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Article

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

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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. \(2016\)](#) provide 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 the instruments needed to analyze cryptocurrencies markets and prices, while [Schar and Berentsen \(2020\)](#) provide a general introduction to cryptocurrencies and blockchain technology for practitioners and students.

The increasing number of traded crypto-assets¹ and the repeated cases of hacks, scams, and projects' failures have 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 sense², 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 literature³ nor in the academic literature, see [Feder et al. \(2018\)](#), [Groby 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/deaths⁴.

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 cent⁵, yet others stress, on top of that, no trading volume, no nodes running, no active community, and de-listing from (almost) all exchanges⁶.

[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-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 again⁷.

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 class⁸. 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 because 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 sample⁹, 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 these unlawful acts.

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. Fourthly, 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 important¹⁰. 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,

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

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 below¹¹:

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

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

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_t^k touched or crossed the zero barrier along the simulated trajectory:

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

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 [Sammur 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 $1 - \alpha$,

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

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 $\hat{M}_{1-\alpha}^* = M$. 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 $\hat{M}_{1-\alpha}^*$. 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, $t_i = \bar{d}_i / \widehat{\text{var}}(\bar{d}_i)$, for $i \in M$, where $\bar{d}_i = m^{-1} \sum_{j \in M} \bar{d}_{ij}$ is the simple loss of the i th 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 $T_{\max} = \max_{i \in M} (t_i)$. 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: $e_{\max,M} = \arg \max_{i \in M} (\bar{d}_i / \widehat{\text{var}}(\bar{d}_i))$.

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 | | | | | |
|----------------------------|-------|---------------------------------------|-------|-----------------|-------|
| <i>Feder et al. (2018)</i> | | <i>Simplified Feder et al. (2018)</i> | | 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 | | | | | |
| <i>Feder et al. (2018)</i> | | <i>Simplified Feder et al. (2018)</i> | | 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 coins¹².

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 observations¹³. 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.

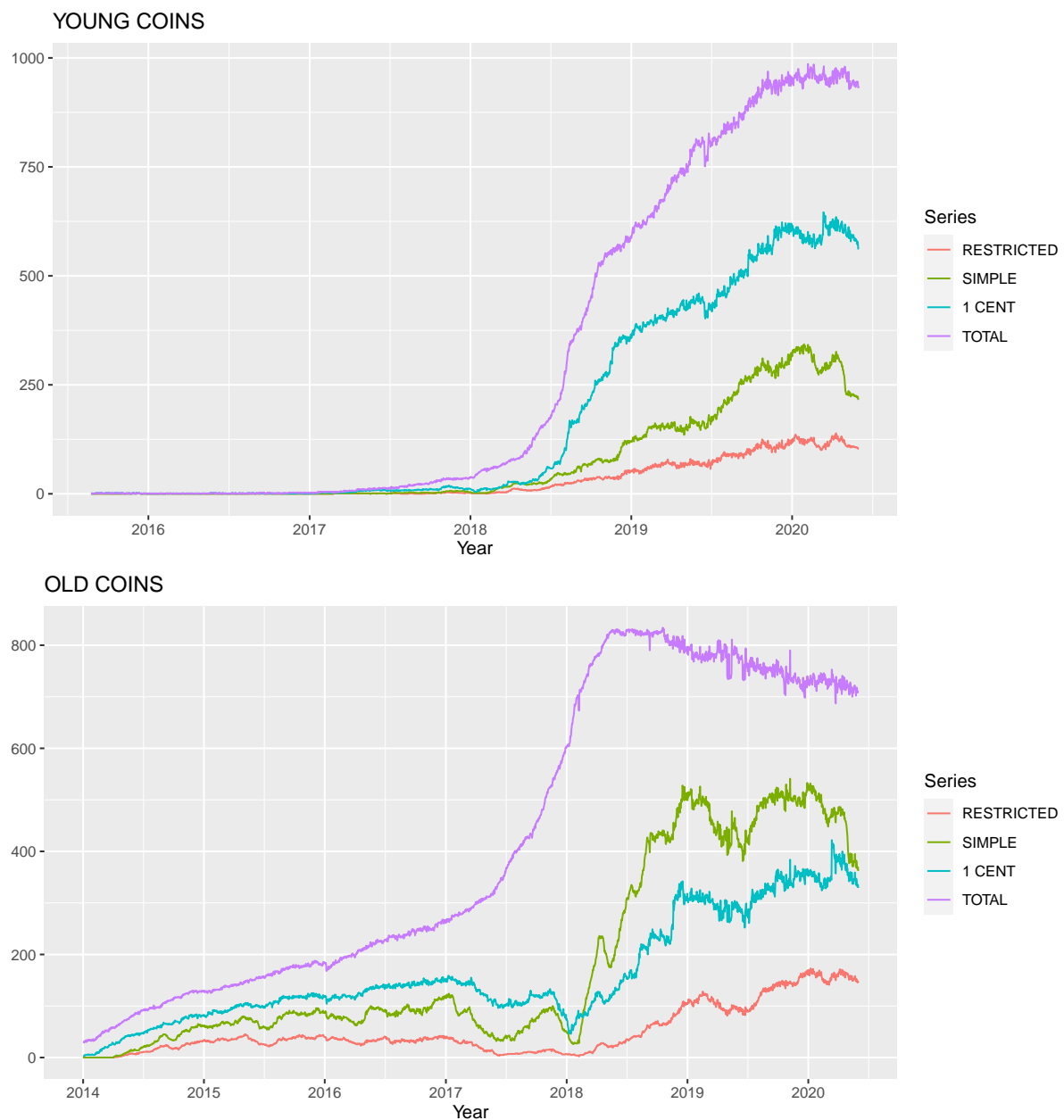


Figure 1. Daily number of total available coins, and the daily number of dead coins computed using the previous three criteria and the price and volume data from <https://coinmarketcap.com>, accessed on 1 June 2022.

