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Title: Predicting cryptocurrency defaults

Year: 2020

Version: Accepted manuscript

Please cite the original version:

Grobys, K. & Sapkota, N. (2020). Predicting cryptocurrency defaults. *Applied Economics* 52(46), 5060-5076. https://doi.org/10.1080/00036846.2020.1752903

Predicting Cryptocurrency Defaults

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Abstract

We examine all available 146 Proof-of-Work based cryptocurrencies that started trading prior to the end of 2014 and track their performance until December 2018. We find that about 60% of those cryptocurrencies were eventually in default. The substantial sums of money involved mean those bankruptcies will have an enormous societal impact. Employing cryptocurrency-specific data, we estimate a model based on linear discriminant analysis to predict such defaults. Our model is capable of explaining 87% of cryptocurrency bankruptcies after only one month of trading and could serve as a screening tool for investors keen to boost overall portfolio performance and avoid investing in unreliable cryptocurrencies.

JEL Classification: G12, G14

Key Words: Cryptocurrency, Bitcoin, Bankruptcy, Default, Credit risk

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[s] We would like to thank Simon Moore for a lively, interesting, and detailed discussion of our paper in the U.S. Business Magazine *Forbes* entitled "How To Tell If Your Cryptocurrency Will Go Bust" on May 28, 2019 . Moreover, valuable comments were received from participants of the *2019 Graduate School Seminar* at the University of Vaasa. We also received valuable comments from the *2019 Aalto University Graduate School of Finance Workshop* at the University of Jyväskyla. In particular, we would like to thank Mika Veihekoski for an encouraging discussion and helpful comments. Furthermore, we are grateful for having received valuable comments from the *2019 Economics & Finance Seminar* at Hanken School of Economics. Especially we would like to thank Timo Korkeamäki, Kenneth Högholm and Emilia Vähämaa for useful comments. Moreover, we received interesting comments from the participants from the *2019 Blockchain Seminar* at the University of Vaasa. We would like to thank Robert Faff and the participants of the FINANCE, PROPERTY, TECHNOLOGY, AND THE ECONOMY CONFERENCE 2019, University of South Australia. Finally, we would like to thank an anonymous reviewer for helpful comments.

1. Introduction

Facing the zeitgeist of digitalization, Bill Gates stated that "the future of money is digital currency."[1] Since the advent of Bitcoin—the first cryptocurrency traded—the number of cryptocurrencies has increased exponentially and there are now over 2,000 cryptocurrencies traded on over 16,000 markets around the world. The main advantages of cryptocurrencies are transparency and 24-hour accessibility. Transactions of cryptocurrencies are all recorded on the open public ledger called the blockchain. This decentralized mechanism gives cryptocurrencies an unparalleled transparency. The technology behind the blockchain is revolutionary, but understanding it is challenging, especially for people without a technical background.

In contrast to traditional investments, cryptocurrencies carry different risks. For instance, Rauchs and Hileman (2017) reports that the chance of cryptocurrency exchanges being hacked is 74–79%. Taking the legal perspective, Kethineni and Cao (2019) argue that cryptocurrencies became the currency of choice for many drug dealers and extortionists because of the opportunities to hide behind the presumed privacy and anonymity. Maume (2019), who explores Initial Coin Offerings (ICO), highlights that the potential lack of regulation and enforcement is particularly tempting for scammers and other miscreants. In contrast to traditional currency markets, cryptocurrency markets also involve credit risk: As a stylized fact, among all the cryptocurrencies launched prior to December 31 2014, 59% went in default by the end of 2018, and the reasons for defaults are manifold.[2]

As of February 2019, the overall market capitalization in the digital asset market is more than USD 120 billion with Bitcoin dominating slightly with more than 50%.[3] In this regard, Fry and Cheah (2016, p.350) highlight that "from an economic perspective the sums of money involved are substantial," and accordingly, the societal impact of losses due to defaults in the digital asset market may be enormous. Howell, Niessner and Yermack (2019, p.1) define three types of digital assets which are often referred to as coins. Specifically, the first type of digital asset is defined as a general-purpose medium of exchange and store of value cryptocurrency, such as Bitcoin. The second type of digital asset is a security token, which represents a conventional security that is recorded and exchanged on a blockchain to

[1] The Bloomberg interview took place on October 2, 2014.
[2] The dead coin tracking website coinopsy.com lists the following as the main reasons for default: abandoned, abandoned/website, abandoned/volume, abandoned/buyback, abandoned/scam, scam, scam project/virus, joke, no exchanges/struggling, failed fork, failed/pre-mine no/low trade volume, pump and dump, and crashed (see https://www.coinopsy.com/dead-coins/).
[3] See https://coinmarketcap.com (accessed on 15 February 2019, 11:00 EST).

reduce transaction costs and create a record of ownership, whereas the third type of digital assets is a utility token, which gives its holder consumptive rights to access a product or service. In Tables 1 and 2, we provide a demographic overview of new and bankrupt cryptocurrencies in different years.

Table 1. Population of cryptocurrencies including tokens

Year	Before Apr 28, 2013	Mar- Dec 2013	2014	2015	2016	2017	2018	2019
New cryptocurrencies	7	60	452	207	298	800	1187	168
Default cryptocurrencies	0	0	**2**	**150**	**363**	**213**	**743**	**307**
Total cryptocurrencies	7	67	517	577	663	1353	2073	2147

Note: This table reports the numbers of new, bankrupt, and total cryptocurrencies during each year from April 2013 till April 2019. It is generated using the historical snapshot available at coinmarketcap.com.

Table 2. Life Span of default cryptocurrencies including tokens

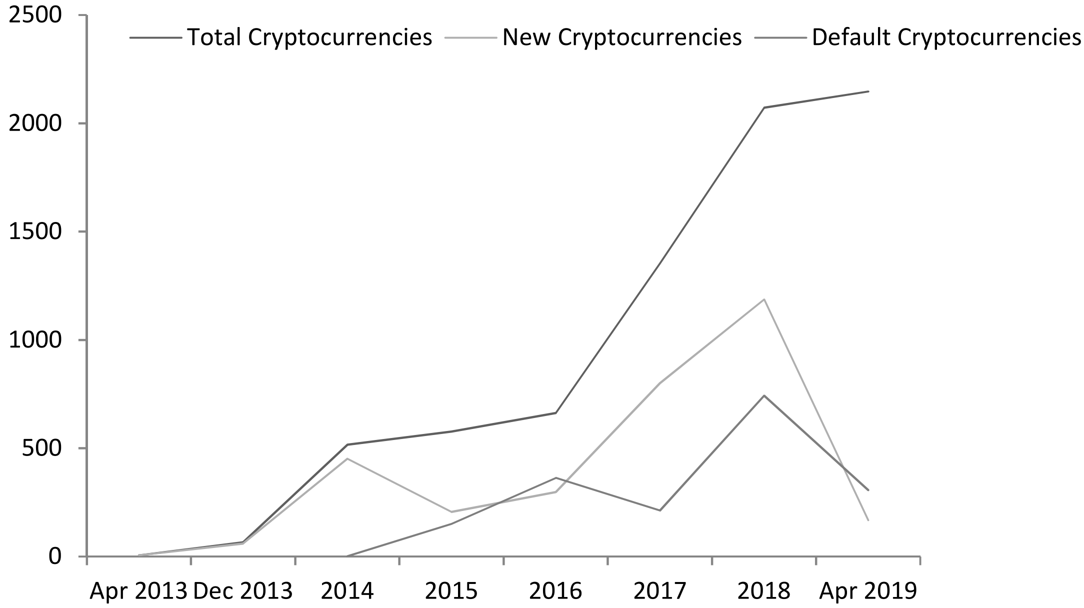
	Default Year	2014	2015	2016	2017	2018	Jan-Apr 2019	Total
	Number of default cryptocurrencies							
Year of issuance	**Before Apr 28, 2013**	0	0	0	0	1	0	**1**
	Mar-Dec 2013	2	1	17	3	11	4	**38**
	2014		149	133	34	58	13	**387***
	2015			213	56	98	20	**387**
	2016				120	174	26	**320**
	2017					401	72	**473**
	2018						172	**172**
	Total number of default cryptocurrencies	**2**	**150**	**363**	**213**	**743**	**307**	**1778**

Note: This table reports the numbers of bankrupt cryptocurrencies with their specific year of issuance and year of bankruptcy. It is generated using the historical snapshot available at coinmarketcap.com.

