12-2023

In search of cryptocurrency failure

Donglian MA

Jun TU
Singapore Management University, tujun@smu.edu.sg

Zhaobo ZHU

In Search of Cryptocurrency Failure*

Donglian Ma†

Jun Tu‡

Zhaobo Zhu§

January 2023

Abstract

This paper explores the determinants of cryptocurrency failure and the pricing of crypto failure risk. We document different significant market- and characteristic-based predictors for coin and token failures. The introduction of Bitcoin futures and the outbreak of COVID-19 affect the importance of many predictors. Investors require extra return for bearing high failure risk of crypto assets. The return difference across high and low failure risk crypto assets is not explained by the market, size and momentum factors in the cryptocurrency market. Finally, investors benefit from diversifying into high failure risk crypto assets that is little correlated with the stock market.

JEL Classification: G11, G12

Keywords: Cryptocurrency; Failure risk; Risk-return tradeoff; Asset allocation; COVID-19

---

* We would like to thank Tse-Chun Lin, Yukun Liu, Daniel Rabetti, Jianfeng Yu, Haoxi Yang, and Yueteng Zhu, and seminar and conference participants in the 2022 Financial Engineering and Quantitative Finance Forum in Xiamen University, the 2022 China International Risk Forum (Modern Risk Society - CCER Database Research Excellence Award in Big Data and Fintech), the 2022 Risk Management Conference at the National University of Singapore, the 2022 FinTech Innovation and Risk Management Conference (Best Paper Award), and the 2022 Chinese Finance Annual Meeting for their helpful comments. We thank Luying Wang for excellent research assistant. Any remaining errors are ours alone.
† Faculty of Business, Hong Kong Polytechnic University, Hong Kong. Email: donglian.ma@polyu.edu.hk.
‡ Department of Finance, Lee Kong Chian School of Business, Singapore Management University, Singapore. Email: tujun@smu.edu.sg.
§ Shenzhen Audencia Financial Technology Institute, Shenzhen University, Shenzhen, China; Audencia Business School, Nantes, France. Email: zb.zhu@szu.edu.cn.

"Cryptocurrencies lose $205 billion in 24 hours"

Fortune[1]

1. Introduction

The cryptocurrency market has experienced rapid growth in recent years.[2] There have been about 12 thousands of cryptocurrencies with market capitalization of $1,885 billion until September 2021.[3] Proponents for crypto assets advocate that at least some blockchain-based cryptocurrencies with anonymous and decentralized nature must have a stake in the future of the payment and have positive real economic outcomes (e.g., Böhme et al., 2015; Howell, Niessner, and Yermack, 2020). In contrast, critics argue that cryptocurrencies are a speculative and shady business without enough government regulations because current cryptocurrencies are neither a revenue-producing asset nor a store of value (e.g., Gandal et al., 2018; Foley, Karlsen, and Putninš, 2019; Griffin and Shams, 2020).

Nevertheless, no matter whether cryptocurrencies themselves have real economic value or not, it is not yet fully clear how investors can assess the failure probability of crypto assets regardless of failures due to the burst of bubbles or scams.[4] Moreover, should investors hold some cryptocurrencies despite their high failure risk? Whether and how investors should diversify some of their wealth into crypto assets? To address these important questions, in this paper, we explore the determinants of cryptocurrency failure and assess the economic importance of risky crypto assets from the failure risk-return

[1] Cited in https://fortune.com/2022/01/21/cryptocurrency-crash-bitcoin-ether-cardano-doge-205-billion-loss/.
[2] Crypto.com estimated that about 106 million people are now using cryptocurrencies around the world.
[3] These numbers are estimated based on the data in coinmarketcap.com.
[4] The terms cryptocurrency and crypto are used interchangeably in this paper.

tradeoff perspective and the asset allocation perspective, providing novel insights on the bright and dark sides of crypto assets.

We first aim to build a deep understanding of failure risk in the crypto market. Existing studies pay little attention to the failure risk in the crypto market and its determinants and pricing despite high crypto failures, while common risk factors in cryptocurrency, crypto market manipulation, and initial coin offering (ICO) attract much attention.[5] Standard risk factor models in existing studies such as Liu et al. (2022) do not explicitly consider *failure* risk. Losses associated with failures are *permanent* for investors regardless of leverage, while losses due to price manipulation may recover for unleveraged investors.[6] In addition, this paper focuses on cryptocurrencies traded in crypto exchanges, while more and more cryptocurrencies traded in exchanges were not issued through ICOs.[7] Our study complements existing studies about the risk of cryptos from a novel perspective.

Crypto failure risk warrants our attention for several reasons. First, failure probability is astonishingly high in the crypto market, which is much higher than that in the stock and bond markets. It is estimated that there are over 2,300 failure events during the period of 2014 to 2020. During this period, about 1,000 newly listed cryptocurrencies (i.e., about 28% newly listed coins and 15% newly listed tokens) failed within the first year after they listed

[5] Studies about factor models for the crypto market include Liu and Tsyvinski (2021), Liu, Tsyvinski, and Wu (2022), and Bianchi and Babiak (2022). Studies about crypto market manipulation such as pump-and-dump schemes, wash trading, scams within the exchange, and other forms of manipulation include Gandal et al. (2018), Griffin and Shams (2020), Cong et al. (2021), Li, Shin, and Wang (2021), Dhawan and Putninš (2022), Amiram, Lyandres, and Rabetti (2022). Studies about the determinants of ICO and post-ICO performance include, among others, Liu, Sheng, and Wang (2021), Lyandres, Palazzo, and Rabetti (2022).
[6] We admit that price manipulation for *small* cryptos may lead to permanent losses for investors, especially for investors with high leverage. However, these *event* studies focus on a small set of cryptos.
[7] In our sample, less than 10% (40%) of coins (tokens) listed in CoinMarketCap experience ICO. Our study focuses on cryptocurrencies that meet the listing criteria in main crypto exchanges, while many ICOs do not meet the exchange listing criteria. Our sample is quite different from that in Lyandres et al. (2022). We focus on the secondary crypto market, while Lyandres et al. (2022) focus on the primary crypto market.

in CoinMarketCap. Moreover, about 80% of newly listed cryptocurrencies would be dead within 5 years. Second, high failure probability leads to astonishingly large economic losses. Based on the data in CoinMarketCap, our estimated total losses of cryptocurrency failures are about $33.6 billion during 2014 to 2020, with an average annual loss of $4.8 billion. On average, investors in aggregate suffer from about $8.2 million in each coin failure event and $26.9 million in each token failure event. Third, unlike potentially temporary losses from large or popular cryptos due to price manipulation or market crashes for unleveraged investors, *permanent* losses are associated with crypto failures even for unleveraged investors.[8]

It is therefore crucial and necessary to explore the determinants of cryptocurrency failure and the economic value of crypto failure in asset allocation and risk management. Because cryptocurrency is an emerging virtual asset that is fundamentally different from traditional financial assets such as equity and bond in many aspects, we start with some basic empirical questions that should be answered in the context of an emerging crypto asset. In particular, how should we define cryptocurrency failure? What is the probability that a cryptocurrency fails?

Our empirical work begins with defining *cryptocurrency failure*. In a seminal study, Campbell, Hilscher, and Szilagyi (2008) broadly consider firm bankruptcies, financially driven delistings, and default credit ratings as corporate failure. Because cryptocurrencies have no fundamental value and credit rating and there is no delisting mechanism in the

[8] Note that a substantial portion of the mega losses such as $205 and $275 billion in January and May in 2022 are due to large price decreases of some main cryptocurrencies such as Bitcoin and Ethereum, which do not fail. The investors *without* leverage can recover their losses when the prices of these main cryptocurrencies rebound.

crypto exchanges, we cannot identify whether a cryptocurrency is financially distressed, has a default rating, or is delisted from exchanges. From a practical perspective, we define that a cryptocurrency *fails* if it has no trading activity over the next 26 consecutive weeks in exchanges.[9] There are totally 1,570 coin failure events and 775 token failure events during the period of 2014 to 2020.[10] About 28% of coins and 15% of tokens failed within the first year after they listed in CoinMarketCap. The failure probability in the crypto market is obviously much higher than that in the stock and bond markets.

Next, we explore the determinants of cryptocurrency failure. Following Shumway (2001) and Campbell et al. (2008), we use a dynamic logit model to estimate the probability of cryptocurrency failure over the next period. A key element of our empirical work is identifying promising variables that predict cryptocurrency failure. Existing studies about corporate failure use both equity market and accounting information (e.g., Shumway, 2001; Chava and Jarrow, 2004; Campbell et al., 2008). In this paper, we use crypto market-based and characteristic-based information as predictors in the logit model. Crypto market-based variables include six standard variables such as the market capitalization, age, past returns, return volatility, illiquidity, and the skewness-related variable. Existing studies show that some of these crypto market-based variables have predictability for the cross section of cryptocurrency returns (e.g., Liu et al., 2022; Bianchi and Babiak, 2022).

[9] We consider both short and medium horizons to identify crypto failure. We use the horizon of 26 weeks as a conservative criterion. We also report the results based on the horizon of 4 weeks in this paper.

[10] Although some failed cryptocurrencies resurrect after a long period of dormancy, these cryptocurrencies are not much traded and most of them finally become dead. Gandal et al. (2021) examine the coin abandonment and resurrection during the period of February 2014 to February 2018. They find that about 71% of abandoned coins subsequently resurrect. Because tokens become popular from 2017, their estimates of token abandonment and resurrection are conservative. More importantly, cryptocurrency failure in our definition are more severe than abandonment in their definition. In addition, we expect that these failed cryptocurrency due to unethical scams are unlikely to be resurrected later.

However, unlike stocks, cryptocurrencies have no accounting data. According to the media coverage, security issues, unethical scams, bad publicity, and unclear progression paths of projects are main reasons for cryptocurrency failure. Then we use the metadata from CoinMarketCap to capture the crypto-specific information about product publicity, information disclosure, technical sophistication, and the industry classification. Some of these information is used to predict ICO success and post-ICO performance (e.g., Howell et al., 2020; Liu et al., 2021; Lyandres et al., 2022).

For example, the failure of the DAO is a typical example due to security issues.[11] A valuable lesson about security issues is the importance of security technology. Liu et al. (2021) construct a measure of the technical sophistication of cryptocurrencies from ICO whitepapers. Because it is impossible to precisely measure the degree of technology sophistication for several thousands of sample cryptocurrencies due to data availability and a large number of sample cryptocurrencies are not issued via ICO in our paper, we simply use the availability of *technical document* or *source code*, and the type of *consensus algorithm* (e.g., PoW) to identify whether a cryptocurrency owns reliable technology.[12]

Unethical scams are another main reason for cryptocurrency failure. Because of the popularity of buzzwords such as blockchain among ordinary investors over recent years, cryptocurrency Ponzi schemes have been received widespread media coverage. Because these Ponzi schemes have no solid business plans that solve real problems, the failure of

[11] An intelligent hacker exploited a loophole in the code written for the DAO only a few months after it emerged in 2016. Unsurprisingly, the hacker attach was the key driver of the failure of the DAO. The platform (i.e., Ethereum) itself has no flaw, but the code written for the DAO that was built on Ethereum had flaws that were vulnerable to attack.

[12] Because many cryptocurrencies listing in exchanges do not have whitepapers, we cannot construct the measure of technology sophistication for all sample cryptocurrencies in our study as Liu et al. (2021) do. The information for proxies for technical sophistication in our paper is available in CoinMarketCap for all sample cryptocurrencies.

these unethical cryptocurrencies is inevitable. We use the dummy variables, the availability of *twitter*, type of *consensus algorithm*, and *ICO*, to identify whether a cryptocurrency is likely to be a scam.[13] In addition, poor publicity is also an important reason for crypto failure. Existing studies document that investor attention proxies significantly forecast future cryptocurrency returns (e.g., Liu and Tsyvinski, 2021; Sockin and Xiong, 2021). We use these dummy variables, the availability of *twitter*, to identify whether a cryptocurrency is likely to be public to more investors.

