: 30-day ahead probability of death					
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
Logit (expanding window)	0.86	0.84	0.75	**0.004**	**0.075**	0.079	**INCLUDED**	**INCLUDED**	not included
Probit (expanding window)	0.85	0.79	0.75	0.005	0.090	0.082	**INCLUDED**	not included	not included
Cauchit (expanding window)	**0.88**	**0.84**	0.74	0.005	0.083	0.087	**INCLUDED**	not included	not included
Random Forest (expanding window)	0.75	0.80	0.79	0.005	0.079	**0.070**	**INCLUDED**	not included	**INCLUDED**
Logit (fixed window)	0.81	0.76	0.67	0.004	0.086	0.100	**INCLUDED**	not included	not included
Probit (fixed window)	0.79	0.75	0.64	0.005	0.087	0.100	**INCLUDED**	not included	not included
Cauchit (fixed window)	0.88	0.81	0.75	0.005	0.088	0.100	**INCLUDED**	not included	not included
Random Forest (fixed window)	0.58	0.56	0.58	0.008	0.110	0.107	not included	not included	not included
ZPP - Random walk	0.82	0.80	0.48	0.247	0.201	0.304	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.70	0.50	0.69	0.061	0.128	0.146	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.74	0.55	**0.79**	0.078	0.126	0.169	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.62	0.57	0.76	0.069	0.118	0.157	not included	not included	not included
ZPP - MSGARCH(1,1)	0.74	0.68	0.69	0.069	0.099	0.088	not included	not included	not included

Table 8. *Cont.*

Models	AUC (Restrictive)	AUC (Simple)	AUC (1cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1cent)	MCS (Restrictive)	MCS (Simple)	MCS (1cent)
Big-cap coins: 365-day ahead probability of death									
Logit (expanding window)	0.85	0.61	0.69	0.021	0.144	0.052	not included	**INCLUDED**	**INCLUDED**
Probit (expanding window)	0.83	0.60	0.69	0.020	**0.143**	0.054	not included	**INCLUDED**	**INCLUDED**
Cauchit (expanding window)	0.85	**0.62**	0.71	0.012	0.145	**0.051**	not included	**INCLUDED**	**INCLUDED**
Random Forest (expanding window)	0.58	0.60	0.64	**0.008**	0.145	0.062	**INCLUDED**	**INCLUDED**	not included
Logit (fixed window)	0.83	0.53	0.66	0.040	0.185	0.058	not included	not included	**INCLUDED**
Probit (fixed window)	0.81	0.53	0.62	0.046	0.186	0.058	not included	not included	not included
Cauchit (fixed window)	**0.87**	0.57	**0.71**	0.026	0.231	0.052	not included	not included	**INCLUDED**
Random Forest (fixed window)	0.72	0.53	0.60	0.014	0.150	0.087	not included	not included	not included
ZPP - Random walk	0.75	0.58	0.57	0.612	0.544	0.594	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.73	0.53	0.69	0.710	0.653	0.721	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.82	0.53	0.66	0.250	0.299	0.280	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.69	0.48	0.65	0.251	0.300	0.280	not included	not included	not included
ZPP - MSGARCH(1,1)	0.80	0.53	0.70	0.255	0.276	0.227	not included	not included	not included

Table 9. Small-cap coins: AUC scores (highest values are in bold fonts), Brier scores (smallest values are in bold fonts), and models included in the MCS across three competing criteria to classify a coin as dead or alive. Feder et al. (2018) approach = "*restrictive*"; simplified Feder et al. (2018) approach = "*simple*"; professional rule = "*1 cent*".