*It includes all cryptocurrencies and tokens using different consensus mechanisms. Out of which 86 cryptocurrencies that we used for our analysis are based on PoW consensus protocols.

Figure 1 shows that the numbers of default cryptocurrencies are increasing in comparison to the new cryptocurrencies added to the digital finance world after 2018. Specifically, we find that as of April 2019 there are altogether 1778 defaulted coins, however, 2147 coins are still in the digital asset market.[4]

Fig. 1. Demography of cryptocurrencies (Apr 2013 – Apr 2019)



Note: This figure shows the evolutions of new, default and total cryptocurrencies. Cryptocurrencies correspond to all three types of digital assets as defined in Howell, Niessner and Yermack (2019, p.1) where the first type is defined as a general-purpose medium of exchange and store of value cryptocurrency, such as Bitcoin. The second type of cryptocurrencies is a security token, which represents a conventional security that is recorded and exchanged on a blockchain to reduce transaction costs and create a record of ownership, whereas the third type of cryptocurrencies is a utility token, which gives its holder consumptive rights to access a product or service.

It should not be surprising that in a zero-interest regime even the asset management industry pays ever more attention to digital assets as an investment alternative. Given the likelihood of digital assets ending up in default, it is surprising that there is no paper available exploring the extent to which a default of a digital asset is forecastable. This current paper fills this important gap in the new age of digital finance literature.

[4] Note that Howell, Niessner and Yermack (2019, p.1) define three types of coins, Figure 1 accounts for the whole universe of digital assets. For instance, as of 2014, 146 out of 517 coins were cryptocurrencies that have the Proof-of-Work consensus protocol which are subject of examination in this study.

In our paper, we exclusively focus on the first category of digital asset defined as cryptocurrencies. As this type of digital asset is considered general-purpose medium of exchange, it is an alternative to traditional currency. We start our analysis by exploring which cryptocurrency-specific variables are accessible to the naïve investor. As we are interested in forecasting potential cryptocurrency defaults at an early stage, we focus on variables that are a part of the information set of the investor at most one month after a cryptocurrency started trading. Accordingly, we downloaded data for all cryptocurrencies launched before 2015 and followed those cryptocurrencies until the end of 2018.[5] Specifically, our data set consists of 146 cryptocurrencies, of which 86 went bankrupt before the end of 2018. We divided our dataset into two subsamples: The first subsample contains data on those cryptocurrencies that went into default and the second subsample contains the data of those cryptocurrencies that functioned until the end of our sample period. To analyze which of our variables have discriminative power, we then test which of the mean differences of our cryptocurrency-specific variables for our two subsamples were statistically significant. We made use of those variables that exhibited significant differences in sample means in a multiple linear discriminant model. We compared the estimated bankruptcies with the actual numbers. Moreover, we applied bootstrapping techniques to investigate the robustness of our model involving Type-I and Type-II errors.

Our paper contributes to the new strand of digital finance literature exploring cryptocurrencies. Recent literature investigates the volatility of cryptocurrencies (Katisiampa, 2017; Balcilar, Bouri, Gupta, and Roubaud, 2017; Osterrieder and Lorenz, 2017; Ardia, Bluteau, and Rüede, 2018; Baur and Dimpfl, 2018; Borri, 2019), price spillovers between cryptocurrencies (Fry and Cheah, 2016), predictability of cryptocurrency time series (Catania, Grassi and Ravazzolo, 2019; Lahmiri and Bekiros, 2019; Omane-Adjepong, Alagidede and Akosah, 2019; Shen, Urquhart, and Wang, 2019), cryptocurrencies as investment assets (Urquhart 2016; Dyhrberg, 2016; Dwyer, 2015), and speculative bubbles in the cryptocurrency market (Cheah and Fry, 2015; Chaim and Laurini, 2019; Li, Tao, Su, and Lobont, 2019). Even though empirical evidence shows that the majority of cryptocurrencies

[5] It is also noteworthy that cryptocurrencies exhibit different types of consensus protocols to verify transactions such as Proof-of-Work, Proof-of-Stake or a mixture of both which is often referred to as Hybrid. Before 2015, however, there were only few cryptocurrencies issued that were implemented using the Proof of Stake (PoS) mechanism. PoS was first introduced by Sunny King and Scott Nadal in 2012 and later in 2013 Sunny King created the first cryptocurrency Peercoin (PPC) implementing the PoS protocol. PoS is created to solve the high energy consumption problem of Bitcoin which uses the Proof-of-Work mechanism. In order to keep our sample homogenous, we exclude those cryptocurrencies using a PoS mechanism from our sample.

go into default, there is no paper available on the predictability of such cryptocurrency bankruptcy. Being able to forecast potential cryptocurrency defaults is important because the sums of money involved are substantial (Fry and Cheah, 2016). This paper fills this important gap in the literature while also complementing the large body of literature exploring the predictability of commercial bankruptcy. The publication of Altman's (1968) z-score model for predicting bankruptcy among manufacturing firms in the U.S.A, led to a wealth of research (Satish and Janakiram, 2011; Wang and Campbell, 2010; Lugovskaya, 2010), and Altman (2018) has recently provided an excellent overview of the relevant literature.

Moreover, Cheah and Fry (2015) and Osterrieder and Lorenz (2017) express concern that academic research on cryptocurrency is often focused on the legality of cryptocurrencies (Kethineni and Cao, 2019; Maume, 2019) rather than offering a comprehensive analysis of their statistical or financial aspects. Therefore, our paper contributes to the finance literature by adding a new perspective, credit risk. Finally, and from a more practical point of view, our paper also supports the finance industry by proposing a model that could be used for investment decisions. For instance, new digital asset management could use our model to determine which cryptocurrencies should be treated with caution owing to a high probability of default.

The results of this research show that bankruptcies among cryptocurrencies are predictable. Specifically, our model shows that we can predict 75 out of 86 cryptocurrency defaults. Employing 5000 bootstrap replications shows that the confidence interval for the point estimate indicating *default* does not overlap with the point estimate for the Type-I error. This shows that the discriminative power of our model is significant. Our results are in line with the literature on predicting firm bankruptcy (Altman, 1968, 1983, 2000, 2002; Altman, Haldeman, and Narayanan, 1977; Altman, Hartzell and Peck, 1995; Lugovskaya, 2010). Surprisingly, our model is not suitable for predicting the fate of functioning cryptocurrencies unlike Altman's (1968) z-score model or Altman, Haldeman, and Narayanan's (1977) ZETA model. We strongly encourage future research to elaborate on this issue.

The paper is organized as follows: The next section presents the empirical framework, including the model setup and robustness checks and the last section concludes.

2. Empirical framework

2.1. Multiple Linear Discriminant Analysis

Our analysis is supported by data from the various sources.[6] Each cryptocurrency has certain characteristics related to its history, specification, trading activities, reward, privacy, and scaling among others. Table A.1 in the appendix shows the categorized specification details of cryptocurrencies. We downloaded all cryptocurrencies that incorporated the Proof-of-Work (PoW)[7] mechanism and started trading between 2010 and the end of 2014 and considered a data period of four years ahead.[8] In total, we retrieved 146 cryptocurrencies, of which 86 went into default in the sample period and 60 continued functioning. We define a cryptocurrency as being in a 'default state' when the cryptocurrency stopped trading, that is, there is no more evidence of any trading.[9] Altman (2010, pp.4–5) emphasizes the importance of ratio analysis as an empirical tool in assessing the performance of business enterprises. Identifying variables that exhibit discriminative power is ultimately an empirical question. Therefore, the first step in our analysis was to explore variables that potentially discriminate between cryptocurrencies that ended up in default and those that remained functioning. Moreover, we wanted to account for variables that only the investor has access to at most one month after starting trading that support a decision on whether to invest in the relevant cryptocurrency at an early stage. Table A.2 in the appendix records 20 cryptocurrency-specific variables that exhibit information that could be utilized. Unfortunately, some information was not available for some now defunct cryptocurrencies.

There are many cryptocurrencies that are pre-mined before being offered to the public. Pre-mining has some advantages like rewarding the developers or creating a balanced distribution of coins (e.g., units of a cryptocurrency) between developers and traders. However, a larger number of pre-mined coins could be a negative indication, as when the developer has a large percentage of available coins and could therefore opt to leverage the

[6] We used the following sources: mapofcoins.com (name of cryptocurrency, categorization of 'running' and 'defunct'), coinmarketcap.com (historical price data), deadcoins.com (confirmation of categorization as 'defunct'), coinopsy.com/dead-coins (life span and founder information of dead coins), bitcointalk.org (announcement date and other technical specifications), and personal websites of coins for gathering any missing data.