Empirical results show that these market-based variables, the market capitalization, age, past recent returns, return volatility, and the illiquidity measure, significantly predict coin failure with expected signs. That is, coins that are larger, younger, less volatile, more liquid, or have higher recent returns, are less likely to fail over the subsequent period. In addition, coins with available twitters, technical documents and source codes, and PoW as consensus algorithm are also less likely to fail. Moreover, coins in the infrastructure and payments industries are less likely to fail.

Because coins are quite different from tokens in many aspects, some significant predictors for token failure are different from those for coin failure. The market capitalization, age, return volatility and the illiquidity measure are common significant predictors for both coin and token failures. However, the downside risk measure is a significant predictor for token failure. In addition, the proxy for technical sophistication (i.e., the dummy variable source code) and the payments industry dummy significantly predict token failure. Our results are almost consistent as the forecasting horizon increases

[13] CoinMarketCap imposes stricter listing criteria in recent years, including that a cryptocurrency must have a functional website block explore and real people behind the project. The purpose of stricter requirements is to mitigate unethical scams, although a fake website or fictitious people under the project could be created.

from 1 week to 8 weeks.

Cryptocurrency failure and the determinants of cryptocurrency failure vary over time. In particular, the introduction of Bitcoin futures in December 2017 is significantly correlated with the subsequently high coin failures possibly because the introduction of Bitcoin futures provides investors a new channel to arbitrage the overpricing, inhibiting extremely optimistic investor sentiment and accelerating the crypto bubble burst in 2018. In contrast, the outbreak of COVID-19 is significantly correlated with fewer crypto failures in 2020 possibly because the stagnant society and economy due to the outbreak of COVID-19 leads to the crypto boom in 2020. These events have different impact on the role of some specific predictors for coin and token failures.

Furthermore, we examine the tradeoff between failure *risk* and expected return in the cryptocurrency market. Using fitted probability of failure from the dynamic logit model to measure failure risk for each cryptocurrency, we find a positive relation between crypto failure risk and expected return. That is, cryptocurrencies with high (low) fitted failure probability have high (low) returns. The outperformance of cryptocurrencies with high failure risk is quite persistent and cannot be explained by common crypto risk factors. The positive pricing of failure risk in the crypto market is more pronounced among small and volatile cryptocurrencies.

Finally, we investigate the economic value of risky crypto assets from the asset allocation perspective. Based on certainty-equivalent return and Sharpe ratio, we find that a mean-variance investor who considers high risky crypto assets in his multi-asset portfolio would receive larger economic gains than the counterpart who invests in only the stock market or risk-free T-bills.

This paper provides a comprehensive and up-to-date research on the failure risk in the cryptocurrency market, helping us better understand crypto failure risk that is quite important but ignored in existing literature. Cryptocurrencies have astonishingly high failure probability and thus investors suffer from substantial economic losses in this volatile crypto market. Existing studies pay little attention to the failure risk in the crypto market and its determinants and pricing despite high crypto failures, while common risk factors in cryptocurrency, crypto market manipulation, and ICO attract much attention. Our paper complements existing studies by focusing on the determinants and pricing of crypto *failures*.

Specifically, we document some significant and different market- and characteristic-based predictors for coin and token failures. Moreover, the importance of these significant predictors varies over time when some new trading mechanisms are introduced or some global systematic shocks such as COVID-19 arrive. These findings provide important implications for crypto investors who could minimize their investment losses.

Moreover, our study contributes to the debate on the default risk-return tradeoff from a novel perspective of cryptocurrency failure. The relation between default or distress risks and expected returns in the stock market is mixed. Building on various measures of default risk, some studies find a positive relation between default risk and expected returns (e.g., Vassalou and Xing, 2004; Chava and Purnanandam, 2010; Friewald, Wagner, and Zechner, 2014; Aretz, Florackis, and Kostakis, 2018), while some other studies document a negative relation (e.g., Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008; Da and

Gao, 2010; George and Hwang, 2010).[14] Our finding of a positive failure risk-return tradeoff in the crypto market supports the traditional positive risk-return tradeoff theory in Merton (1987), suggesting that investors require high positive premium for bearing high failure risk of crypto assets. The positive premium of failure risk explains why many investors trade in the crypto market despite high failure risk.

Our study also contributes to the asset allocation literature on alternative investments. Although cryptocurrencies as an emerging asset are highly risky, our study shows that traditional investors could enjoy substantial economic gains by diversifying some of their wealth into risky crypto assets. No matter whether crypto assets themselves have real value or not, cryptocurrencies are economically valuable for investors from the asset allocation perspective. We emphasize the coexistence of dark side and bright side of crypto assets. Our study sheds novel light on how to avoid the dark side and make use of the bright side.

2. Data Description of Cryptocurrency Failure

We obtain trading data and crypto-specific metadata for all sample cryptocurrencies from CoinMarketCap.[15] As the most trusted and accurate source of data for cryptocurrencies, CoinMarketCap aggregates information from major cryptocurrency exchanges around the world and provides historical price and volume data and other crypto-specific information. The data from CoinMarketCap is widely used in empirical studies about cryptocurrency

[14] In addition, some studies find no relation between default risk and stock returns. Anginer and Yildizhan (2018) show that Fama-French risk factors could explain the high expected returns for stocks with high exposures to systematic default risk. Moreover, some studies reconcile the puzzling relation between default risk and expected returns by considering other factors such as shareholder advantage and shareholder recovery (Garlappi, Shu, and Yan, 2008; Garlappi and Yan, 2011).
[15] CoinMarketCap: https://coinmarketcap.com/

(e.g., Fisch, 2019; Griffin and Shams, 2020; Howell et al., 2020; Liu and Tsyvinski, 2021; Liu et al., 2022). CoinMarketCap does not cover all cryptocurrencies worldwide. It covers only cryptocurrencies that meet its minimum listing criteria.[16] Many cryptocurrencies issued through ICOs are not listed in CoinMarketCap because they do not meet the minimum listing criteria, and many cryptocurrencies in CoinMarketCap were not issued through ICOs. CoinMarketCap lists both active and inactive cryptocurrencies. To our best knowledge, CoinMarketCap is the most trusted and accurate dataset for us to explore the determinants and consequence of cryptocurrency failure.

Our sample period is from January 2014 to December 2020. The data from January 2021 to June 2021 is used to identify whether a cryptocurrency is active or inactive at the end of our sample period (i.e., December 2020). Our sample includes only cryptocurrencies that are newly listed in CoinMarketCap from January 2014 due to data availability and quality in CoinMarketCap. Unlike studies focusing on large cryptocurrencies (e.g., Liu et al., 2022), we complement these studies by examining all large and small cryptocurrencies because of the ex-ante expectation that small cryptocurrencies are more likely to fail. Our final sample includes 2,457 coins and 3,731 tokens.

Following Liu et al. (2022), we use daily close price and volume data to construct market-based variables for cryptocurrencies. We consider a comprehensive set of variables, including market capitalization, age, recent past returns, return volatility, the illiquidity measure, and skewness-related measures. See variable definitions in detail in Table A1. To alleviate concerns about extreme values and substantial variations in price and volume in

[16] Listings Criteria: https://support.coinmarketcap.com/hc/en-us/articles/360043659351-Listings-Criteria

the cryptocurrency market, we winsorize most market-based variables except age and the illiquidity measure by the 5th and 95th percentiles each week.

CoinMarketCap also provides rich information about crypto-specific characteristics beyond trading data. The information includes a cryptocurrency's unique ID, name, symbol, category (i.e., coin or token), slug (i.e., web URL friendly shorthand version of cryptocurrency name), listing date (i.e., timestamp of when the cryptocurrency was added to CoinMarketCap), tags (e.g., consensus algorithm, property, platform, and other), urls (e.g., website, twitter, technical document, and source code), and so on. We use these metadata to construct some dummy variables as proxies for information disclosure and asymmetry, technical sophistication, security, and product publicity. We give a simple description of these variables in Table A1.

2.1 Definition of Cryptocurrency Failure

A key element of our empirical analysis is defining cryptocurrency failure. In Campbell et al. (2008), a corporate failure is broadly defined if the firm was bankrupt, its stock was delisted due to financial distress, or its credit rating is default. However, cryptocurrencies are essentially different from firms or stocks. Unlike stocks, there is no official delisting mechanism and credit ratings for cryptocurrencies. It is also difficult to identify whether cryptocurrency-financed projects filed for either Chapter 7 or Chapter 11 bankruptcy when these projects failed. Therefore, from a practical investment perspective, we look at cryptocurrency failure in term of trading activity.

In this paper, cryptocurrency failures are defined broadly to include distress, failure and death based on the specified time horizon of inactivity. Specifically, a cryptocurrency is *distressed* if it has no trading data over the next 4 consecutive weeks in CoinMarketCap. A cryptocurrency is *failed* if it has no trading data over the next 26 consecutive weeks. A cryptocurrency is *dead* if it never reappears after failure in CoinMarketCap. From the practical perspective of investors, death is more severe than failure and failure is more severe than distress because the chance for investors to recover their losses is smaller in cases of death and failure. In our sample period, 21.6% of distressed cryptocurrencies subsequently reappeared after a long period, while only 7.3% of failed cryptocurrencies subsequently reappeared after a long period. Moreover, these distressed or failed cryptocurrencies that resurrected after a long period of dormancy are not active in trading volume after resurrection. To some extent, resurrection is meaningless to most investors (especially highly leveraged investors) due to the lack of active trading in the crypto market.

In our empirical analysis, we classify failed and dead cryptocurrencies into the same group (i.e., failed cryptocurrencies) because about 93% of failed cryptocurrencies never reappeared in our sample period and it is hard to identify truly dead cryptocurrencies.[17] To have a big and clear picture of cryptocurrency failure, we look at both cryptocurrency distress and failure we defined above.

Some cryptocurrencies may experience two or three distress or failure events. For example, a failed coin resurrected after a long period (e.g., about 1 year), but it failed again later (i.e., no trading activity in subsequent 26 consecutive weeks) and never resurrected until the end of our sample period. In this case, this coin has two failure events. In the following empirical analysis, we regard the two failure events as independent events. That

[17] Cryptocurrencies that failed due to unethical scams are unlikely to resurrect. These failed cryptocurrencies are dead.

is, we regard the failed coin that resurrected later as a new coin. In fact, these failed coins that resurrected later are less likely to continue to survive well. Investors, especially speculators on these failed coins, are less likely to recover their prior losses even though some of these failed coins resurrect after a long period.

2.2 Cryptocurrency Failure and Economic Consequence

Figure 1 shows the numbers of newly listed, active, failed, and total cryptocurrencies each year during 2014 to 2020. A large number of cryptocurrencies are created each year. In particular, over 2,000 new cryptocurrencies are created in 2020. However, a large number of cryptocurrencies also failed each year. The trend of failure is stable over time. Fewer cryptocurrencies failed in 2017 because there is a Bitcoin bubble in 2017.

Table 1 reports the number of coin and token failures and their estimated maximum economic losses each year during our sample period. We must note that our estimated number and economic losses of failures are conservative because CoinMarketCap does not cover all cryptocurrencies in the real world. CoinMarketCap lists only cryptocurrencies that meet the minimum listing criteria. Some cryptocurrencies failed before they have the chance to list in CoinMarketCap.

Here the number of failures refers to the number of failure events. That is, a failure event occurs if the cryptocurrency has no trading volume for at least 26 consecutive weeks. To some extent, these failed cryptocurrencies are almost dead and investors are less likely to recover their losses from these failures. The maximum loss for a cryptocurrency refers to its historical high of market capitalization.

Table 1 reports that over 2,300 failure events during the period of 2014 to 2020 and corresponding economic losses are astonishingly substantial. Specifically, there are totally 1,570 coin failure events and 775 token failure events. There is an upward trend for token failures in time series. A large number of tokens have been created after 2017. In particular, 1,787 new tokens listed in CoinMarketCap in 2020 when the COVID-19 pandemic spread around the world. Token failures dominate coin failures in term of the number of failure events and economic losses in 2020. Because of a bubble in the cryptocurrency market in 2017, there were fewer coin failure events in 2017 and more failure events in 2018 due to the bubble burst in 2018.