Models	AUC (Restrictive)	AUC (Simple)	AUC (1cent)	Brier Score (Restrictive)	Brier Score (Simple)	Brier Score (1cent)	MCS (Restrictive)	MCS (Simple)	MCS (1cent)
Small-cap coins: 1-day ahead probability of death									
Logit (expanding window)	0.74	0.75	0.67	0.111	0.224	0.219	not included	not included	not included
Probit (expanding window)	0.72	0.73	0.66	0.117	0.234	0.222	not included	not included	not included
Cauchit (expanding window)	0.79	0.84	0.72	0.103	0.173	0.207	not included	not included	not included
Random Forest (expanding window)	**0.90**	**0.92**	**0.89**	**0.053**	**0.101**	**0.132**	**INCLUDED**	**INCLUDED**	**INCLUDED**
Logit (fixed window)	0.77	0.75	0.72	0.105	0.218	0.223	not included	not included	not included
Probit (fixed window)	0.76	0.74	0.71	0.107	0.222	0.228	not included	not included	not included
Cauchit (fixed window)	0.78	0.82	0.74	0.104	0.183	0.218	not included	not included	not included
Random Forest (fixed window)	0.76	0.82	0.76	0.096	0.196	0.216	not included	not included	not included
ZPP - Random walk	0.76	0.74	0.69	0.185	0.253	0.283	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.65	0.59	0.64	0.130	0.375	0.351	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.58	0.54	0.65	0.120	0.363	0.361	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.58	0.56	0.41	0.123	0.372	0.366	not included	not included	not included
ZPP - MSGARCH(1,1)	0.69	0.67	0.73	0.117	0.353	0.325	not included	not included	not included

Table 9. *Cont.*

Small-cap coins: 30-day ahead probability of death									
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (simple)**	**MCS (1cent)**
Logit (expanding window)	0.69	0.72	0.67	0.109	0.227	0.219	not included	not included	not included
Probit (expanding window)	0.68	0.68	0.66	0.109	0.242	0.222	not included	not included	not included
Cauchit (expanding window)	**0.75**	0.76	0.71	**0.104**	0.213	0.208	**INCLUDED**	not included	not included
Random Forest (expanding window)	0.72	0.76	0.75	0.107	0.225	0.219	not included	not included	not included
Logit (fixed window)	0.70	0.74	0.71	0.108	0.212	0.224	not included	not included	not included
Probit (fixed window)	0.69	0.74	0.71	0.108	0.213	0.226	not included	not included	not included
Cauchit (fixed window)	0.75	**0.78**	0.73	0.105	**0.208**	0.220	not included	**INCLUDED**	not included
Random Forest (fixed window)	0.67	0.72	0.71	0.116	0.251	0.239	not included	not included	not included
ZPP - Random walk	0.73	0.67	0.69	0.573	0.390	0.408	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.65	0.57	0.60	0.283	0.355	0.319	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.63	0.55	0.58	0.223	0.301	0.371	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.65	0.57	0.57	0.200	0.305	0.355	not included	not included	not included
ZPP - MSGARCH(1,1)	0.68	0.65	**0.77**	0.205	0.266	**0.204**	not included	not included	**INCLUDED**

Small-cap coins: 365-day ahead probability of death									
Models	**AUC (Restrictive)**	**AUC (Simple)**	**AUC (1cent)**	**Brier Score (Restrictive)**	**Brier Score (Simple)**	**Brier Score (1cent)**	**MCS (Restrictive)**	**MCS (Simple)**	**MCS (1cent)**
Logit (expanding window)	0.54	0.49	0.569	0.137	0.351	**0.234**	not included	**INCLUDED**	**INCLUDED**
Probit (expanding window)	0.53	0.52	0.560	**0.135**	0.346	0.235	**INCLUDED**	**INCLUDED**	not included
Cauchit (expanding window)	0.59	0.55	0.610	0.141	0.367	0.237	not included	not included	not included
Random Forest (expanding window)	0.59	0.56	0.562	0.150	0.368	0.265	not included	not included	not included
Logit (fixed window)	0.57	0.53	0.618	0.150	0.372	0.249	not included	not included	not included
Probit (fixed window)	0.56	0.48	0.598	0.153	0.369	0.276	not included	not included	not included
Cauchit (fixed window)	0.59	0.56	0.616	0.148	0.389	0.258	not included	not included	not included
Random Forest (fixed window)	0.60	**0.58**	0.588	0.147	**0.345**	0.249	not included	**INCLUDED**	not included
ZPP - Random walk	**0.67**	0.54	0.615	1.059	0.733	0.864	not included	not included	not included
ZPP - Normal GARCH(1,1)	0.65	0.53	0.545	0.964	0.670	0.820	not included	not included	not included
ZPP - Student'st GARCH(1,1)	0.67	0.55	0.555	0.412	0.415	0.381	not included	not included	not included
ZPP - GH Skew-Student GARCH(1,1)	0.66	0.53	0.536	0.379	0.410	0.362	not included	not included	not included
ZPP - MSGARCH(1,1)	0.61	0.50	**0.692**	0.383	0.357	0.316	not included	**INCLUDED**	not included