[7] PoW is the very first consensus algorithm in decentralized public blockchain where miners solve complex cryptographic puzzles to add a block to the blockchain in exchange for coin as rewards.

[8] We downloaded price history from the coinmarketcap.com. The earliest data provided by this website starts on 28 April 2013. Though Bitcoin (BTC), Litecoin (LTC), Namecoin (NMC), Terracoin (TRC), Devcoin (DVC) and, Novacoin (NVC) started trading before this date. To have uniformity and consistency across our data set, however, we set 28 April 2013 as the first day of trade for the above mentioned coins.

[9] There are a few cryptocurrencies in the list of functioning cryptocurrencies in coinmarketcap.com even though these cryptocurrencies do not exhibit any trading activities. In our data set, we adjusted for these errors.

price before selling quickly. Cryptocurrencies exhibiting higher levels of pre-mining are under constant attack and carry a high manipulation risk[10]. Therefore, investors are generally concerned about whether a particular cryptocurrency is pre-mined or not (which we account for by using a simple binary dummy variable), and also the fractions of pre-mined coins (it measures the extent to which the developers retain control over that particular cryptocurrency if the total coins are mined as the *Pre-mined-to-Total-Coins-Ratio* (PMTTCR)). Moreover, we accounted for block time, Day-1 return, Week-1 return, and Month-1 return after the respective cryptocurrency started trading. For instance, a positive return in the initial trading period could indicate the popularity of a particular cryptocurrency. We also compounded the corresponding time-congruent volatilities (Day-1, Week-1, and Month-1) simply as the corresponding squared return. Instead of interpreting each variable in isolation, our variables should be considered in the respective context. For instance, a slightly negative first day trading return with a low volatility in association with a high monthly volatility could indicate that the cryptocurrency did not attract attention following the announcement owing to a lack of social promotion, but the cryptocurrency could be subject to excessive speculation within the first month after trading. Generally, assets that are subject to excessive speculation may end up in trouble—or in default—at a later stage. Furthermore, *reward per block* shows the level of coin supply during that particular block interval. We include *Minimum-Reward-To-Total-Coin-Ratio* (MTTCR) as a common comparative tool to measure the minimum level of controlled supply among the cryptocurrencies in our sample. Our model includes both an individual and a comparative level of minimum controlled supply. Finally, we also coded dummy variables for identifying both the cryptocurrency-specific algorithm and whether the cryptocurrency has a known founder.[11]

We report the descriptive statistics of our selected variables in Table A.3 in the appendix. Moreover, Table 3 reflects the variable means and the results of testing the difference in means for significance. We used a simple two-sample *t*-test to test the difference in sample means (Snedecor and Cochran, 1989). The sample differences of minimum reward, Day-1 and Month-1 returns, Day-1 volatility, and PMTTCR are statistically significant on at least a 5% level (see Table 3). Moreover, the Month-1 volatility is at least marginally significant on a 10% level. Interestingly, we also find that among functioning cryptocurrencies, 58% of the founders remain anonymous, whereas among bankrupt

[10] See https://cryptodaily.co.uk/2018/08/premined-coins-like-xrp-trx-xlm-and-neo-are-causing-problems-for-index-funds (published on August 29, 2018).

[11] We categorized algorithms into three types; 'SHA' (Secure Hash Algorithm), 'Scrypt', and 'others'. 'Others' contains all other algorithms besides SHA and Scrypt family algorithms.

cryptocurrencies that figure rises to 79%. For a 95% confidence interval, the critical values for the binary-distributed variable *known founder* in the sample of functioning cryptocurrencies is between 0.50 and 0.66, implying that the sample of bankrupt cryptocurrencies exhibits a significantly higher probability of the founder being anonymous, given a 5% significance level. Moreover, for a 95% confidence interval, the critical value for the binary-distributed variable *scrypt algorithm* in the sample of functioning cryptocurrencies is between 0.52 and 0.68. As the sample average in the default sample is 0.80, we can reject the null hypothesis that the sample means are equal, implying that those cryptocurrencies that ended up in default exhibit this specific algorithm more frequently.

More precisely, the definitions of our variables are as following:

$$Ret\_D1_t = \frac{(Day_1 Close)_t - (Day_1 Open)_t}{(Day_1 Open)_t},$$

where Ret_D1_t denotes the first day's return of cryptocurrency *t*, $(Day_1 Close)_t$ denotes the first day's closing price of cryptocurrency *t*, and $(Day_1 Open)_t$ denotes the first day's opening price of cryptocurrency *t*.

$$Ret\_W1_t = \frac{(Day_7 Close)_t - (Day_1 Open)_t}{(Day_1 Open)_t},$$

where Ret_W1_t denotes the first week's return of cryptocurrency *t*, $(Day_7 Close)_t$ denotes the closing price after the seventh day of cryptocurrency *t*, and $(Day_1 Open)_t$ denotes the first day's opening price of the cryptocurrency *t*.

$$Ret\_M1_t = \frac{(Day_{30} Close)_t - (Day_1 Open)_t}{(Day_1 Open)_t},$$

where Ret_M1_t denotes the first month's return of the cryptocurrency *t*, $(Day_{30} Close)_t$ denotes the closing price of cryptocurrency *t* after 30 trading days, and $(Day_1 Open)_t$ denotes the first day's opening price of cryptocurrency *t*.

$$Vol\_D1_t = (Ret\_D1_t)^2,$$

where Vol_D1_t denotes the first day's volatility of cryptocurrency *t*, and Ret_D1_t denotes the first day's return of cryptocurrency *t*.

$Vol\_W1_t = (Ret\_W1_t)^2,$

where Vol_W1_t denotes the first week's volatility of cryptocurrency t, and Ret_W1_t denotes the first week's return of cryptocurrency *t*.

$Vol\_M1_t = (Ret\_M1_t)^2,$

where Vol_M1_t denotes the first month's volatility of cryptocurrency *t*, and Ret_M1_t denotes the first month's return of cryptocurrency *t*.

Moreover, PMTTCR (*Pre-Mined-To-Total-Coins-Ratio*) indicates the fraction of coins that are allocated to the developers in relation to the total coins in circulation, given that a cryptocurrency is fully mined. (Note that developers with a large portion of coins in stake can manipulate the market with a so-called pump-and-dump strategy. Note also that if a large proportion of a cryptocurrency is pre-mined, this cryptocurrency could be subject to potential scam.) Further,

$PMTTCR_t = \frac{(NUMBER\ OF\ PRE-MINED\ COINS)_t}{(TOTAL\ COINS\ WHEN\ FULLY\ MINED)_t},$

where $PMTTCR_t$ denotes the *Pre-Mined-To-Total-Coins-Ratio* of cryptocurrency *t*, $(NUMBER\ OF\ PRE-MINED\ COINS)_t$ denotes the number of pre-mined coins of cryptocurrency *t*, and $(TOTAL\ COINS\ WHEN\ FULLY\ MINED)_t$ denotes the number of total coins of cryptocurrency *t* when being fully mined.

The number of coins received by miners as a reward per block for any cryptocurrency shows how new coins are generated after every *block time* interval (which, in turn, varies among cryptocurrencies). Specifically, *block time* is the time it takes to verify one block. This also indicates how frequently the new coins are generated to reward the miners for verifying the block. Moreover, the coins rewarded for the miners are the new coins supplied to the market. Due to the limited supply of coins (at least for the majority of cryptocurrencies), the reward decreases over time. *Minimum reward* measures the lowest number of coins as a reward given to the miners. The mining of a cryptocurrency continues only if the rewards cover the mining cost. If the *minimum reward* is meager such that the mining cost cannot be covered, miners will stop mining and eventually that cryptocurrency is likely to end up in default. Therefore, *minimum reward* may be an important factor to consider in our current research's context. On the other hand, MTTCR (*Minimum-Reward-to-Total-Coins-Ratio)* measures the minimum level of controlled supply until the cryptocurrency is fully mined. Both, too much or too little supply of coins are not beneficial for the crypto economy. Further,

$$MTTCR_t = \frac{(MINIMUM\ REWARDS\ PER\ BLOCK\ EXCLUDING\ BONUS\ REWARDS)_t}{(TOTAL\ COINS\ WHEN\ FULLY\ MINED)_t},$$

where $MTTCR_t$ denotes the *Minimum-Reward-to-Total-Coins-Ratio* of cryptocurrency *t*, $(MINIMUM\ REWARDS\ PER\ BLOCK\ EXCLUDING\ BONUS\ REWARDS)_t$ denotes the minimum number of coins rewarded for the miners of cryptocurrency *t*, and $(TOTAL\ COINS\ WHEN\ FULLY\ MINED)_t$ denotes the number of total coins of cryptocurrency *t*, given the cryptocurrency is fully mined.