The estimated total losses of cryptocurrency failures are about 33.6 billion USD during 2014 to 2020, with an average annual loss of 4.8 billion USD.[18] Specifically, the estimated total economic losses of coin failures and token failures are about 12.8 and 20.8 billion USD during 2014 to 2020, respectively. The economic loss of each token failure event is larger than that of each coin failure event. On average, investors in aggregate suffer from about $8.15 million in each coin failure event and $26.88 million in each token failure event.

Figure 2 plots the number of coin and token failure events and corresponding cumulative maximum economic losses of these failure events from 2014 to 2020. Economic losses are more pronounced during 2018 to 2020 than during 2014 to 2016 because a large number of tokens failed in recent years and the average loss of each token failure is larger than that of each coin failure.

[18] An average daily loss of $13.15 million in our sample is between a conservative estimated daily loss of $9 million and the maximum daily loss of $23 million in cryptocurrency scams in the first two months of 2018 reported in news in Bitcoin.com.

2.3 Failure Probability

Table 2 reports the probability that a coin or token will fail in a specified period. We test the *conditional* probability that a coin or token will be delisted from CoinMarketCap before a specified time horizon in our sample period. The time (0 to 156 weeks) in the column refers to the time period that a cryptocurrency is traded before delisting from CoinMarketCap. The time (4 to 260 weeks) in the row refers to the time period that a cryptocurrency with a given life (that is specified by the time horizon in the column) will fail before a specified period. Note that here a failure refers to death we defined above.

For example, 2.41% in [0 week, 4 weeks] in Table 2 refers to that a newly listed coin has 2.41% probability of delisting from CoinMarketCap within 4 weeks. 59/2446 refers to that among 2,446 newly listed coins during January 2014 to December 2020, 59 coins failed within first 4 weeks. When we look at failure probability in a longer horizon, 27.87% in [0 week, 52 weeks] refers to that a newly listed coin has 27.87% probability of delisting within first 52 weeks. 633/2271 refers to that among 2,271 newly listed coins during January 2014 to June 2020, 633 coins failed within first 52 weeks.[19] Furthermore, when we look at failure in a 5-year horizon, 862 coins out of 1,075 coins failed within their first 5 years. We find similar results for tokens. These results show that cryptocurrency failure probability increases dramatically as the horizon increases, suggesting that it is highly risky

[19] We collect data from CoinMarketCap from January 2014 to June 2021. There are 2,446 newly listed coins in [0 week, 4 weeks] during January 2014 to December 2020. But there are only 2,271 newly listed coins in [0 week, 52 weeks] during January 2014 to June 2020 because the newly listed coins in the denominator of failure probability in [0 week, 52 weeks] must have a life of maximum 52 weeks (i.e., June 2021 backwards to June 2020). Therefore, only newly listed coins during January 2014 to June 2020 are included and newly listed coins during July 2020 to June 2021 are not included in the denominator in [0 week, 52 weeks]. Similarly, there are only 1,075 coins in the denominator in [0 week, 260 weeks] because we need to count coins backwards from June 2021 to July 2016 (i.e., 260 weeks).

to invest in cryptocurrencies (especially old coins and tokens) because they are short-lived.

Then we examine the *unconditional* probability that a coin or token will fail within a specified period. Figure 3 shows the cumulative cryptocurrency failure events (based on the future 4-week or 26-week horizon) within a specified period during 2014 to 2020. Overall, the number of failure events based on 4-week horizon (i.e., distress events) is larger than that of failure events based on the 26-week horizon in various specified periods because a failure event requires a stricter criterion on the inactive trading than a distress event. It is obvious that most failed cryptocurrencies failed within first two years. There is no obvious increase in failure event after three years.

2.4 Summary Statistics

To get a clear picture of differences between active and failed cryptocurrencies, Table 3 presents summary statistics for active and failed cryptocurrencies. Panel A in Table 3 reports the results for market-based variables. Because of substantial variations in trading prices and market capitalizations, we report the median values across the weeks in the sample of the median values within each week of various market-based variables. There is one week gap between these variables and the failure events. It is apparent that larger coins and tokens are less likely to fail. Failed coins or tokens have worse recent returns, higher return volatility, and downside risk. Active tokens have relatively higher prices than failed tokens. Active coins are older than failed coins possibly due to survival bias, while active tokens are a little younger than failed tokens possibly due to that a large number of new tokens were created in 2020 in our sample and these new tokens are in the early stage of life cycle.

Panel B in Table 3 reports the results for crypto-specific dummy variables. Active coins have higher probability of having twitter, source code, and technical document than failed coins. Active coins are more likely to use PoW or hybrid as the consensus algorithm. Active coins have higher percentage of initial coin offerings (ICO) than failed coins. In addition, we also find that failed coins are reluctant to disclose their industry classification, so the number about the main industry dummies for failed coins is very low. These findings suggest that active coins are quite different from failed coins in term of crypto-specific characteristics.

Tokens are different from coins in many aspects. Tokens become popular from 2017. We observe some obvious differences on some variables between coins and tokens. For instance, active tokens have lower probability of having twitter than failed tokens, although the difference is not large. Active tokens have higher probability of having technical document and source code than failed token, although the difference is not large. Active tokens have lower percentage of ICO than failed coins, although the difference is small. In addition, failed tokens are more likely to in the platform *Ethereum*. Like coins, failed tokens are reluctant to disclose their industry classification.

3. A Logit Model of Cryptocurrency Failure

In this section, we explore the factors that predict the cryptocurrency failure. Following Shumway (2001), Chava and Jarrow (2004), and Campbell et al. (2008), we use a dynamic logit model to identify important market-based variables and crypto-specific variables for cryptocurrency failure over the next specified period.

3.1 A Dynamic Logit Model

In this section, we use a dynamic logit model to estimate the failure probability over the next specified period. A dynamic logit model allows us to include both time-varying market-based variables and static crypto-specific characteristics in a regression. Following Campbell et al. (2008), we use the following dynamic logit model:

$$P_{t-1}(Y_{i,t+1} = 1) = \frac{1}{1 + \exp(-\alpha - \beta_i x_{i,t-1})}$$

where $Y_{i,t+1}$ equals to one if there is a failure event in week t+1, and $x_{i,t-1}$ refers to a vector of explanatory variables which indicate the known information at the end of week t-1. We skip 1-week between the known information for predictors in week t-1 and the future failure event in week t+1 so that our models are more practically useful.

Table 4 reports the logit regression results for various specifications for coin failures. In columns 1 to 4, we report results for coin failure that is determined based on the future 4-week horizon. In the first column, we estimate the model with market-based variables: the market capitalization (*MCAP*), age (*AGE*), past 4-week return (*RET_4W*), return volatility over the past four weeks (*RETVOL*), the illiquidity measure (*ZERO%*), and the downside risk (*NCSKEW*).[20]

Column 1 shows that the coefficients of *MCAP* and *RET_4W* are significantly negative, and the coefficients of *RETVOL* and *ZERO%* are significantly positive. These

[20] We also consider the price, beta, return skewness, and the maximum daily return over past 4 weeks in predicting cryptocurrency failure in the dynamic logit models. Because of high correlation between these variables and the chosen market variables in the main models, we include only *MCAP*, *AGE*, *RET_4W*, *RETVOL*, *ZERO%*, and *NCSKEW* as market-based variables.

results suggest that coins that are larger, have higher recent past returns, or have lower return volatility and illiquidity are less likely to fail in subsequent 1 week. These significant predictors (*MCAP*, *RET*, and *RETVOL*) in the coin market are consistent with those for corporate failure in Campbell et al. (2008).[21] It is not surprising that the illiquidity measure, *ZERO%*, is significantly and positively correlated with the subsequent failure because less frequent trading is a signal of distress. In addition, *AGE* becomes a significant predictor with a positive sign in column 4 that includes market variables, coin specific characteristics, and the industry classification, suggesting that older coins are more likely to fail.[22]

In columns 2 and 3, we examine some coin-specific characteristics that are related to information disclosure, technological sophistication, product publicity and marketing, the industry classification. Column 2 shows that the coefficients of dummy variables (*twitter*, *technical document*, *source code*, *ICO*, *PoW*, and *hybrid consensus algorithm*) are negative and significant, suggesting that coins with twitter, technical document, source code, or PoW as consensus algorithm are less likely to fail than their counterparts. These results suggest that coins with better product publicity, more sophisticated technology, or less information asymmetry are less likely to fail than other coins. *ICO* becomes insignificant in column 4 that includes market variables and industry dummies possibly due to that ICO is highly correlated with *MCAP* and the industry dummy *infrastructure*.

Column 3 shows that the coefficient of the *financial* industry dummy is significantly positive and the coefficients of other four industry (*infrastructure*, *media*, *payments*, and

[21] The significance of return volatility declines after we add skewness-related variables such as return skewness, maximum daily returns, and downside risk in the regressions because of high correlations among these variables, though these skewness-related variables are not significant.
[22] In comparison, Shumway (2001) finds that firm age does not significantly predict firm bankruptcy.

services) dummies are significantly negative, suggesting that compared to coins in other industries, coins in the *financial* industry are more likely to fail and coins in the *infrastructure*, *media, payments*, or *services* industries are less likely to fail. The *financial, infrastructure*, and *payments* industry dummies are still significant in column 4.

Columns 5 to 8 in Table 4 report results for coin failure that is determined based on the future 26-week horizon. We find similar results for coin failures determined based on the future 4-week or 26-week horizons. The *only* difference is that the *financial* industry dummy becomes insignificant in predicting failure based on the 26-week horizon, but the sign is still positive.

Table 5 reports the logit regression results for various specifications for token failure. Because coins are different from tokens in many aspects, some significant predictors for coin failure are different from those for token failure. We find that some market variables such as *MCAP*, *AGE*, *RETVOL*, and *ZERO%* are common significant predictors for both coin and token failures in various specifications. However, *RET_4W* becomes insignificant but *NCSKEW* as a proxy for the downside risk is significantly and positively correlated with the subsequent token failure.

Moreover, only the proxy for technology, *source code*, is significantly and negatively correlated with token failure (columns 4 and 8). Another proxy for technical sophistication, *technical document*, becomes insignificant with the expected sign in models that include market variables and industry dummies (columns 4 and 8). These results suggest that the technical sophistication may be the most important *ex ante* predictor for both coin and token failures. In addition, only the *payments* industry dummy is significant in predicting token failure in models including market variables and crypto-specific variables (columns

4 and 8), although the *infrastructure* and *services* industry dummies are also significant in the model with only industry dummies. These results suggest that the *payments* industry dummy is the only common industry predictor for coin and token failures.

In sum, results from dynamic logit regressions show that market variables such as *MCAP*, *AGE*, *RETVOL*, and *ZERO%*, the proxy for technical sophistication such as the dummy *source code*, and the *payments* industry dummy are common significant predictors for both coin and token failures. Because coins are different from tokens in many aspects, some significant predictors for coin failure are different from those for token failure. In our sample period, we document more significant predictors for coin failure than token failure. The Pseudo-R^2 in the best specifications for coin failure is 0.133, while the Pseudo-R^2 in the best specifications for token failure is 0.084. These results suggest that the dynamic logit model better predicts coin failure than toke failure.

The relatively low R^2 is not surprising because it is well-known that it is difficult to precisely forecast extreme events such as failure events for highly volatile cryptocurrencies. Following the method in Conrad, Kapadia, and Xing (2014) that forecasts jackpot, we use the ROC (Receiver Operating Characteristic) curve to assess our model's accuracy. The ROC curve refers to the graph that shows the true positive rate versus the false positive rate at different classification thresholds. The ROC curves for logistic models in predicting the failure events of coins and tokens are presented in Figure A1.