6. Conclusions

This paper examined a set 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, and different forecasting horizons.

To achieve this aim, we first employed a set of models to forecast the probability of death including credit-scoring models, machine-learning models, and time-series methods based on the zero-price-probability (ZPP) model, which is a methodology to compute the probabilities of default using only market prices. Secondly, we performed a forecasting exercise using a unique set of 2003 crypto-coins that were active from the beginning of 2014 till the end of May 2020. Our results showed that the choice of the coin-death definition significantly affected the set of the best forecasting models to compute the probability of death. However, this choice was not critical, and the best models turned out to be the same in most cases. In general, we found 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, whereas credit-scoring models and machine-learning methods using lagged trading volumes and online searches were better choices for older coins.

Finally, we performed a set of robustness checks to verify that our results also held with different data samples. To achieve this aim, we considered the models' forecasting performances before and after the burst of the bitcoin bubble at the end of 2017, and, when we separated crypto-coins with large market capitalization from coins with small market capitalization, the two robustness checks did not produce any major changes compared to the baseline case.

The general recommendation for investors that emerged from our analysis is to use the cauchit model when dealing with coins with a short time series and/or with trading volumes and Google searches close to zero. In the case of a large information set and the main interest is on short-term forecasting, the random forests model is definitely the model of choice, whereas the ZPP-based models using the simple random walk or the MS-GARCH(1,1) are to be preferred in case of long-term forecasts up to 1-year ahead.

Another implication of the findings of our work is the need to have more transparency and better reporting about the credit risk of crypto-assets. Given the large losses incurred by investors in previous years, the lack of focus on risk-management practices is somewhat astonishing. One of the best practices that this work clearly suggests is for crypto-exchanges to publish the estimated probability of death for the traded crypto-assets daily, using one of the models discussed in this paper, or the simple average of the estimates provided by several models. The reported probabilities of death would warn investors about the risk of investing in crypto-assets, thus helping them making more considered investment decisions.

We should note that our empirical analysis highlighted that the major drawback of the ZPPs computed using GARCH models is the need to have time series long enough to obtain decent parameter estimates. This problem makes them unsuitable for newly established coins. Moreover, the extreme volatility of crypto-coin markets and the frequent presence of structural breaks make things worse. Therefore, it was not a surprise that the ZPPs calculated using the simple random walk or the Markov-Switching GARCH(1,1) model were the best in this class of models. The retrieval of high-frequency data and the use of Bayesian methods to solve these computational issues are left as avenues for future research.

Another possibility of future work will be to explore the feasibility of forecast combinations methods. Given that ZPP-based models seem to better distinguish between future dead and alive coins, while credit-scoring and ML models provide smaller loss functions, our empirical evidence suggests the possibility of forecasting gains using combinations methods. This is why this extension could be an interesting issue for future research.