Table 3. Testing the differences-in-means between functioning and default cryptocurrencies

	Default (D)	Functioning (F)	Difference (F-D)
Minimum Reward	65880.65	3377.064	-62503.6** (-1.97)
Block time	160.79	152.92	7.87 (0.30)
Ret_D1	0.0403	0.7124	0.6721*** (3.17)
Ret_W1	0.2541	0.2849	0.0309 (0.19)
Ret_M1	0.2454	0.1197	-0.1257** (-2.31)
Vol_D1	3.1776	10.2559	7.0783** (2.43)
Vol_W1	2.7361	4.8749	2.1388 (0.93)
Vol_M1	0.6147	0.3131	-0.3016* (-1.78)
MTTCR	3.2E-05	8.0E-06	-2.4E-05 (-1.57)
PMTTCR	0.0152	0.0041	-0.0111** (-2.47)
Pre-mined	4.89E+07	6.14E+08	-5.65E+08** (-2.03)
Known founder	0.79	0.58	-0.21*** (-8.62)
Scrypt algorithm	0.80	0.60	-0.20*** (-8.33)

Note: This table reports the differences of the means of our predictor variable candidates between our sample of functioning cryptocurrencies and those that went into default. As potential predictor variable candidates we consider the minimum reward, block time, first day return (Ret_D1), first week return (Ret_W1), first month return (Ret_M1), first day volatility (Vol_D1), first week volatility (Vol_W1), first month volatility (Vol_M1), Minimum-Reward-to-Total-Coins-Ratio (MTTCR), Pre-Mined-To-Total-Coins-Ratio (PMTTCR), and pre-mined coins (pre-mined). Our data set consists of all cryptocurrencies that incorporated the Proof-of-Work mechanism and started trading prior to December 31, 2014. We followed those cryptocurrencies until the end of 2018. We retrieved 146 cryptocurrencies, of which 86 went into default (D) in the sample period and 60 remained functioning (F). (F-D) measures the mean-difference between the functioning and default sample. The corresponding *t*-statistics are given in parentheses.

*Statistically significant on a 10% level.

**Statistically significant on a 5% level.

***Statistically significant on a 1% level.

Next, we employed Multiple Linear Discriminant Analysis (MLDA) to address our research question. MDLA, which is a type of cluster analysis, has been used to model credit risks. For instance, in his seminal paper, Altman (1968) explored bankruptcy among companies in the manufacturing industry and proposed the z-score to predict the probability that a firm will go bankrupt within two years. That research led to many modifications being applied to predict various types of financial failure (Altman, 1983; 2002; Altman, Hartzell, and Peck, 1995; Altman, Haldeman, and Narayanan, 1977; Altman, Danovi, and Falini, 2013; Altman, and Rijken, 2010). This is the first paper to make use of MLDA to model defaults in the cryptocurrency market. Again, all input variables used in our model were available to the naïve investor within one month after a cryptocurrency started trading. Since there are different methodologies to perform cluster analysis, below we explain how we set up our model.

We divided the data into two groups, the default group, and the group that consists of functioning cryptocurrencies. We stacked the data of those two groups into two matrices defined as $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, where $\boldsymbol{X_1}$ denotes the default group and $\boldsymbol{X_2}$ denotes the functioning group. Moreover, the matrix $\boldsymbol{X}$ defines the whole data set, that is,

$$\boldsymbol{X} = \begin{bmatrix} \boldsymbol{X_1} \\ \boldsymbol{X_2} \end{bmatrix} = \begin{bmatrix} [\boldsymbol{x}_{1,1} & \cdots & \boldsymbol{x}_{1,K}] \\ [\boldsymbol{x}_{2,1} & \cdots & \boldsymbol{x}_{2,K}] \end{bmatrix}. \tag{1}$$

Let us assume that we consider K variables of the cryptocurrency-specific data and let us also assume that we deal with T_1 cryptocurrencies that went into default and T_2 cryptocurrencies that were functioning during our sample period. For instance in Equation's (1) notation, $\boldsymbol{x}_{1,1}$ defines a T_1x1 column vector that contains the values for variable 1 for the default sample (e.g., group 1), whereas $\boldsymbol{x}_{1,K}$ defines a T_1x1 column vector that contains the values for variable K in the default sample, and so forth. More concretely,

$$\boldsymbol{x}_{1,1} = \begin{bmatrix} x_{1,1} \\ x_{2,1} \\ \vdots \\ x_{T_1,1} \end{bmatrix}, \text{ or } \boldsymbol{x}_{1,K} = \begin{bmatrix} x_{1,K} \\ x_{2,K} \\ \vdots \\ x_{T_1,K} \end{bmatrix}, \text{ and analogously } \boldsymbol{x}_{2,1} = \begin{bmatrix} x_{T_1,2} \\ x_{T_1+1,2} \\ \vdots \\ x_{T,2} \end{bmatrix}, \text{ or } \boldsymbol{x}_{1,K} = \begin{bmatrix} x_{T_1,K} \\ x_{T_1+1,K} \\ \vdots \\ x_{T,K} \end{bmatrix}.$$

Then for the matrices $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, the sample average of each column can be stacked into the 1xK vectors $\boldsymbol{\mu}_1$ and $\boldsymbol{\mu}_2$, given by

$$\boldsymbol{\mu}_1 = [\overline{\boldsymbol{x}}_{1,1} \quad \cdots \quad \overline{\boldsymbol{x}}_{1,K}] \qquad \text{and} \qquad \boldsymbol{\mu}_2 = [\overline{\boldsymbol{x}}_{2,1} \quad \cdots \quad \overline{\boldsymbol{x}}_{2,K}]. \tag{2}$$

For instance, the element $\overline{\boldsymbol{x}}_{1,1} = \frac{1}{T_1}\sum_{t=1}^{T_1} x_{t,1}$ defines the sample average of the first cryptocurrency-specific variable of the default group and $\overline{\boldsymbol{x}}_{2,1} = \frac{1}{(T-T_1)}\sum_{t=T_1+1}^{T} x_{t,2}$ defines the corresponding sample average of the first cryptocurrency-specific variable of the functioning group. Moreover, the global mean vector $\boldsymbol{\mu}$ stacks the overall sample averages for each column of the matrix $\boldsymbol{X}$ into a *1*x*K* row vector. Note that $\boldsymbol{\mu}$ can be simply calculated as

$$\boldsymbol{\mu} = \frac{1}{T}(T_1\boldsymbol{\mu}_1 + (1 - T_1)\boldsymbol{\mu}_2) = \frac{1}{T}(T_1\boldsymbol{\mu}_1 + T_2\boldsymbol{\mu}_2) \equiv [\mu_1 \quad \mu_2 \quad \cdots \quad \mu_K]. \tag{3}$$

Then we calculated the mean-corrected matrices $\boldsymbol{X_1^0}$ and $\boldsymbol{X_2^0}$ defined as

$$\boldsymbol{X_1^0} = \begin{bmatrix} \boldsymbol{x}_{1,1} - \boldsymbol{\mu} \\ \boldsymbol{x}_{2,1} - \boldsymbol{\mu} \\ \vdots \\ \boldsymbol{x}_{T_1,1} - \boldsymbol{\mu} \end{bmatrix} \quad \text{and} \quad \boldsymbol{X_2^0} = \begin{bmatrix} \boldsymbol{x}_{T_1+1,2} - \boldsymbol{\mu} \\ \boldsymbol{x}_{T_1+2,2} - \boldsymbol{\mu} \\ \vdots \\ \boldsymbol{x}_{T,2} - \boldsymbol{\mu} \end{bmatrix}, \tag{4}$$

where obviously $T - T_1 = T_2$ and given Equation's (4) notation, $\boldsymbol{x}_{t,i} - \boldsymbol{\mu}$ defines a *1*x*K* row vector i in each respective matrix, $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$, subtracted by the global mean vector $\boldsymbol{\mu}$. For instance,

$\boldsymbol{x}_{1,1} - \boldsymbol{\mu} = [(x_{1,1} - \mu_1) \quad (x_{1,2} - \mu_2) \quad \cdots \quad (x_{1,K} - \mu_K)]$, or
$\boldsymbol{x}_{2,1} - \boldsymbol{\mu} = [(x_{2,1} - \mu_1) \quad (x_{2,2} - \mu_2) \quad \cdots \quad (x_{2,K} - \mu_K)]$, for the default group and analogously,

$\boldsymbol{x}_{T_1+1,2} - \boldsymbol{\mu} = \left[(x_{T_1+1,1} - \mu_1) \quad (x_{T_1+1,2} - \mu_2) \quad \cdots \quad (x_{T_1+1,K} - \mu_K)\right]$, or
$\boldsymbol{x}_{T_1+2,2} - \boldsymbol{\mu} = \left[(x_{T_1+2,1} - \mu_1) \quad (x_{T_1+2,2} - \mu_2) \quad \cdots \quad (x_{T_1+2,K} - \mu_K)\right]$, for the functioning group respectively.