To explicitly assess the model accuracy with a score, we use the AUC (Area Under Curve) that represents the area under the ROC curve. AUC is an important and popular indicator to measure the performance of a classification model, ranging from 0 to 1. The bigger AUC, the more accurate the model.[23] In this paper, we use AUC to obtain logistic models' accuracy in predicting crypto distress and failure events. AUC for coin (token) failure events model in Figure A1 is 0.83 (0.79). For comparison, the model in Conrad et al. (2014) has an accuracy ratio of 0.77 in predicting realized jackpot. Overall, our models perform well.

3.2 Forecasting at Long Horizons

The best specifications at the 1-week horizon capture about 13.3% of the variation in coin failure and 8.4% in token failure. In this subsection, we explore the determinants of cryptocurrency failure over the relatively longer horizons. Because cryptocurrencies are different from public firms and stocks in the lifecycle and short-lived, following Campbell et al. (2008), we estimate the conditional probability of failure over next 4 and 8 weeks.[24] The forecasting model is described as follows:

$$P_{t-1}\left(Y_{i,t+n} = 1\right) = \frac{1}{1 + \exp\left(-\alpha - \beta_i x_{i,t-1}\right)}$$

where $Y_{i,t+n}$ equals to one if there is a failure event in week *t+n*, and $x_{i,t-1}$ refers to a vector of explanatory variables at the end of week *t-1*.

Table 6 reports the results for coin and token failures over the next 1, 4, and 8 weeks, respectively. Overall, our results show that these significant predictors over the next 1-week horizon are still significant for coin failure over the next 4- and 8-week horizons. For

[23] Typically, an AUC value between 0.7 and 0.8 is considered fair, a value between 0.8 and 0.9 is considered good, and a value above 0.9 is considered excellent (S&P Global Market Intelligence).
[24] Because cryptocurrencies are traded 24/7 without the market close, 8 weeks in the crypto market equals about 40 weeks in the stock market in term of trading time.

example, these market-based variables, *MCAP*, *AGE*, *RET_4W*, *RETVOL*, and *ZERO%*, are still significant predictors for coin failure over the next 4- and 8-week horizons. The coefficients and significance levels for *only* predictors such as *MCAP*, *RETVOL*, and *ZERO%* decline as the horizon increases. In addition, as we would expect, the Pseudo-R^2 decreases as the horizon increases.

Our results also show that most significant predictors over the next 1-week horizon are also significant predictors for token failure over the next 4- and 8-week horizons. However, some significant variables become insignificant but some insignificant variables become significant as the horizon increases. For example, *NCSKEW* becomes insignificant over the next 4- and 8-week horizons, while the dummy *twitter* becomes significant over the next 4-week horizon, the dummy *Ethereum* becomes marginally significant over the next 8-week horizon, and the *infrastructure* and *services* industry dummies also become significant over longer horizons. the Pseudo-R^2 does not decrease substantially as the horizon increases, though it is expected to decrease as the horizon increases. We conclude that most significant predictors still perform well in predicting coin or token failures over a relatively longer horizon such as 4- or 8-week horizon.

3.3 Cryptocurrency Futures

The Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) introduced Bitcoin futures contracts in December 2017. Many influential crypto exchanges and platforms started to provide Bitcoin futures contracts around the world after 2017. Other cryptocurrency futures have also been launched by various exchanges in recent years. In a volatile ecosystem with wild price swings, Bitcoin futures contracts provide a more regulated and stable environment to hedge exposure against wild price movements. Because of the change in the trading environment, we expect that the introduction of cryptocurrency futures would have significant impact on some predictors for crypto failure. In this subsection, we explore whether and how the introduction of Bitcoin futures affects the determinants of cryptocurrency failure.

To evaluate how the introduction of Bitcoin futures affects the determinants of failure in the cryptocurrency market, we include the interactions between this specific event (i.e., the initial Bitcoin futures offerings) and crypto-level variables in the dynamic logit model in the subsection 3.1.

We first assess the impact of the introduction of Bitcoin futures in December 2017 on cryptocurrency failure. We expect that more cryptocurrencies would fail in 2018 after the introduction of Bitcoin futures in December 2017 because the Bitcoin bubble was in the peak in December 2017. The introduction of Bitcoin futures contracts provides investors a new channel to arbitrage the overpricing of Bitcoin, inhibiting extremely optimistic investor sentiment and the formation of bubble in the crypto market to some extent. Moreover, the introduction of Bitcoin futures would accelerate the crypto bubble burst subsequently. Some studies argue that the introduction of Bitcoin futures is significantly responsible for the subsequent fall in prices of Bitcoins and several main cryptocurrencies (e.g., Hale et al., 2018; Liu et al., 2020).

Column 1 in Table 7 shows that the coefficient of the initial cryptocurrency futures offerings (IFO) for coins is positive and significant, suggesting that the introduction of Bitcoin futures is significantly and positively related to subsequent coin failure probability. This finding suggests that the introduction of Bitcoin futures seems to prevent extremely optimistic investor sentiment. In contrast, column 5 shows that the coefficient of IFO for tokens is negative but insignificant, suggesting that the introduction of Bitcoin futures in December 2017 is not significantly correlated with toke failure probability in 2018 and 2019. One potential explanation is that tokens as an alternative of coins started to become popular in 2017 and more popular in 2018.

Given the adverse impact of the IFO on the failure probability in the crypto market, then we evaluate whether and how the introduction of Bitcoin futures affects the role of predictors in predicting cryptocurrency failure. Column 2 in Table 7 shows that the coefficients of the interactions between *IFO* and *AGE*, *RETVOL*, and *ZERO%* are positive and significant, and the interaction between *IFO* and *RET_4W* is negative and significant. These results suggest that the role of coin age, return volatility, and illiquidity in predicting the failure becomes stronger after the introduction of Bitcoin futures. However, the role of recent returns is weakened after the introduction of Bitcoin futures. These results hold when we include crypto-specific dummy variables (column 4) except that the interaction between *IFO* and *RETVOL* becomes insignificant with the same sign.

Column 3 in Table 7 shows that the coefficients of the interactions between *IFO* and these dummy variables (*technical document*, *source code*, *PoW*, and *hybrid consensus algorithm*) are negative and significant, suggesting that the role of these dummy variables becomes weaker after the introduction of Bitcoin futures. The sign and significance of the interaction of between *IFO* and proxies for technical sophistication (*technical document* and *source code*) hold when we include market-based variables (column 4). The results in Table 4 shows that coins with technical document and source code are less likely to fail than coins without them in the full sample period. However, the introduction of Bitcoin futures seems to weaken the role of technical sophistication in predicting coin failure. One potential explanation is that investors may not regard the technology as important when investor sentiment in the cryptocurrency market becomes low after the introduction of Bitcoin futures.

Columns 5 to 8 in Table 7 report the results for tokens. In contrast, column 8 shows that the coefficients of the interaction between *IFO* and *MCAP* is negative and significant, and the coefficients of the interactions between *IFO* and *AGE* and *ZERO%* are positive and significant, suggesting that token size, age, and illiquidity become more important in predicting token failure after the introduction of Bitcoin futures. In contrast, the coefficients of the interaction between *IFO* and *RET_4W* is positive and significant, suggesting that recent returns become less important in predicting token failure after the introduction of Bitcoin futures. These findings show that the importance of market-based predictors for coin failure differs from that of predictors for token failure after the introduction of Bitcoin futures in 2017.

Column 8 also shows that only the coefficient of the interaction between *IFO* and the platform *Ethereum* is significant and negative, suggesting that the platform as a predictor becomes more important in predicting token failure after the introduction of Bitcoin futures. In contrast, the importance of other token specific predictors such as information disclosure and technical sophistication remains unchanged before and after the introduction of Bitcoin futures.

In sum, the introduction of Bitcoin futures in December 2017 has different impact on coin and token failures and the determinants of their failures. The introduction of Bitcoin futures in 2017 seem to have larger impact on coin failures than token failures subsequently possibly due to that the Bitcoin bubble was in the peak in the end of 2017 and tokens become more popular from 2018. In addition, the introduction of Bitcoin futures has larger impact on some predictors for coin and token failures than other predictors. Moreover, the introduction of Bitcoin futures has different impact on predictors of coin and token failures.

3.4 The COVID-19 Pandemic

The COVID-19 pandemic has great impact on social and economic activities around the world (e.g., Ding, Levine, Lin, and Xie, 2021; Goldstein, Koijen, and Mueller, 2021). Unlike the adverse impact of the pandemic on most social and economic activities, we observe that more new cryptocurrencies have been offered since 2020 than before 2020. In particular, more than 1,787 new tokens are offered around the world in 2020. Moreover, the ratio of failed to new coins or tokens in 2020 is lower than that in prior years. In this subsection, we explore how the shock of the COVID-19 pandemic affects the failure and the role of predictors for failure in the cryptocurrency market.

To evaluate how the COVID-19 pandemic affects the cryptocurrency market, we include the interactions between the outbreak of COVID-19 pandemic event and crypto-level variables in the dynamic logit model in the subsection 3.1.

We first assess the impact of the outbreak of COVID-19 on cryptocurrency failure. The stagnant society and economy due to the outbreak of COVID-19 leads to the crypto boom. Therefore, we expect a lower failure probability after the outbreak of COVID-19. Column 1 in Table 8 shows that the coefficient of the outbreak of COVID-19 (*COVID19*) as a dummy variable is negative and significant, suggesting that the outbreak of COVID-19 is significantly and negatively correlated with the subsequent coin failure. Column 5 shows the same result for tokens.

Given the positive impact of the COIVD-19 pandemic on the cryptocurrency market, then we evaluate whether and how the outbreak of COIVD-19 affects the role of predictors in predicting failure. Columns 1 to 4 in Table 8 report the results for coins. Column 2 shows that only the coefficient of the interaction between *COVID19* and *AGE* is significant and negative, suggesting that the positive relation between coin age and failure probability is weakened after the outbreak of COVID-19. Column 3 shows that the coefficient of the interaction between *COVID19* and the dummy variable *twitter* is marginally significant and negative, but the coefficient becomes insignificant after we control for market-based variables in column 4. In addition, column 4 shows that the coefficient of interaction between *COVID19* and the dummy variable *PoW* is significant and negative, suggesting that the negative relation between *PoW* and coin failure probability is weakened by the outbreak of COVID-19.

Columns 5 to 8 in Table 8 report the results for tokens. Column 8 shows that the coefficient of the interaction between *COVID19* and *RETVOL* is significant and negative, suggesting that the positive relation between return volatility and failure probability is weakened by the outbreak of COVID-19. The positive relation between the downside risk proxied by NCSKEW and failure probability is also weakened during the COVID-19 pandemic. However, column 8 shows that the coefficient of the interaction between *COVID19* and the dummy variable *source code* is significant and negative, suggesting that the negative relation between the technical sophistication and failure probability is strengthened during the COVID-19 pandemic.

Overall, our results show that the COVID-19 pandemic has significant impact on the failure and the role of some specific predictors in predicting failure in the cryptocurrency market.

3.5 Size Effect

The above results show that the market capitalization is a robust and significant predictor for both coin and token failures in various specifications. Liu et al. (2022) document that size is a common risk factor in the cryptocurrency market. Large cryptocurrencies earn lower future returns than small cryptocurrencies. In this subsection, to further check the size effect in the cryptocurrency market, we examine how determinants of cryptocurrency failure vary across different size subsamples.

We divide the whole sample into two equal subsamples based on their market capitalizations at the end of each week. We find that most failure events occur among small cryptocurrencies. For instance, there are 90 failure events among large coins, while there are 638 failure events among small coins. We use the dynamic logit model in the section 3.1 to estimate the failure probability in large and small cryptocurrency subsamples.

Table 9 reports the results for coin and token failures that are determined based on the future 20-week horizon. For coins, these significant predictors in the full sample are still significant in the subsample of small coins except the *infrastructure* and *payments* industry dummies. In contrast, *MCAP*, *RET_4W*, and *RETVOL* become insignificant in predicting coin failure in the subsample of large coins. However, the Pseudo-R^2 in the model for large coins is larger than that for small coins.