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

Appendix A. 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		

Notes

1 At the end of December 2021, almost 15,000 crypto-assets were listed on Coinmarketcap.com, accessed on 1 June 2022. CoinMarketCap is the main aggregator of cryptocurrency market data, and it has been owned by the crypto-exchange Binance since April 2020; see https://crypto.marketswiki.com/index.php?title=CoinMarketCap, accessed on 1 June 2022 for more details.

2 Lansky (2018), p. 19, formally defined a crypto-currency as a system that satisfies these six conditions: "*(1) The system does not require a central authority, its state is maintained through distributed consensus. (2) The system keeps an overview of cryptocurrency units and their ownership. (3) The system defines whether new cryptocurrency units can be created. If new cryptocurrency units can be created, the system defines the circumstances of their origin and how to determine the ownership of these new units. (4) Ownership of cryptocurrency units can be proved exclusively cryptographically. (5) The system allows transactions to be performed in which ownership of the cryptographic units is changed. A transaction statement can only be issued by an entity proving the current ownership of these units. (6) If two different instructions for changing the ownership of the same cryptographic units are simultaneously entered, the system performs at most one of them.*"

3 https://www.investopedia.com/news/crypto-carnage-over-800-cryptocurrencies-are-dead/, accessed on 1 June 2022; https://www.coinopsy.com/dead-coins/, accessed on 1 June 2022.

4 We will use the terms "probability of death" and "probability of default" interchangeably.

5 https://www.investopedia.com/news/crypto-carnage-over-800-cryptocurrencies-are-dead/, accessed on 1 June 2022

[6] https://www.coinopsy.com/dead-coins/, accessed on 1 June 2022

[7] Note that Schmitz and Hoffmann (2020) presented this method as the Feder et al. (2018) approach when, in reality, the latter involves many more restrictions. The methodology used by Schmitz and Hoffmann (2020) in their empirical analysis is even more simplified, and it assumes that a coin is (temporarily) inactive if data gaps are present in its time series.

[8] See Section 5 in Giudici and Figini (2009) for a review.

[9] In-sample analysis is also known as *training*, while the out-of-sample analysis can be named as *validation*.

[10] Note that this result is already known in the traditional financial literature because "*the ratio of default and (normally distributed) market risk losses is proportional to the square-root of the holding period. Since the ratio goes to 0 as the holding period goes to 0, over short horizons market risk is relatively more important, while over longer horizons losses due to default become more important*"(Basel Committee on Banking Supervision (2009), pp. 16–17).

[11] Fantazzini and Zimin (2020) proposed a multivariate approach to compute the ZPP of 42 coins. Given the very large dataset at our disposal, such an approach is not feasible in our case due to the curse of dimensionality. An extension of this methodology to large portfolios is left as an avenue for further research.

[12] For ease of reference, we will refer to the Feder et al. (2018) approach as "*restrictive*", to the simplified Feder et al. (2018) approach as "*simple*", while to the professional rule as "*1 cent*".

[13] The experience of the author (both in academia and in the professional field) with credit-risk management for SMEs and with potentially noisy and fraudulent data suggested a minimum dataset of 50.000–100.000 data to have robust estimates.

[14] We remark that the datasets used for the estimation of credit scoring, ML models and time series-based models were different, so there were dates for which forecasts from all models were not available. This situation had no impact on individual metrics such as the AUC, but it affected the computation of the model confidence set using the Brier score: in the latter case, we used only dates where forecasts from all models were available.

[15] The author wants to thank three anonymous professionals working in the crypto-industry for pointing his work in this direction.

[16] The development of ZPP models allowing for direct forecasts is left as an avenue for further research.

[17] We also tried to add these regressors in the mean equation of the simple random walk model, but the results did not change qualitatively (results not reported). This was not a surprise because it is the variance modelling that is the key ingredient when computing the ZPP, see Fantazzini and Zimin (2020)—Section 4.3—and references therein for more details.

[18] See Romesburg (2004) and Everitt (2011) for an introduction to cluster analysis at the textbook level.

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