We compounded the corresponding empirical sample covariance matrices as

$$\boldsymbol{C_1} = \frac{\boldsymbol{X_1^0}^T \boldsymbol{X_1^0}}{T_1} \quad \text{and} \quad \boldsymbol{C_2} = \frac{\boldsymbol{X_2^0}^T \boldsymbol{X_2^0}}{T_2}, \tag{5}$$

where the dimension of $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ must be the same, that is, *K*x*K* as we want to investigate the characteristic-specific differences in cryptocurrencies. Then we employed the estimated sample covariance matrices $\boldsymbol{C_1}$ and $\boldsymbol{C_2}$ to calculate the pooled within-group covariance matrix, simply defined as $\boldsymbol{C}(r, s)$ and given by

$$\boldsymbol{C}(r,s) = \frac{1}{(T_1+T_2)} \sum_{i \in (1,2)} T_i \cdot \boldsymbol{C_i}(r,s), \tag{6}$$

where $r = 1, \dots, K$ and $s = 1, \dots, K$. As $rank(\boldsymbol{C}) = K$ was satisfied, we then compounded the inverse of $\boldsymbol{C}$**,** defined as $\boldsymbol{C}^{-1}$. Moreover, the prior-probability vector, based on the empirical data, can simply be calculated as

$$\boldsymbol{P} = \begin{bmatrix} p_1 \\ p_2 \end{bmatrix} = \begin{bmatrix} \left(\frac{T_1}{(T_1+T_2)}\right) \\ \left(\frac{T_2}{(T_1+T_2)}\right) \end{bmatrix}. \tag{7}$$

Finally, for our T cryptocurrencies, we can estimate the discriminant function depending on the default and non-default cluster as

$$f_{1,t} = \boldsymbol{\mu}_1 \boldsymbol{C}^{-1} \boldsymbol{x}_{t,K}^T - 0.5 \cdot \boldsymbol{\mu}_1 \boldsymbol{C}^{-1} \boldsymbol{\mu}_1^T + ln(p_1), \qquad \text{and} \tag{8.a}$$

$$f_{2,t} = \boldsymbol{\mu}_2 \boldsymbol{C}^{-1} \boldsymbol{x}_{t,K}^T - 0.5 \cdot \boldsymbol{\mu}_2 \boldsymbol{C}^{-1} \boldsymbol{\mu}_2^T + ln(p_2), \tag{8.b}$$

where $\boldsymbol{x}_{t,K}^T$ is the corresponding transposed *1*x*K* vector of characteristics of cryptocurrency *t*. If $f_{1,t} > f_{2,t}$, cryptocurrency *t* is predicted to be in the default group, otherwise it is predicted to be in the functioning group. Given the subsamples, we defined $f_{1,t} > f_{2,t}$ as *success* for the default group and $f_{1,t} < f_{2,t}$ as *success* for the functioning group meaning that the discriminant model correctly assigned the respective cryptocurrency to its corresponding group. Furthermore, for each group, we coded two vectors of dummy variables denoted as $\boldsymbol{d}_1$ and $\boldsymbol{d}_2$ that have a value of one in case of *success* and a value of zero otherwise. The prediction accuracy of predicting a cryptocurrency's default within four years is then simply given by $\sum_{t=1}^{T_1} d_{1,t}/T_1$, whereas the Type-I error of this model is $1 - \sum_{t=1}^{T_1} d_{1,t}/T_1$. In the same manner, the prediction accuracy for predicting a cryptocurrency's continued functioning can be calculated as $\sum_{t=1}^{T_2} d_{2,t}/T_2$, while the Type-II error is then given by $1 - \sum_{t=1}^{T_2} d_{2,t}/T_2$.

Setting up the empirical model is ultimately an empirical question. After our initial analysis of differences in sample means, we decided to employ the following cardinal variables in our discriminant analysis: Day-1 return, Month-1 return, and the corresponding volatilities, PMTTCR, and minimum reward. We also account for a set of dummy variables for measuring the qualitative variables *algorithm*, *anonymous founder*, and *pre-mined*. Specifically, we employ K=9 predictor variables in our analysis. Since we have $T_1 = 86$ cryptocurrencies that ended up in default and $T_2 = 60$ that remained functioning, our matrices $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ have the dimension 86x12 and 60x12, respectively. Our model operates with 12 instead of nine columns because we employ three dummy variables for indicating the algorithm (scrypt, SHA, or others), one binary dummy variable for indicating whether a cryptocurrency is pre-mined, one dummy variable indicting whether the founder is anonymous, and continuous variables for Day-1 return, Day-1 volatility, Month-1 return, Month-1 volatility, actual amount of pre-mined coins, actual amount of minimum reward, and PMTTCR. The estimated discriminant function is reported in Table A.4. and A.5. in the appendix. Finally, these estimates are used to calculate the results reported in Table 4. For example, from Table A.4. we learn that the discriminant function correctly predicts in 75 out of 86 cryptocurrencies that they are in group 1 because the value of the discriminant function is larger for group1 than for group 2. Consequently, 87.21% of cryptocurrency defaults are predicted correctly.

Table 4. Predicting cryptocurrency default

	Predicted group by the Multiple Linear Discriminant Function	
Actual Group	Default group	Functioning group
Default group	87.21%	12.79%
Functioning group	43.33%	56.67%

Note: This table reports the results of our multiple linear discriminant analysis. Our dataset consists of all cryptocurrencies that incorporated the Proof-of-Work mechanism and started trading between 2009 and the end of 2014. We followed up those cryptocurrencies until the end of 2018. We retrieved 146 cryptocurrencies, of which 86 went into default in the sample period and 60 remained functioning. Our model incorporates the following predictor variables: minimum reward, pre-mined, Day-1 return, Month-1 return, Day-1 volatility, Month-1 volatility, and PMTTCR. Moreover, we include a set of dummy variables for indicating ‘algorithm’ and ‘founder anonymity’.

Given the data of bankrupt and functioning cryptocurrencies, as reported in Table A.6. that are in either the default group or the functioning group our model is able to correctly predict 87% of the defaults corresponding to a Type-I error of 13%. Our estimates are close to models that predict bankruptcy of enterprises. For instance, the popular multiple discriminant model from Altman (1968) predicted 94% of bankruptcies of U.S. firms in the manufacturing industry. It is important to note, however, that first Altman’s (1968) benchmark model uses recent information on those companies investigated because he employed data from balance sheets that were released about one year before the bankruptcy occurred. Second, he matched that sample of companies that went bankrupt with a sample of matched companies having the same number of firms and the same firm characteristics, whereas our analysis accounts for the whole sample of available cryptocurrencies. Furthermore, we use only information available at an early stage, that is, after one month of trading. Its chosen sample means our model predicts bankruptcy within the next four years, which is very different from Altman’s findings. Even though Altman’s (1968) model performed remarkably well for a one- and two-year period prior to bankruptcy, a robustness check shows that its success rate is only 29% for a four year period.[12] Even though our results suggest that our cryptocurrency default prediction model is an accurate forecaster of failure, Table 4 shows that the Type-II error is 43%. This result implies that our model struggles to predict functioning cryptocurrencies.