We find similar results for token failure. These significant predictors in the full sample are still significant in the subsample of small tokens, while *MCAP*, *ZERO%*, the dummy variable *source code*, and the *payments* industry dummy become insignificant in the subsample of large tokens. However, the Pseudo-R^2 in the model for large tokens is larger than that for small tokens.

Overall, we find that most significant predictors in the full sample are still significant in predicting coin or token failures among small coins or tokens because most failure events occur among small coins or tokens. Similar results hold if we define failures based on the next 4-week horizon. However, the Pseudo-R^2 is larger in the subsample of large coins or tokens than in the subsample of small coins or tokens. An unreported table shows similar results if we divide sample coins or tokens into two subgroups of high-priced and low-priced coins or tokens because the market capitalization is highly correlated with price.

4. The Failure Risk-Return Tradeoff in the Cryptocurrency Market

In this section, we explore the asset pricing implications of our failure model in the cryptocurrency market. Recent studies on cryptocurrency focus on the pricing of some traditional variables using standard asset pricing methods (e.g., Liu and Tsyvinski, 2021; Liu et al., 2022). No study has explicitly examined the pricing of *failure risk* in the cryptocurrency market. An examination of the pricing of failure risk in the crypto market sheds novel light on the debate on the default risk-return tradeoff in the financial markets.

The relation between default or distress risks and expected returns in the stock market is mixed. Building on various measures of default risk, some studies find a positive relation between default risk and expected returns (e.g., Vassalou and Xing, 2004; Chava and Purnanandam, 2010; Friewald et al., 2014; Aretz et al., 2018), while other studies document a negative relation (e.g., Dichev, 1998; Griffin and Lemmon, 2002; Campbell et al., 2008;

Da and Gao, 2010; George and Hwang, 2010). In addition, Anginer and Yildizhan (2018) show that Fama-French risk factors could explain the high expected returns for stocks with high exposures to systematic default risk. Xing, Yu, and Zhu (2022) find a positive risk premium for bankruptcy risk but no premium for other-failure risk.

In addition, the risk-return tradeoff is different in the stock and bond markets. Bai, Bali, and Wen (2021) find a significantly positive relation between systematic risk and corporate bond returns, while there is no significant relation between idiosyncratic volatility and bond returns. In contrast, there has been a debate on the relation between risks (in particular, measured by idiosyncratic volatility) and returns in the stock market. Bai et al. (2021) provide some evidence that different investor preferences for stocks and bonds explain the different risk-return tradeoffs in the stock and bond markets. In particular, sophisticated institutional investors dominate in the bond market, leading to a positive risk-return tradeoff in the bond market.

Because cryptocurrencies and stocks are different in many aspects and the default risk-return relation in the stock market is mixed, we cannot conclude that cryptocurrencies with high failure probability have higher or lower future returns than those with low failure probability. However, explanations for the positive risk-return tradeoff in the bond market in Bai et al. (2021) shed some light on the risk-return tradeoff in the crypto market.

We expect a *positive* failure risk-return tradeoff in the cryptocurrency market for two reasons. First, investors in the cryptocurrency market are more speculative than those in the stock market because cryptocurrencies are more speculative than stocks. Speculative investors in the cryptocurrency market are less likely to diversify their investments. Moreover, it is well known that cryptocurrencies have high failure probability. Therefore, motived by theories that idiosyncratic risk is positively related to expected returns in the cross section in the stock market (e.g., Merton, 1987), we expect that these under-diversified speculative investors require positive returns for bearing high failure risk in the cryptocurrency market. Second, as institutional investors in the bond market, investors in the cryptocurrency market are more sophisticated than common individual investors in the stock market. These more sophisticated investors are expected to require positive returns for bearing high failure risk. Because we do not have data available to identify whether sophisticated investors dominate in the crypto market and these investors hold under-diversified crypto assets, it is ultimately an empirical question in the cryptocurrency market.

4.1 Failure Risk and Expected Return in the Cross Section

We adopt the portfolio analysis approach to identify the failure risk-return tradeoff in the cryptocurrency market. We first use the dynamic logit model in the section 3.1 to estimate failure probability for each coin or token using historical data. Specifically, in each week, we use past three-year historical data to estimate the coefficients of significant predictors. The estimated coefficients are updated each week. For example, we use the data from January 2014 to December 2016 to calculate the coefficients of coin predictors in the first week in 2017. Because we use the future 4-week or 26-week information to identify *current* crypto failure events, the coefficients calculated in the first week in 2017 are used to calculate the estimated failure probability in the fifth week in 2017 to avoid the look-ahead bias. Therefore, the first observation in the out-of-sample evaluation period is the fifth week in 2017 for coins.[25] The out-of-sample evaluation period is from February 2017 to December 2020 for coins and November 2017 to December 2020 for tokens.

Predictors used in the model for coins include the market capitalization (*MCAP*), age (*AGE*), past 4-week return (*RET_4W*), recent return standard deviation (*RETVOL*), the illiquidity measure (*ZERO%*), the downside risk (*NCSKEW*), and crypto-specific dummy variables (i.e., *twitter*, *source code*, *technical document*, *ICO*, *PoW*, and *hybrid consensus algorithm*). Same predictors are used for tokens expect that the platform dummy (i.e., *Ethereum*) replaces the two dummy variables (i.e., *PoW* and *hybrid consensus algorithm*). Here we do not include industry dummies.

It is important to carefully handle the returns to distressed and failed cryptocurrencies. Because most failed cryptocurrencies will not resurrect after a long period of dormancy, we assign a return of -100% to such a failure event. Some distressed cryptocurrencies will resurrect after a period of dormancy, but most resurrected distressed cryptocurrencies are not actively traded. Therefore, we assign a return of -50% or -100% to such a distress event.[26] In addition, because the variations in returns to cryptocurrencies are very large and some extreme observations will potentially bias the results, we limit the maximum weekly returns to 1000%.[27]

---

[25] To use the latest estimated coefficients, we use the future 4-week information to identify current crypto failure events. Our results are consistent if we use the future 26-week information to identify failure events.

[26] Most existing studies on cryptocurrency do not consider the adjustment on returns when these cryptos fail. We get very similar results using either -50% or -100% for a distress event. In the main analysis, we report the results based on the distress return of -50%. The results based on the distress return of -100% is available upon request.

[27] Extreme returns are mainly driven by extremely low-priced cryptocurrencies. Although we use the value-weighted returns in the main analysis, some extreme returns would affect the results to some extent. Good news is that the number of extreme returns is very few. Our results are consistent when various maximum weekly returns (e.g., 300% or 500%) are used.

We follow the way in Liu et al. (2022) to construct the three factors in the crypto market. Because we examine coins and tokens separately, we construct the size factor (CSMB) and the momentum factor (CMOM) for the coin and token sample, respectively. Liu et al. (2022) show that the mean and standard deviation of the crypto market returns are the same as those of Bitcoin's returns. Therefore, we use Bitcoin's returns as a measure of the market factor. When constructing the size and momentum factors in coin or token sample, we also exclude coins or tokens with market capitalizations of less than $1,000,000.

Following prior studies such as Campbell et al. (2008), we use the standard portfolio analysis to test the risk-return tradeoff in the cryptocurrency market. We first examine the unconditional relation between distress risk and return for coins or tokens, respectively. We assign all sample coins or tokens into five quintile portfolios based on their estimated failure probabilities.[28] These portfolios are hold for 1 week.

Table 10 reports the average equal-weighted and value-weighted excess returns and risk-adjusted returns for portfolios of coins or tokens sorted on their estimated failure probabilities (FP). Panel A reports the results for coins. We find that coins with high FP outperform coins with low FP. Specifically, coins in the highest FP quintile portfolio outperform coins in the lowest FP quintile portfolio by an average weekly equal-weighted (value-weighted) excess return of 11.13% (5.28%) with a t-statistic of 9.02 (3.05). The outperformance is robust even after controlling for three crypto factors. Moreover, the outperformance is mainly from coins with high FP. For example, coins in the highest FP

[28] In this subsection, we examine the relation between failure risk and expected returns in the whole sample that includes all sample coins or tokens. We do not use the size screen such as $1,000,000 to exclude small cryptos. In the subsection 4.3, we examine the role of crypto characteristics such as size in the failure risk-return relation.

quintile portfolio have an average value-weighted CAPM alpha of 4.97%, while coins in the lowest FP quintile portfolio have an average value-weighted CAPM alpha of 0.05%.

The average excess and risk-adjusted returns *monotonically* increase with failure probability in term of equal-weighted returns. In contrast, the monotonic relation between failure risk and expected returns does not hold in term of value-weighted returns. However, coins in the highest FP quintile portfolio consistently have much higher expected returns than coins in other quintile portfolios. We find similar results if we sort sample coins into ten decile portfolios.[29]

There is no obvious variation in factor loadings across the FP portfolios in term of equal-weighted returns in Panel A of Table 10. All five FP portfolios have positive and significant loadings on the market factor and the size factor, but insignificantly negative loadings on the momentum factor. In contrast, the size loadings increase with the FP portfolios in term of value-weighted returns. The market capitalizations of coins decrease across the FP portfolios. That is, distressed coins are much smaller than safe coins. Overall, excess returns of all FP portfolios are smaller than risk-adjusted returns, suggesting that these crypto factors can partly explain the failure risk-return tradeoff. However, these crypto factors cannot significantly explain the pricing of crypto failure risk.

Panel B of Table 10 reports the results for tokens. Overall, we find similar results for tokens. Compared with tokens in other portfolios, tokens in the highest FP quintile portfolio have significantly much higher expected returns. Crypto three factors cannot significantly explain the high and positive expected returns of high failure risk, although abnormal

[29] An unreported result shows that coins in the highest FP decile portfolio have extremely high expected returns.

returns of high failure risk decrease under the three-factor model.

In sum, our results suggest that failure risk is significantly and positively priced in the cryptocurrency market. Common risk factors such as crypto size and momentum factors could not significantly explain the pricing of crypto failure risk. Crypto size and return volatility are two most important characteristics that are related to the pricing of failure risk. Distressed cryptos are much smaller and volatile than safe cryptos.

This new finding in the crypto market is against the distress anomaly in the stock market documented in Campbell et al. (2008), while it is consistent with the classical theory that supports a positive risk-return tradeoff in Merton (1987) and the positive risk-return tradeoff in the bond market in Bai et al. (2021). Two potential explanations for the positive risk-return tradeoff in the crypto market are that investors in the cryptocurrency market hold under-diversified portfolios of crypto assets and that these investors are more sophisticated than individual investors in the stocks and they require high positive premium for bearing high failure risk of crypto assets.[30]

4.2 Failure Risk and Expected Return in Event Time

We track the relatively long-term performance of FP portfolios in the subsection 4.1 to better understand the pricing of crypto failure risk. Following Jegadeesh and Titman (1993), we calculate the average portfolio returns for various FP portfolios in each of 12 weeks following the portfolio formation week. This event-time return analysis sheds additional insights on the persistence of the pricing of crypto failure risk and riskiness of

[30] We argue that the substantially positive returns of high-FP cryptocurrencies, which eventually do not fail, compensate for the losses of failed cryptocurrencies in a representative investor's portfolio.

the trading strategy based on failure risk.

Table 11 presents the value-weighted market-adjusted returns of portfolios sorted on estimated failure probability in each of 12 weeks following the portfolio formation week. Coins or tokens in the highest FP quintile portfolio have significantly positive abnormal returns in each of 12 weeks following the portfolio formation week. The return spread between the highest and lowest FP portfolios is significant and positive. The highest FP portfolio has significantly much higher expected abnormal returns than other FP portfolios in event time. Moreover, the magnitude of high returns of the highest FP quintile portfolio does not decay over time, suggesting that the positive pricing of high failure risk is quite persistent. In contrast, coins in the lowest FP quintile portfolio have almost zero abnormal returns in each of 12 weeks following the portfolio formation week. Moreover, tokens in the lowest FP quintile portfolio have large negative abnormal returns in event time.