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 observations¹⁴.

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

| <i>Coins</i> | <i>Time</i> | Alive (dep. Variable) | Regressor 1 | ... | Regressor <i>n</i> |
|---------------|-------------|------------------------------|--------------------|-----|---------------------------|
| COIN 1 | t_1 | 0 | ... | ... | ... |
| | t_2 | 0 | ... | ... | ... |
| | t_3 | 1 | ... | ... | ... |
| | t_4 | 0 | ... | ... | ... |
| | t_5 | 0 | ... | ... | ... |
| COIN 2 | t_1 | 0 | ... | ... | ... |
| | t_2 | 0 | ... | ... | ... |
| | t_3 | 0 | ... | ... | ... |
| | t_4 | 0 | ... | ... | ... |
| | t_5 | 0 | ... | ... | ... |
| COIN 3 | t_3 | 0 | ... | ... | ... |
| | t_4 | 1 | ... | ... | ... |
| | t_5 | 0 | ... | ... | ... |
| COIN 4 | t_2 | 0 | ... | ... | ... |
| | 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 Tables 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 Tables A4 and 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 considered¹⁵.

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 forecasts¹⁶.

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”.

| Models | Young coins: 1-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) | % Not Converged |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|--------------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | | |
| 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 |

| Models | Young coins: 30-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) | % Not Converged |
|----------------------------------|--|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|--------------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | | |
| 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”.

| Models | Old coins: 1-day ahead probability of death | | | | | | | | | |
|----------------------------------|--|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|--------------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) | % Not Converged |
| Logit (expanding window) | 0.74 | 0.74 | 0.69 | 0.109 | 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 |
| Models | Old coins: 30-day ahead probability of death | | | | | | | | | |
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) | % Not Converged |
| Logit (expanding window) | 0.71 | 0.73 | 0.68 | 0.104 | 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 | Old coins: 365-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) | % Not Converged |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|--------------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | | |
| 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 models¹⁷. 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.

Tables 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”.

| <i>Old coins: 1-day ahead probability of death (2016–2017)</i> | | | | | | | | | |
|---|----------------------|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| <i>Models</i> | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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 |
| <i>Old coins: 30-day ahead probability of death (2016–2017)</i> | | | | | | | | | |
| <i>Models</i> | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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 |
| Logit (expanding window) | 0.67 | 0.61 | 0.68 | 0.071 | 0.189 | 0.299 | INCLUDED | not included | not included |

Table 6. Cont.

| Models | Old coins: 365-day ahead probability of death (2016–2017) | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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 | Old coins: 1-day ahead probability of death (2018–2020) | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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 |
| ZPP - MSGARCH(1,1) | 0.68 | 0.67 | 0.67 | 0.116 | 0.411 | 0.213 | not included | not included | not included |

Table 7. Cont.

| <i>Old coins: 1-day ahead probability of death (2018–2020)</i> | | | | | | | | | |
|--|----------------------|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| <i>Models</i> | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| <i>Old coins: 30-day ahead probability of death (2018–2020)</i> | | | | | | | | | |
| <i>Models</i> | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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 |
| <i>Old coins: 365-day ahead probability of death (2018–2020)</i> | | | | | | | | | |
| <i>Models</i> | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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 approach¹⁸. 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.

Tables 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”.

| Models | Big-cap coins: 1-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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 |

| Models | Big-cap coins: 30-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
|----------------------------------|--|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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 | Big-cap coins: 365-day ahead probability of death | | | | | | | | |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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 | Small-cap coins: 1-day ahead probability of death | | | | | | | | |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
| 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.

| Models | Small-cap coins: 30-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (simple) | MCS (1 cent) |
|----------------------------------|--|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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 |

| Models | Small-cap coins: 365-day ahead probability of death | | | | | | MCS (Restrictive) | MCS (Simple) | MCS (1 cent) |
|----------------------------------|---|-----------------|-----------------|------------------------------|-------------------------|-------------------------|----------------------|-----------------|-----------------|
| | AUC (Restrictive) | AUC (Simple) | AUC (1 cent) | Brier Score (Restrictive) | Brier Score (Simple) | Brier Score (1 cent) | | | |
| 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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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 | Cryptocoin |
| 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 | Termio |
| 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 | GNV | 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 | Rivetx | 728 | x42 Protocol |
| 429 | Vetri | 529 | Bitsdaq | 629 | Coinsuper Ecosystem Network | 729 | Cubixex |
| 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 | Scanchain |
| 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 Betherium |
| 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 Omnitudo |
| 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 Tritium | 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 Uptrend | 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 ROlyal 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 Elementum | 988 Iungo | 1088 TrueVett | |
| 889 LALA World | 989 MESH | 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 Crowdfunding | |

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 | BrkToTheFuture | 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 | Synthetic 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 | SwiftCoin | 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 | CPCChain | 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 | Ruppee | 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 Quebeccoin |
| 473 UNIVERSAL CASH | 578 EverGreenCoin | 683 Capricoin | 788 BriaCoin |
| 474 CannabisCoin | 579 IDEX Membership | 684 MktCoin | 789 SpreadCoin |
| 475 NuShares | 580 Zeussshield | 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

- At the end of December 2021, almost 15,000 crypto-assets were listed on [Coinmarketcap.com](https://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.
- 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.”
- <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.
- We will use the terms “probability of death” and “probability of default” interchangeably.
- <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.

- 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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