2.2. Robustness checks

Since we only have one sample available, our estimates reported in Table 4 are only point estimates. To investigate how sensitive our model is with respect to resampling and to compound confidence intervals for our estimates, we employed bootstrapping. It seems reasonable to assume that characteristic k of cryptocurrency t is uncorrelated with the characteristic k of cryptocurrency s, that is, $cov(x_{t,k}, x_{s,k}) = 0$.[13] However, characteristic k of cryptocurrency t is not necessarily uncorrelated with characteristic l, meaning $cov(x_{t,k}, x_{t,l}) \neq 0$. We have ensured this is ex-ante by simply choosing our research set-up because all cryptocurrencies have the same consensus protocol and are therefore

[12] The average success rate of Altman’s (1968) model between year one and four prior to bankruptcy is 61%.

[13] Note that Altman (1968, p.592) highlights that “there is reason to believe that some of the measurements will have a high degree of correlation or collinearity with each other.”

homogenous. However, characteristics of a cryptocurrency could be – at least potentially – correlated with other characteristics of the same cryptocurrency. To account for this issue, we employed a pairs bootstrap as detailed by Godfrey (2009, pp.$183-185$). In doing so, we constructed new data matrices defined as $\boldsymbol{X}_1^b$ and $\boldsymbol{X}_2^b$ where each row vector in $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ is randomly resampled with replacement where each row in $\boldsymbol{X_1}$ and $\boldsymbol{X_2}$ is drawn with probability $1/T_1$ and $1/T_2$ respectively. We employ $B = 5000$ bootstrap samples and re-estimate the corresponding discriminant functions to estimate the empirical confidence interval.

More concretely, for each bootstrap run *b*, we employ the original data matrix $\boldsymbol{X_1}$ that has the dimension 86x12, as described in section 2.1. Then we randomly draw with replacement and with probability 1/86=0.0116 a row from matrix $\boldsymbol{X_1}$ and add that row into matrix $\boldsymbol{X}_1^b$ to construct a new data matrix. For each run *b*, this procedure is stopped when all 86 rows in the new data matrix $\boldsymbol{X}_1^b$ are filled. In the same manner, for each bootstrap run *b*, we employ the original data matrix $\boldsymbol{X_2}$ that has the dimension 60x12, as described in section 2.1. Then we randomly draw with replacement and with probability 1/60=0.0167 a row from matrix $\boldsymbol{X_2}$ and add that row into matrix $\boldsymbol{X}_2^b$ to construct a new data matrix. For each run *b*, this procedure is stopped when all 60 rows in the new data matrix $\boldsymbol{X}_2^b$ are filled. These new data matrices are used to run the linear discriminant analysis described in section 2.1 for each bootstrap iteration $b = 1, \dots ,5000$. The corresponding point estimates are stored in vector. These vectors are sorted in an increasing order. Then, the 125th observation gives us the value of the lower bound and the 4875th observation gives us the upper bound of our confidence interval covering 95% probability.

The results of our analysis can be found in Table 5. Using bootstrapping, the 95% confidence interval for our point estimate concerning successfully predicting cryptocurrency default is between 83.72% and 89.53% again suggesting a high level of accuracy. However, the 95% confidence interval for the Type-II error ranges between 41.67% and 53.33%. Assuming that the point estimate for the Type-II error is distributed as $N(\mu_1, \sigma)$ with $\mu_1 = 47.50$ and $\sigma = 2.97$, and that the corresponding point estimate for the correctly predicted functioning cryptocurrencies is distributed as $N(\mu_2, \sigma)$ with $\mu_2 = 52.50$, 60.99% of the confidence intervals are overlapping.[14] This result implies that our model overpredicts defaults in the sample of functioning cryptocurrencies.

[14]Note, $\mu_1 = \frac{(41.67+53.33)}{2} = 47.50$, $\sigma = \frac{(53.33-47.50)}{1.96} = \frac{(58.33-52.50)}{1.96} = 2.9745$, $\mu_2 = \frac{(46.67+5\ \ .33)}{2} = 52.50$.

Table 5. Estimated confidence intervals using bootstrapping

	Predicted group by the Multiple Linear Discriminant Function	
Actual Group	Default group	Functioning group
Default group	[83.72%; 89.53%]	[10.47%; 16.28%]
Functioning group	[41.67%; 53.33%]	[46.67%; 58.33%]

Note: This table reports the results of $B = 5000$ bootstrap replications using a pairs bootstrap. We constructed new data matrices by random resampling with replacement using a probability of $1/T_1$ for the subsample of default cryptocurrencies and a probability of $1/T_2$ for the subsample of functioning cryptocurrencies. Then we re-estimated our model B times and sorted the estimated probabilities in an increasing order. The 125th observation gives us the value of the lower bound and the 4875th observation gives us the upper bound of our confidence interval covering 95% probability.

It is important to note that the new digital financial markets evolve fast over time. For instance, during 2016 few cryptocurrencies were launched implementing SHA algorithms.[15] Moreover, we would like to stress that new cryptocurrencies are applying more advanced algorithms and security mechanisms; there are only few new cryptocurrencies implementing the SHA hashing algorithms and PoW mechanism because these methods have slower speeds and higher energy consumption. Moreover, as technology advances so too does the blockchain. The most common algorithms for the cryptocurrencies issued before 2015 were SHA and Scrypt, but new cryptocurrency algorithms like X11–X17 were created specifically for Graphical Processing Unit (GPU) mining and provide good profit levels to the Portable Instant Mining Platform (PiMP) community since the rise of large Application-Specific Integrated Circuits (ASICs) for Scrypt. Table A.7. in the appendix provides a brief overview of those new algorithms X11–X17. New research needs to account for technological changes associated with cryptocurrencies.

In the same way like Altman (1968) proposed in his seminal paper a model that had the ability to predict bankruptcies for firms in a specific industry in the U.S. (e.g., manufacturing industry), our paper takes the first step in exploring predictable patterns in defaults in new emerging digital financial markets. Expecting that we could propose a universal model being capable of predicting defaults across different categories of digital

[15] See footnote 8.

asset would be an illusion. As pointed out in Howell, Niessner and Yermack (2019) there are three types of digital assets.

While cryptocurrencies that are defined as "general-purpose medium of exchange and store of value cryptocurrency" can be considered as alternative to traditional fiat currency, utility tokens or security tokens have a very different purpose, which is financing business projects. Due to their nature, those digital assets have very different characteristics compared to cryptocurrencies. While our paper specifically governs cryptocurrencies that incorporate the PoW consensus protocol – which obviously was the dominant consensus protocol in our sample of investigation – future research is needed to explore the predictability of defaults for either cryptocurrencies that follow other consensus protocols (e.g., Proof-of-Stake or Hybrid), or other types of digital currencies, such as tokens issued in Initial Coin Offerings.

Moreover, the research methodology of our paper is related to the literature applying MLDA to predict various types of financial failure (e.g., Altman, 1968; Altman, 1983; 2002; Altman, Hartzell, and Peck, 1995; Altman, Haldeman, and Narayanan, 1977; Altman, Danovi, and Falini, 2013; Altman, and Rijken, 2010). However, there are other strands of literature dealing with analyzing credit risks and employ methodologies such as Probit/Logit models. Future research is encouraged to investigate the predictability of defaults using other methodologies than MLDA also.

3. Conclusion

In this age of digital finance, investors can now choose from more than 2,000 cryptocurrencies to invest in. Among cryptocurrencies that started trading prior to December 2014, we found 59% went bankrupt by the end of 2018. This paper proposes a model to predict cryptocurrency default. We downloaded data for all cryptocurrencies launched between January 2009 and December 2014 and established if they went bankrupt by December 2018. We explored almost two dozen cryptocurrency-specific variable candidates that might serve as predictor variables. From those variables, we only used data for the model setup available to the naïve investor one month after a new cryptocurrency started trading. For each of the selected variables, we estimated the sample means for both the default sample and the functioning sample. Our model correctly predicts 75 of 86 bankruptcies (87%). Employing bootstrapping established that the estimates are statistically significant. Notably, the new digital asset markets are subject to technological changes: For instance, many cryptocurrencies issued after 2015 adopted the PoS (minting) consensus mechanism due to greater energy consumption of PoW (mining). Other major changes that we identified are among others that new cryptocurrencies adopt more efficient and profitable algorithms like X11, X12, and X17 over previously popular algorithms like SHA and Scrypt. Therefore, future research on such technological changes is warranted. Nevertheless, our proposed model could be employed in the asset management industry, for instance, as a screening tool for investment decision making. A rational investor would avoid investing in digital assets exhibiting overly high default risks. Portfolios that pre-condition the set of digital assets on those cryptocurrencies that are not predicted as at risk of bankruptcy might generate a better risk-return profile for investors.