Figure 5 presents the cumulative returns of portfolios with various estimated failure probability. The highest FP quintile portfolio experiences substantial cumulative abnormal returns in the 12-week holding period.

4.3 Crypto Characteristics and the Pricing of Failure Risk

The variation in some crypto characteristics across different FP portfolios suggests that some crypto characteristics play an important role in the relation between failure risk and expected returns. Because some characteristics such as size and return volatility are significant predictors for crypto failure, it is not surprising that the pricing of crypto failure risk varies across crypto characteristic portfolios. Campbell et al. (2008) show that the distress anomaly in the stock market varies across characteristic groups. We examine the extent to which crypto characteristics affect the pricing of crypto failure risk.

To explore the role of crypto characteristics in the pricing of failure risk, we use the double-sorting portfolio analysis as in Campbell et al. (2008). For example, we first equally divide sample coins into three portfolios based on their market capitalizations. Then within each size portfolio, we assign coins into five quintile portfolios based on their estimated failure probability. The portfolios are hold for 1 week. We report the average value-weighted market-adjusted returns for these double-sorted portfolios.

Table 12 reports the results. The positive relation between failure risk and expected return is more pronounced among smaller coins. The return spread between the highest and lowest FP portfolios is 7.02% per week (t-statistic is 3.82) in the subsample of small coins, compared to the return difference of 4.92% (t-statistic is 2.96) in the whole sample. In contrast, the return spread is -1.36% (t-statistic is -1.63) in the subsample of large coins. These results suggest that holding large coins with relatively high FP does not have positive risk premium. On average, large coins have relatively lower estimated failure probability and much lower returns than small coins. We find similar results for tokens.

We also find that high expected returns of high failure risk are more pronounced among coins or tokens with poor recent past returns. Moreover, the expected returns *monotonically* increase across FP portfolios only in the subsample of coins or tokens with poor recent past returns. In contrast, we find no such a positive relation between failure risk and expected returns among coins with good recent past returns. Moreover, high-FP tokens have large negative abnormal returns in the subsample of tokens with good recent past returns. These results show that the monotonically positive relation between failure risk and expected is concentrated among past losers. On average, past losers do not have significantly higher estimated failure probability than past winners.

The high positive premium of failure risk is more pronounced in the subsample of cryptos with high recent return volatility. Moreover, the monotonically positive relation between failure risk and expected returns also exists only in the subsample of cryptos with high recent return volatility. In contrast, there is no obvious relation between failure risk and expected returns in the subsample of cryptos with low recent return volatility. These results suggest that arbitrage costs may be a potential explanation for the positive premium of high failure risk in the crypto market.

There is no obvious age effect in the pricing of failure risk for coins. High FP coins regardless of age have significantly higher positive expected abnormal returns, while other coins do not have high abnormal returns. In contrast, the positive premium of failure risk is more pronounced among young tokens than among old tokens, although high FP tokens still have higher expected returns than low FP tokens among old tokens.

In sum, the positive tradeoff between crypto failure risk and expected returns is more pronounced among cryptos that are small and have poor recent performance and high recent return volatility. Cryptos with such characteristics are more likely to fail based on the results from the dynamic logit models for failure.

4.4 Additional Analysis and Discussion

4.4.1 Direct Trading Costs

Trading costs account for the profitability of most stock market anomalies (Novy-Marx and Velikov, 2016). Therefore, trading costs may be a main concern about the implementability and real profitability of the strategy based on crypto failure risk. Like Liu et al. (2022), we focus on long-only strategies and long-short strategies.

There are two main reasons for the concern about trading costs for our strategies. First, the long leg includes very small cryptos that may have high trading fees and bid-ask spreads. Second, there may be a lack of availability of cryptos shorted and high shorting fees. In our opinion, direct trading costs may not be a big concern. It is difficult to precisely measure trading fees and bid-ask spreads for small cryptos in our sample. Trading prices and trading fees are quite volatile in the cross section and time series in the crypto market.[31] Assuming that small cryptos in the long leg have ten times the trading fees and bid-ask spreads for the largest 20 coins mentioned in Liu et al. (2022), the long-only strategies are still profitable. For example, the returns of the long leg are still larger than relatively conservative trading costs of 5%. The event-time return analysis suggests that investors could buy and hold cryptos in the long leg for a longer time to mitigate the concern about trading costs. Moreover, trading fees and bid-ask spreads quickly declined in recent years.

For the long-short strategies, it is easier and less costly to short Bitcoin than cryptos in our short legs in recent years (Liu et al., 2022). Therefore, shorting costs could not be a big concern for the implementability and profitability of the long-short crypto failure risk-based strategies. Moreover, because the profitability of the long-short failure risk-based strategies is mainly driven by the long leg, investors could focus on the long-only strategies.

4.4.2 Arbitrage Costs

[31] DataTrek Research provides some examples of transaction fees for cryptocurrencies. https://www.datatrekresearch.com/crypto-currencies-and-transaction-fees/

Table 12 shows that the highly positive premium of high failure risk is concentrated among high-volatile and small cryptos. These findings are consistent with the argument about limits to arbitrage in Shleifer and Vishny (1997) and Pontiff (2006). The main arbitrage risk such as short-sale constraints could be mitigated by focusing on the long-only strategies in our setting because the profitability of the long-short strategies is mainly from the long leg. A natural question arises: why arbitrageurs do not arbitrage high returns of high-FP cryptos immediately?

Figure 7 presents the time series of excess returns and crypto market-adjusted returns of coins or tokens in the highest FP quintile portfolios. There are many times of negative returns in term of excess or market-adjusted returns in time series. Because many investors in the cryptocurrency market have high leverage and hold *un-diversifiable* crypto portfolio, high frequency of negative returns of high-FP cryptos in time series is high arbitrage costs to investors.

5. Asset Allocation

To further assess the economic value of the crypto failure risk, we examine the performance of trading strategies that combine high failure risk cryptocurrencies with the stock market and the risk-free asset from an asset allocation perspective. Following Rapach, Strauss, and Zhou (2010) and Ferreira and Santa-Clara (2011), we calculate the certainty equivalent return (CER) gain and Sharpe ratio for these trading strategies. A better strategy has higher CER and Sharpe ratio.

Suppose a mean-variance investor with the relative risk aversion parameter A who allocates her wealth into a risk-free asset (i.e., T-bill) and N risky assets (i.e., coins or tokens, and the stock market; $N = 2$) with returns R_f and R.[32] The investor chooses a proportion of w_j to invest in risky asset j (here $j = 1, 2$). The portfolio is rebalanced weekly. His portfolio's value is

$$R_p = w'R + (1 - w'1_N)R_f = R_f + w\left(R - R_f\right)$$

Let $r = R - R_f$ *with mean* μ *and covariance* $\sum$,

here $\mu = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$, $\qquad \Sigma = \begin{bmatrix} \sigma_1^2 & Cov(R_1, R_2) \\ Cov(R_1, R_2) & \sigma_2^2 \end{bmatrix}$

The problem is to find the optimal *w* to maximize his expected utility in next period,

$$\max_{w} E\left[U\left(R_p\right)\right] = E\left[U\left(R_f + w\left(R - R_f\right)\right)\right]$$

$$i.e., \quad \max_{w} \; w'\mu - \frac{A}{2} w' \sum w$$

The optimal portfolio weight is

$$w^* = \frac{1}{A} \sum^{-1} \mu$$

Here we limit the weight for cryptocurrencies and the stock market to the range from 0 to 1 so that the trading strategy is more practical for normal investors.

Then the CER of the portfolio is

$$CER = w'\mu - \frac{A}{2} w' \sum w \Big|_{w=w^*}$$

The CER gain is the difference between the compensation to the investor who invests

[32] In this section, we focus on coins and tokens in the highest failure probability quintile portfolio defined in the section 4. That is, we only consider these high-FP coins and tokens because these high-FP cryptos have high expected returns.

in high failure risk crypto assets, the stock market, and the risk-free asset and the compensation to the investor who invests only in the stock market and the risk-free asset. The out-of-sample evaluation period is from January 2019 to December 2020 for both coins and tokens.

Table 13 reports the annualized CER gains and Sharpe ratio, and portfolio weights for various optimal portfolios hold by a mean-variance investor with different degree of risk aversion. Transaction cost for stocks is set at 50 bps per week. Because direct and indirect transaction costs for coins and tokens are larger than those for stocks, we consider the transaction cost of 500 bps, which are conservative or large enough even for small coins and tokens in recent years.

Our results show that the CER gains can still be large even after we adjust for relatively conservative transaction costs, suggesting that the mean-variance investor could obtain substantial economic gains by additionally investing in high failure risk, coins and tokens, on top of the stock market and the risk-free asset. For example, the annualized CER gain is 11.60% for the portfolio including high failure risk coins when the risk aversion is 15. In addition, the portfolios including high failure risk crypto assets deliver attractive Sharpe ratio, which could be 1.84 in the case of coins. The CER gain and Sharpe ratio are also economically significant for portfolios that allocate capital into tokens.

The CER gain and portfolio weights are sensitive to the degree of risk aversion. As for crypto assets, they are unlike traditional financial assets and investors may have ambiguity aversion regarding these emerging crypto assets on top of the usual risk aversion. Therefore, it seems reasonable to assume that investors consider the ambiguity aversion together with the usual risk aversion when they allocate capital into ambiguous assets such as crypto assets in our setting. More specifically, according to Trojani and Vanini (2004), a risk aversion of 10 and ambiguity of 5 would be considered as equivalent to a risk aversion of 15 approximately. Although the CER gain can be very large when risk aversion is relatively low, the corresponding portfolio weight assigned to high risky crypto assets tend to be too high. For example, when the risk aversion is 3, the weight on coins is as large as 0.34. When taking into account the high risk and ambiguity aversion together, the effective risk aversion can become as large as 15. The corresponding optimal weight on coins decreases to 0.07.[33] This is the case for token as well. The relatively small weight of 7% on high risky crypto assets looks more reasonable and reflects that investors recognize the high risk, such as the high failure risk in our setting, plus the ambiguity associated with the crypto assets.[34]

Overall, these results suggest that mean-variance investors should diversify some of their wealth into crypto assets because investing in the crypto market provides substantial economic value from an asset allocation perspective. The crypto market seems to be a good complement to traditional financial markets. Moreover, our results also show that mean-variance investors seem quite rational and allocate a relatively small weight on high risky crypto assets possibly because these crypto assets are high risky, including the high failure risk documented in this paper, and ambiguous to them.

6. Conclusion

[33] Figure A2 shows the time series of optimal weights on crypto assets (coins and tokens) and the stock market from 2019 to 2020.

[34] For simplicity, we do not assume difference risk aversion coefficients for stocks and crypto assets. However, we admit that for stocks, the ambiguity can be much smaller than crypto assets.

This paper aims to examine the failure risk in the cryptocurrency market that is largely ignored by the literature. We show that cryptocurrencies have astonishingly high failure probability that may lead to substantial economic losses for investors in this unregulated crypto market. We document some significant market-based and characteristic-specific predictors for crypto failure. Some significant predictors for coin failure are different from those for token failure. Moreover, the importance of these predictors varies over time. The introduction of Bitcoin futures and the outbreak of COVID-19 significantly affect the significance of some predictors .

Moreover, our study shows that the relation between failure risk and expected return is positive. The outperformance of cryptocurrencies with high failure risk is quite persistent and cannot be explained by common crypto risk factors. The positive crypto failure risk-return tradeoff suggests that crypto investors require a return premium for bearing high failure risk of crypto assets. In addition, we show that cryptocurrencies can generate sizable economic gains for investors from the asset allocation perspective.

Overall, we show both the apparent dark side (high failure risk and corresponding large economic losses) and potential bright side (high economic gains associated with high failure risk) of crypto assets, that seem a good complementary to the existing literature on crypto markets.

Reference

Anginer, Deniz, and Celim Yildizhan, 2018, Is there a distress risk anomaly? Corporate bond spreads as a proxy for default risk, *Review of Finance* 22, 633-660.

Amiram, Dan, Evgeny Lyandres, and Daniel Rabetti, 2022, Competition and Product Quality: Fake Trading on Crypto Exchanges, Working paper.

Aretz, Kevin, Chris Florackis, and Alexandros Kostakis, 2018, Do stock returns really decrease with default risk? new international evidence, *Management Science* 64, 3821–3842.

Bai, Jennie, Turan G. Bali, and Quan Wen, 2021, Is there a risk-return tradeoff in the corporate bond market? Time-series and cross-sectional evidence. *Journal of Financial Economics* 142, 1017–1037.

Bianchi, Daniele, and Mykola Babiak, 2022, A Factor Model for Cryptocurrency Returns, Working paper.

Böhme, Rainer, Nicolas Christin, Benjamin Edelman, and Tyler Moore, 2015, Bitcoin: Economics, Technology, and Governance, *Journal of Economic Perspectives* 29, 213–238.

Campbell, John Y., Jens Hilscher, and Jan Szilagyi, 2008, In search of distress risk, *Journal of Finance* 63, 2899–2939.

Chava, Sudheer, and Robert A. Jarrow, 2004, Bankruptcy prediction with industry effects, *Review of Finance* 8, 537–569.

Chava, Sudheer, and Amiyatosh Purnanandam, 2010, Is default risk negatively related to stock returns? *Review of Financial Studies* 23, 2523–2559.

Cong, Lin William, Xi Li, Ke Tang, and Yang Yang, 2021, Crypto Wash Trading, Working paper.

Conrad, Jennifer, Nishad Kapadia, and Yuhang Xing, 2014, Death and jackpot: Why do individual investors hold overpriced stocks? *Journal of Financial Economics* 113, 455–475.

Da, Zhi, and Pengjie Gao, 2010, Clientele change, liquidity shock, and the return on financially distressed stocks, *Journal of Financial and Quantitative Analysis* 45, 27–48.

Dhawan, Anirudh, and Tālis J. Putniņš, 2022, A new wolf in town? Pump-and-dump manipulation in cryptocurrency markets, *Review of Finance*, Forthcoming.

Dichev, Ilia D., 1998, Is the risk of bankruptcy a systematic risk? *Journal of Finance* 53, 1131–1147.

Ding, Wenzhi, Ross Levine, Chen Lin, and Wensi Xie, 2021, Corporate immunity to the COVID-19 pandemic, *Journal of Financial Economics* 141, 802–830.

Ferreira, Miguel A., and Pedro Santa-Clara, 2011, Forecasting stock market returns: The sum of the parts is more than the whole, *Journal of Financial Economics* 100, 514–537.

Fisch, Christian, 2019, Initial coin offerings (ICOs) to finance new ventures, *Journal of Business Venturing* 34, 1–22.

Foley, Sean, Jonathan R. Karlsen, and Talis J. Putnins, 2019, Sex, drugs, and Bitcoin: How much illegal activity is financed through cryptocurrencies? *Review of Financial Studies* 32, 1798–1853.

Friewald, Nils, Christian Wagner, and Josef Zechner, 2014, The cross-section of credit risk premia and equity returns, *Journal of Finance* 69, 2419–2469.

Gandal, Neil, J. T. Hamrick, Tyler Moore, and Tali Oberman, 2018, Price manipulation in the Bitcoin ecosystem, *Journal of Monetary Economics* 95, 86–96.

Gandal, Neil, J. T. Hamrick, Tyler Moore, and Marie Vasek, 2021, The rise and fall of cryptocurrency coins and tokens, *Decisions in Economics and Finance* 44, 981–1014.

Garlappi, Lorenzo, Tao Shu, and Hong Yan, 2008, Default risk, shareholder advantage, and stock returns, *Review of Financial Studies* 21, 2743–2778.

Garlappi, Lorenzo, and Hong Yan, 2011, Financial Distress and the Cross-section of Equity Return, *Journal of Finance* 66, 789-822.

George, Thomas J., and Chuan-Yang Hwang, 2010, A resolution of the distress risk and leverage puzzles in the cross section of stock returns, *Journal of Financial Economics* 96, 56–79.

Goldstein, Itay, Ralph Koijen, and Holger Mueller, 2021, COVID-19 and Its Impact on Financial Markets and the Real Economy, *Review of Financial Studies* 34, 5135-5148.

Griffin, John M., and Michael L. Lemmon, 2002, Book-to-market equity, distress risk, and stock returns, *Journal of Finance* 57, 2317–2336.

Griffin, John M., and Amin Shams, 2020, Is Bitcoin really untethered? *Journal of Finance* 75, 1913–1964.

Hale, Galina, Arvind Krishnamurthy, Marianna Kudlyak, and Patrick Shultz, 2018, How Futures Trading Changed Bitcoin Prices, *FRBSF Economic Letter*, Federal Reserve Bank of San Francisco.

Howell, Sabrina T, Marina Niessner, and David Yermack, 2020, Initial coin offerings: Financing growth with cryptocurrency token sales, *Review of Financial Studies* 33, 3925–3974.

Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48, 65-91.

Li, Tao, Donghwa Shin, and Baolian Wang, 2021, Cryptocurrency Pump-and-Dump Schemes, Working paper.

Liu, Yukun, Jinfei Sheng, and Wanyi Wang, 2021, Technology and Cryptocurrency Valuation: Evidence from Machine Learning, Working paper.

Liu, Yukun, and Aleh Tsyvinski, 2021, Risks and Returns of Cryptocurrency, *Review of Financial Studies* 34, 2689–2727.

Liu, Yukun, Aleh Tsyvinski, and Xi Wu, 2022, Common Risk Factors in Cryptocurrency, *Journal of Finance* 77, 1133-1177.

Liu, Ruozhou, Shanfeng Wan, Zili Zhang, and Xuejun Zhao, 2020, Is the introduction of futures responsible for the crash of Bitcoin? *Finance Research Letters* 34, 101259.

Lyandres, Evgeny, Berardino Palazzo, and Daniel Rabetti, 2022, Initial Coin Offering (ICO) Success and Post-ICO Performance, *Management Science*, forthcoming.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42, 483–510.

Novy-Marx, Robert, and Mihail Velikov, 2016, A Taxonomy of Anomalies and their Trading Costs, Review of Financial Studies 29, 104-147.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35-52.

Rapach, David E., Jack K. Strauss, Guofu Zhou, 2010, Out-of-Sample Equity Premium Prediction: Combination Forecasts and Links to the Real Economy, *Review of Financial Studies* 23, 821–862.

Shleifer, Andrei, and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35–55.

Shumway, Tyler, 2001, Forecasting bankruptcy more accurately: A simple hazard model, *Journal of Business* 74, 101–124.

Sockin, Michael, and Wei Xiong, 2021, A Model of Cryptocurrencies, Working paper.

Trojani, Fabio, and Paolo Vanini, 2004, Robustness and Ambiguity Aversion in General Equilibrium, *Review of Finance* 8, 279-324.

Vassalou, Maria, and Yuhang Xing, 2004, Default Risk in Equity Returns, *Journal of Finance* 59, 831–868.

Xing, Yuhang, Yan Yu, and Xiaorui Zhu, 2022, Zooming in on Distress Risk: Bankruptcy vs. Other Failures, Working paper.

Figure 1: Active and Failed Cryptocurrencies

This figure presents the number of new, active, and failed cryptocurrencies each year during year 2013 to 2020. A crypto failure event occurs if the cryptocurrency has no trading data over the next 4 consecutive weeks (Event4W) or 26 consecutive weeks (Event26W) in CoinMarketCap.

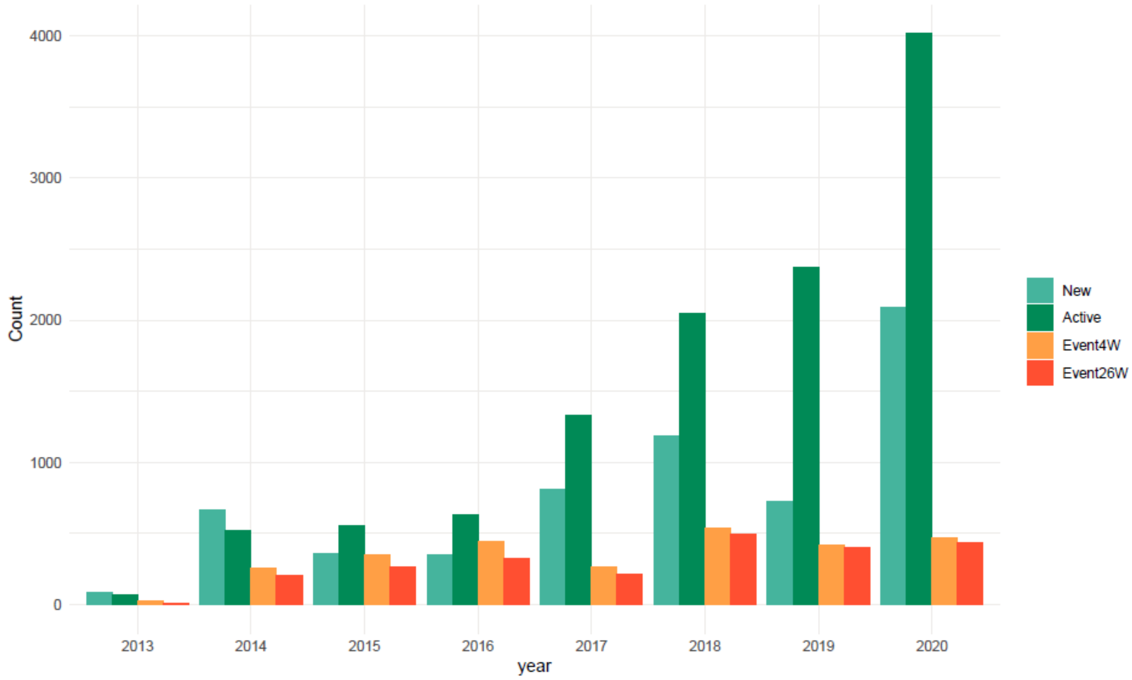
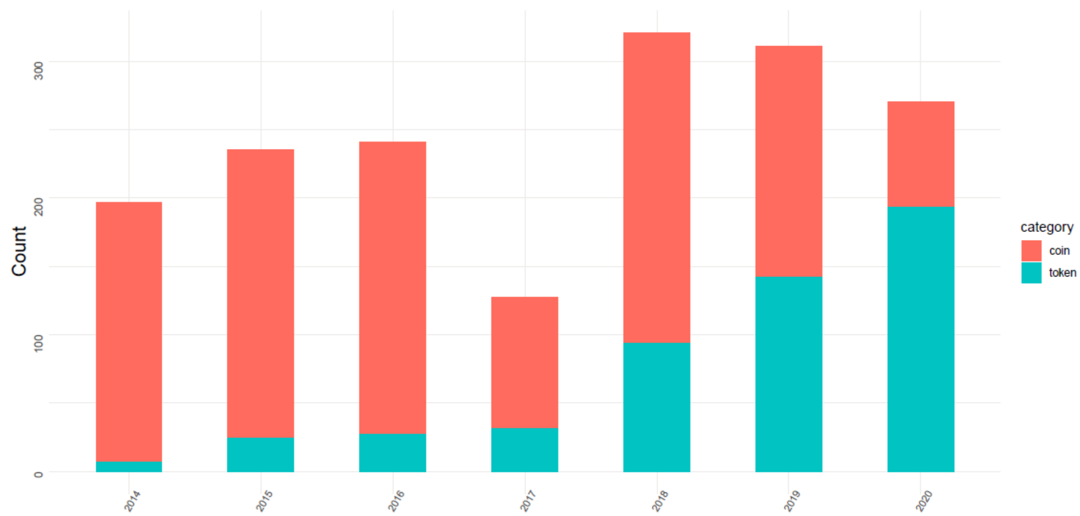


Figure 2: Number of Cryptocurrency Failures and Economic Losses

This figure presents the number of failure events and economic losses for coins and tokens each year of the sample period of 2014 to 2020. A failure event occurs if the cryptocurrency has no trading data over the next 26 consecutive weeks in CoinMarketCap. A cryptocurrency's economic loss is estimated as the maximum market capitalization within its whole life.