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Appendix

Table A.1. Cryptocurrency characteristics

Category	Details
Resource and history	Website, announcement, whitepaper, block explorer, github, etc.
Coin specifications	Coin name, type, founder(s), contributor(s), block time, security mechanism, algorithm, staking maturity, block size, launch type, etc.
Daily trading, supply and distribution	rank, market cap, price ($), price (BTC), volume(24h), market Dominance (Volume, Value), Supply (Max, Total, Circulating), etc.
Economics	Block reward, inflation, fees recipient, funding model, etc.
Privacy	Cryptographic privacy, sender privacy, recipient privacy, hidden transaction amount, transaction link broken, balances visible, anonymous holdings, network trust required, quantum-proof privacy, trusted setup, auditable supply, mobile privacy, etc.
Features and scaling	Instant send, protocol level, governance, voters, multi-signature support, scaling model, transparent transaction size (bytes), private transaction size (bytes), most throughput in a block, prunable blockchain, etc.
Wallets	Ledger, trezor, coinomi, jaxx, native mobile wallet binaries for all major OS, webwallet, etc.
Network and masternodes	Largest miner or pool, entities controlling, staking supply, public nodes, masternodes, masternode cost (coin), masternode cost ($), etc.
Community	Percentage of active users, number of subscribers, facebook likes, Twitter followers, Alexa rank, Google/Bing searches, etc.

Note: This table provides an overview of different features and characteristics of a cryptocurrency.
(Source: https://news.bitcoin.com)

Table A.2. Potential cryptocurrency-specific variables for the model

Potential categorical variable candidates	
1.Security mechanism	PoW/PoS/Hybrid/Others
2.Launch type*	Standard/ICO/Fork/Coinswap/others
3.Algorithms	SHA/Scrypt/others
4.Funding model*	ICO/donations/founders/others
Potential Binary Variable Candidates	
5. Pre-mined, **6.**Privacy choice*, **7.**Sender privacy*, **8.**Recipient Privacy*, **9.**Network trust required*, **10.** Multi-signature Support*, **11.**Founder anonymity	YES/NO
Potential Continuous Variable Candidates	
12. Block time, **13.**Block reward, **14.**Block size*, **15.**Pre-mined ratio, **16.**Total coins, **17.** Volume*, **18.**Return, **19.**Volatility, **20.** Reward percentage	

Note: This table provides an overview of different quantifiable (continuous/categorical/binary) cryptocurrency-specific variables that could potentially be used to develop a model. Our model incorporates 9 variables from the 20 candidates. The remaining variables were excluded owing to the non-accessibility of websites for many dead coins highlighted with an asterisk (*).

Table A.3. Descriptive statistics of functioning and bankrupt cryptocurrencies

	N	Mean	Median	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Panel A. Descriptive statistics of the functioning sample									
PMTTCR	60	0.0041	0.0000	0.0842	0.0000	0.0153	4.5660	23.2754	1236.2090
MTTCR	60	0.0000	0.0000	0.0004	0.0000	0.0000	7.3888	56.3109	7651.0780
Ret_D1	60	0.7124	-0.3779	18.3576	-0.9655	3.1486	3.7353	18.8502	767.6010
Ret_W1	60	0.2849	-0.0753	16.2296	-0.8501	2.2079	6.4717	46.9459	5246.9390
Ret_M1	60	0.1197	0.0000	2.6973	-0.7500	0.5512	2.6563	11.9317	269.9996
Vol_D1	60	10.2559	0.4855	337.0018	0.0000	45.5486	6.4127	45.7924	4989.2090
Vol_W1	60	4.8749	0.0694	263.4009	0.0000	33.9713	7.5306	57.8118	8077.9110
Vol_M1	60	0.3131	0.0116	7.2756	0.0000	1.1050	5.0058	29.2786	1976.9990
Block time	60	152.9167	60.0000	600.0000	5.0000	185.9005	1.7929	4.6947	39.3247
Minimum reward	60	3377.0640	50.0000	100000.0000	0.0000	14473.7900	5.6653	36.1092	3061.5140
Pre-mined	60	6.1400E+08	0.0000E+00	3.6800E+10	0.0000E+00	4.7500E+09	7.5509E+00	5.8017E+01	8.1373E+03
Total coins	60	2.9500E+10	8.4000E+07	5.0000E+11	4.2000E+01	1.0000E+11	3.8711E+00	1.6909E+01	6.3351E+02
Panel B. Descriptive statistics of the default sample									
PMTTCR	86	0.0152	0.0000	0.5000	0.0000	0.0754	6.1213	39.2322	5241.1920
MTTCR	86	0.0000	0.0000	0.0024	0.0000	0.0003	9.0733	83.5495	24429.4600
Ret_D1	86	0.0403	-0.4245	13.4928	-0.9815	1.7926	5.4962	39.2686	5146.5500
Ret_W1	86	0.2541	-0.0911	13.4928	-0.9827	1.6441	6.3551	50.4816	8657.5260
Ret_M1	86	0.2454	0.0405	4.6154	-0.4512	0.7490	3.7423	18.5781	1070.3270
Vol_D1	86	3.1776	0.3235	182.0544	0.0000	19.8910	8.6488	77.9195	21185.1800
Vol_W1	86	2.7361	0.1414	182.0544	0.0000	19.6609	8.9798	82.3686	23728.5600
Vol_M1	86	0.6147	0.0152	21.3018	0.0000	2.6716	6.1461	44.6106	6745.7830
Block time	86	160.7907	60.0000	3600.0000	10.0000	407.9158	7.2223	60.3602	12537.5000
Minimum reward	86	65880.6500	50.0000	5000000.0000	0.2500	541325.8000	8.9668	82.1671	23610.7400
Pre-mined	86	4.8800E+07	0.0000E+00	1.8200E+09	0.0000E+00	2.3400E+08	6.1705E+00	4.3285E+01	6.3612E+03
Total coins	86	1.4000E+10	1.0000E+08	5.5000E+11	3.2000E+04	6.3300E+10	7.3333E+00	6.1404E+01	1.2994E+04

Note: This table reports the descriptive statistics for the following 12 variables: Pre-Mined-To-Total-Coin-Ratio (PMTTCR), Minimum-Reward-To-Total-Coin-Ratio (MTTCR), first day return (Ret_D1), first week return (Ret_W1), first month return (Ret_M1), first day volatility (Vol_D1), first week volatility (Vol_W1), first month volatility (Vol_M1), block time (in seconds), minimum reward for the miners per block (minimum reward), number of coins mined before issued to the public (pre-mined), and the total number of coins of the Cryptocurrency (total coins). The figures are reported for both, the running sample (Panel A) and the default sample (Panel B).

Table A.4. Discriminant function for the default group

t	Predicted group 1	Predicted group 2	t	Predicted group 1	Predicted group 2
1	27.3805	27.7258	44	24.5862	23.9807
2	25.7955	26.5482	45	25.1247	24.3461
3	29.1404	28.5218	46	23.6011	24.0290
4	28.5050	28.3511	47	23.7185	24.0802
5	28.4949	28.3009	48	26.6271	27.7649
6	26.7095	25.0682	49	23.6858	24.0478
7	29.0677	29.6769	50	22.7344	22.5435
8	27.3892	27.7573	51	24.1190	23.7822
9	28.7611	28.5356	52	24.6971	24.2462
10	23.3757	22.8601	53	25.1351	24.5761
11	26.2717	23.9860	54	24.8930	24.4421
12	-24.1924	-24.2417	55	23.4671	23.1464
13	24.5396	23.8052	56	25.5403	24.3222
14	25.0503	24.3044	57	25.0424	23.9827
15	25.2780	24.4149	58	27.0499	25.4708
16	28.3193	28.2433	59	29.1556	28.5972
17	28.7954	28.5569	60	25.4615	24.2150
18	27.1257	25.3986	61	25.7609	24.4991
19	27.4460	25.7223	62	25.6308	24.3650
20	24.9086	23.8277	63	25.5393	24.4207
21	28.8249	28.2669	64	24.8019	23.8088
22	24.3948	23.4981	65	26.0950	24.7936
23	25.5785	24.3492	66	24.2334	23.3495
24	24.5392	23.7033	67	25.4390	24.2220
25	25.5527	24.3702	68	25.3581	24.1425
26	25.2765	24.4344	69	25.9102	24.6305
27	25.1694	24.2734	70	26.1701	24.7816
28	27.1309	24.7269	71	23.4963	23.2327
29	25.4649	24.5927	72	25.0475	24.2988
30	25.4501	24.6327	73	24.6484	23.9325
31	24.4508	24.0105	74	25.4414	24.5399
32	26.4005	25.3303	75	25.3188	24.4492
33	25.0495	24.2478	76	26.1223	25.0992
34	25.7881	24.8164	77	24.1029	25.0230
35	24.8941	24.1895	78	24.9693	24.2222
36	28.7836	28.5683	79	25.9494	24.9470
37	27.7893	27.7997	80	24.8711	24.0899
38	25.4256	24.4933	81	25.8052	24.8806
39	24.8828	24.1603	82	23.0776	22.8346
40	23.6977	23.4344	83	24.9735	23.4067
41	28.5788	28.3744	84	24.4830	23.9345
42	28.5522	28.3965	85	24.4737	23.8478
43	28.6334	28.1262	86	24.1142	24.5685

Note: This table reports the values for the discriminant function (Equation 8.a) for the default group (e.g., group 1).

Table A.5. Discriminant function for the functioning group

t	Predicted group 1	Predicted group 2	t	Predicted group 1	Predicted group 2
1	27.82065	27.73309	31	23.81871	23.66742
2	28.21115	28.06119	32	22.69601	22.69963
3	27.56446	27.8617	33	25.47647	24.56926
4	24.88217	26.79222	34	26.46251	27.41852
5	24.18907	23.8235	35	24.05865	24.03279
6	27.64701	27.89729	36	23.55639	23.60259
7	28.47438	28.74628	37	26.2968	27.56041
8	28.23995	28.78224	38	26.63752	27.78143
9	28.43512	28.02157	39	23.94774	24.32457
10	27.85306	27.72618	40	27.08734	28.17422
11	24.93163	23.89347	41	26.38169	27.58451
12	25.24417	24.02586	42	26.65863	27.79309
13	24.07879	23.36516	43	26.46865	27.67717
14	25.39226	24.0771	44	21.97226	22.86871
15	25.19025	24.36664	45	28.81073	29.50451
16	31.00211	30.156	46	24.47789	24.03402
17	24.91486	24.19066	47	24.29782	25.81669
18	25.57118	24.62532	48	25.75796	24.53365
19	26.27598	25.23614	49	26.17337	25.1366
20	25.00121	24.35303	50	28.75249	28.56327
21	28.64485	28.4349	51	24.91487	24.19067
22	26.96299	27.15382	52	25.01501	24.15877
23	24.91487	24.19067	53	25.19886	24.33645
24	24.4346	23.66766	54	24.09113	24.42255
25	26.47026	26.85933	55	23.3386	23.74375
26	26.01675	25.00639	56	-23.2155	-22.1288
27	22.73395	23.34834	57	28.3670	28.27678
28	24.55047	23.99539	58	24.27292	23.87617
29	25.37536	24.50556	59	25.17099	24.26115
30	22.85169	23.04122	60	-22.6525	-21.7619

Note: This table reports the values for the discriminant function (Equation 8.b) for the functioning group (e.g., group 2).

Table A.6. Name and symbol of cryptocurrencies used for the study

Panel A. Name and symbol of running cryptocurrencies

S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol
1	Blakecoin	BLC	13	Fedoracoin	TIPS	25	Reddcoin	RDD	37	Bitcoin	BTC	49	SmartCoin	SMC
2	Maxcoin	MAX	14	Novacoin	NVC	26	NobleCoin	NOBL	38	Peercoin	PPC	50	Gridcoin	GRC
3	Zurcoin	ZUR	15	Spots	SPT	27	Mooncoin	MOON	39	Zetacoin	ZET	51	Lucky7Coin	LK7
4	DimeCoin	DIME	16	Diamond	DMD	28	Phoenixcoin	PXC	40	Unobtanium	UNO	52	42coin	42C
5	Quark	QRK	17	Royalcoin	RYC	29	Fastcoin	FST	41	Bytecoin	BCN	53	Goldcoin	GLD
6	Animecoin	ANI	18	Worldcoin	WDC	30	Argentum	ARG	42	Terracoin	TRC	54	Huntercoin	HUC
7	Primecoin	XPM	19	Mincoin	MNC	31	Florincoin	FLO	43	Namecoin	NMC	55	Curecoin	CURE
8	Vertcoin	VTC	20	Megacoin	MEC	32	Annoncoin	ANC	44	Tekcoin	TEK	56	Stellar	XLM
9	Litecoin	LTC	21	Feathercoin	FTC	33	Grandcoin	GDC	45	Skeincoin	SKC	57	Trollcoin	TROLL
10	Bullion	CBX	22	Dogecoin	DOGE	34	Supercoin	SUPER	46	CDNcoin	CDN	58	SecureCoin	SRC
11	Communitycoin	COMM	23	Galaxycoin	GLX	35	Betacoin	BET	47	Bela Coin	BELA	59	Marscoin	MARS
12	Emerald	EMD	24	BitBar	BTB	36	iXcoin	IXC	48	Redcoin	RED	60	Pandacoin	PND

Panel B. Name and symbol of default cryptocurrencies

S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol	S.No.	Cryptocurrency	Symbol
1	Datacoin	DTC	18	Sexcoin	SXC	35	Doubloons	DBL	52	Metiscoin	MTS	69	Cagecoin	CAGE
2	Tagcoin	TAG	19	Xivra	XIV	36	CHNCoin	CNC	53	Unioncoin	UNC	70	Electric	VOLT
3	Nyancoin	NYAN	20	Extremecoin	EXC	37	Globalcoin	GLC	54	Frozencoin	FZ	71	Bottlecaps	CAP
4	Paycoin	XPY	21	Americancoin	AMC	38	Krugercoin	KGC	55	KingdomCoin	KING	72	Neocoin	NEC
5	Infinitecoin	IFC	22	Lottocoin	LOTTO	39	Franko	FRK	56	Memecoin	MEM	73	Bitgem	BTG
6	Qubitcoin	Q2C	23	Graincoin	GRA	40	Netcoin	NET	57	Solcoin	SOL	74	Lebowskis	LBW
7	Freicoin	FRC	24	Xencoin	XNC	41	BBQcoin	BQC	58	Hypercoin	HYC	75	Growthcoin	GRW
8	AllAgesCoin	AAC	25	Batcoin	BAT	42	Catcoin	CAT	59	Craftcoin	CRC	76	Prospercoin	PRC
9	Joincoin	J	26	Junkcoin	JKC	43	Memorycoin	MMC	60	Nanotoken	NAN	77	Hobbitcoin	HBC
10	Cthulhu Offerings	OFF	27	StarCoin	STR	44	Luckycoin	LKY	61	GIL	GIL	78	Hotcoin	HTC
11	Colossuscoin	COL	28	Zenithcoin	ZTC	45	Yacoin	YAC	62	Usecoin	USE	79	Lovecoin	LOVE
12	Particle	PRT	29	HoboNickels	HBN	46	AsicCoin	ASC	63	AlphaCoin	ALF	80	Bells	BEL
13	Pennies	CENT	30	Philosopherstone	PHS	47	Tigercoin	TGC	64	Richcoin	RCH	81	Zeuscoin	ZEU
14	Qqcoin	QQC	31	CACHeCoin	CACH	48	Devcoin	DVC	65	Zedcoin	ZED	82	ELACoin	ELC
15	Applecoin	APC	32	Microcoin	MRC	49	Teacoin	TEA	66	Stablecoin	SBC	83	EzCoin	EZC
16	ZcCoin	ZCC	33	Kittehcoin	MEOW	50	Copperlark	CLR	67	Socialcoin	SOC	84	Noirbits	NRB
17	Onecoin	ONE	34	Gamecoin	GME	51	Chaincoin	CHC	68	ElephantCoin	ELP	85	Nibble	NBL
												86	Globe	GLB

Note: This table reports the name and symbol of cryptocurrencies with PoW consensus protocol issued prior to the end of year 2014. These cryptocurrencies were tracked till the end of year 2018 and categorized them into running (Panel A) and default (Panel B) samples.

Table A.7. Algorithms X11. X13. X14. X15. and X17

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
Blake	BMW	Groestl	JH	Keccak	Skein	Luffa	Cubehash	Shavite	SIMD	Echo						
X11											Hamsi	Fugue				
X13													Shabal			
X14														Whirlpool		
X15															Loselose	Djb2
X17																

Note: This table shows the chain of different hashing algorithms X11. X13. X14. X15. and X17 with their sub-algorithms (Source: getpimp.org)