Panel A: Number of Failure Events



Panel B: Economic Losses

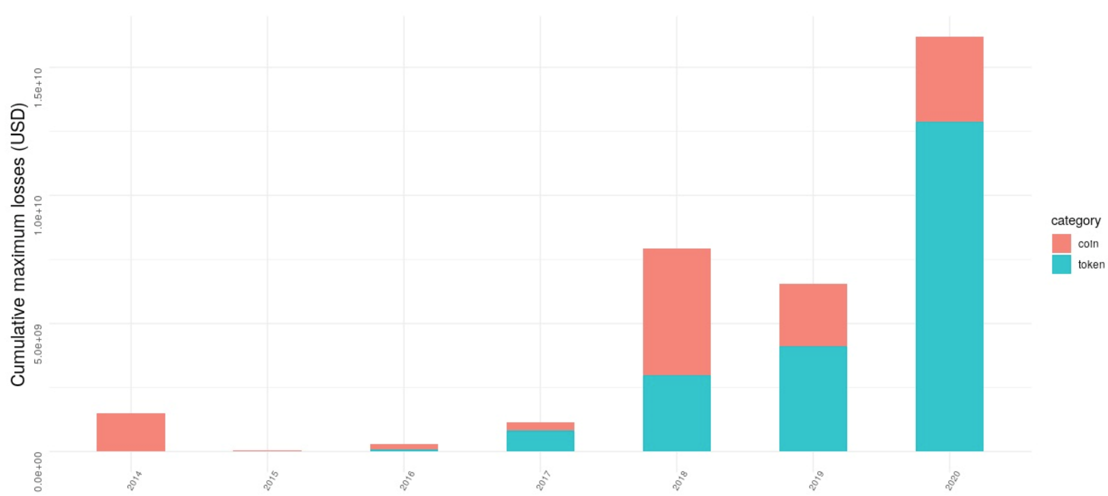


Figure 3: The Cumulative Cryptocurrency Failure Events

This figure presents the cumulative cryptocurrency failure events based on the future 4-week (Event 4W) or 26-week horizon (Event 26W) within a specified period during 2014 to 2020. These specified periods include the first 4 weeks (4W), 8 weeks (8W), 13 weeks (13W), and so on.

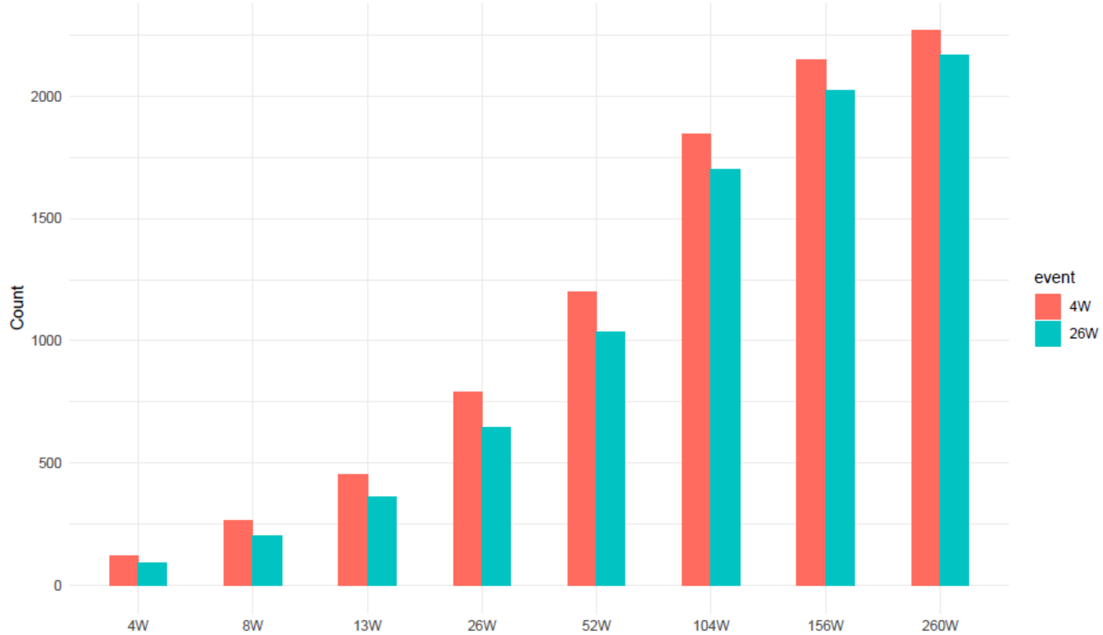
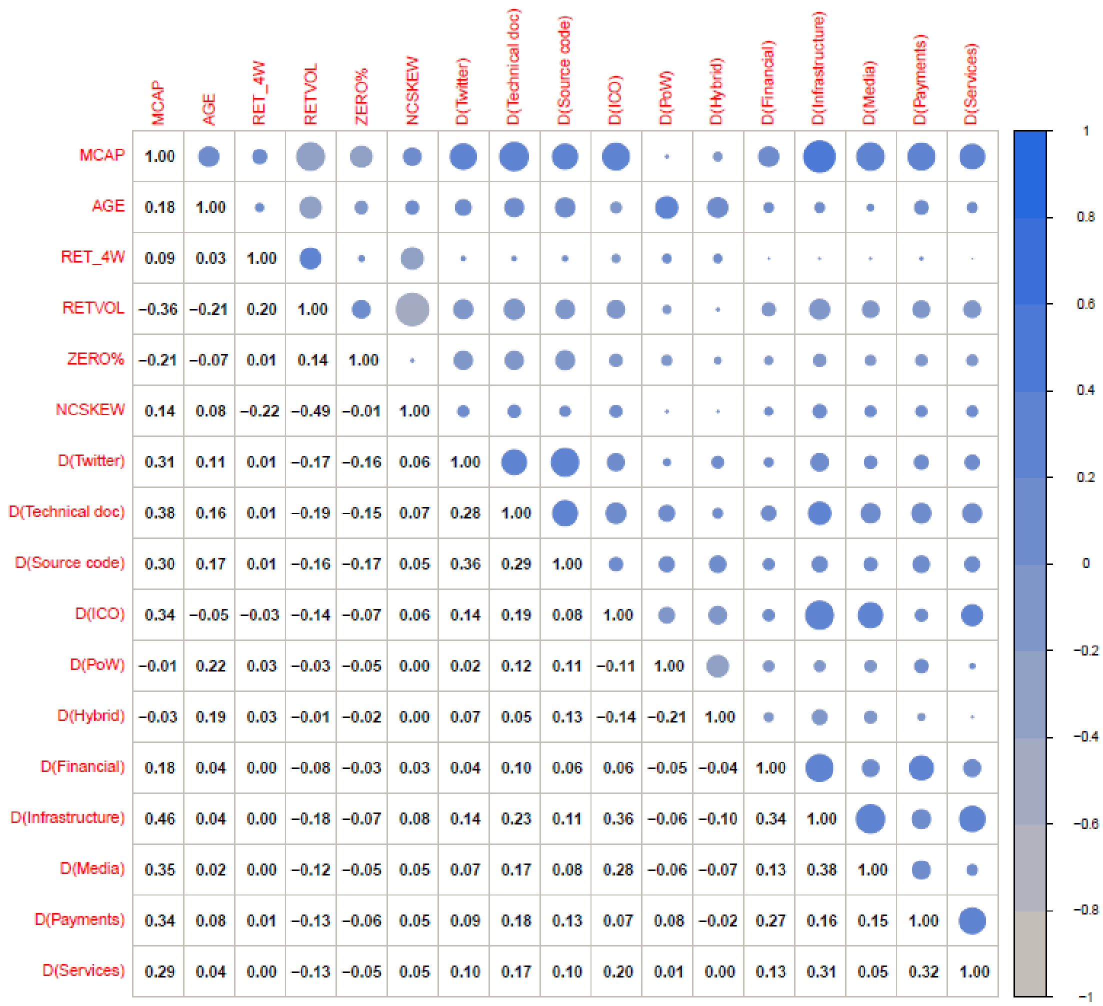


Figure 4: Correlation Matrix

This figure shows the Pearson correlations among market-based and crypto-specific variables that are used in the dynamic logic models. The definition of these variables is in Table A1.

Panel A: Correlation Matrix for Coins



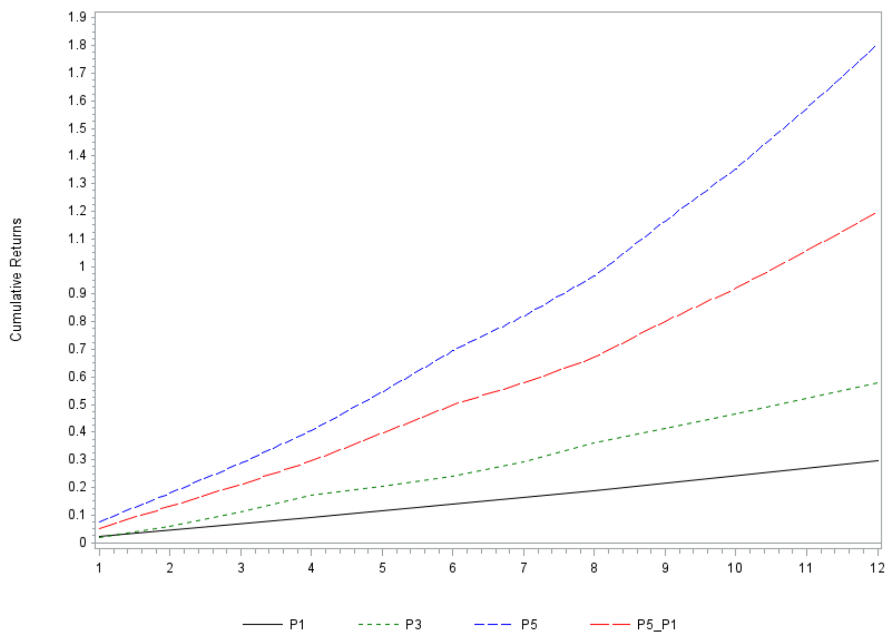
Panel B: Correlation Matrix for Tokens

	MCAP	AGE	RET_4W	RETVOL	ZERO%	NCSKEW	D(Twitter)	D(Technical doc)	D(Source code)	D(ICO)	D(Ethereum)	D(Financial)	D(Infrastructure)	D(Media)	D(Payments)	D(Services)
MCAP	1.00															
AGE	−0.09	1.00														
RET_4W	0.12	0.01	1.00													
RETVOL	−0.35	−0.04	0.18	1.00												
ZERO%	−0.09	−0.04	0.01	0.08	1.00											
NCSKEW	0.12	0.00	−0.25	−0.51	0.00	1.00										
D(Twitter)	0.07	0.01	0.00	0.01	−0.22	−0.02	1.00									
D(Technical doc)	0.16	0.05	0.00	−0.07	−0.09	0.02	0.21	1.00								
D(Source code)	0.02	0.00	−0.01	−0.03	−0.09	0.01	0.18	0.09	1.00							
D(ICO)	0.09	0.07	−0.01	−0.07	−0.07	0.03	0.23	0.18	0.13	1.00						
D(Ethereum)	0.02	−0.01	−0.02	0.00	−0.15	−0.01	0.25	0.14	0.14	0.15	1.00					
D(Financial)	0.19	0.05	0.01	−0.09	−0.02	0.04	0.00	0.07	−0.02	−0.02	0.01	1.00				
D(Infrastructure)	0.33	0.11	0.01	−0.15	−0.04	0.06	0.08	0.16	0.08	0.09	−0.01	0.17	1.00			
D(Media)	0.17	0.07	0.01	−0.09	−0.03	0.04	0.07	0.10	−0.04	0.10	0.01	−0.03	0.19	1.00		
D(Payments)	0.23	0.10	0.00	−0.11	−0.02	0.05	−0.09	0.06	−0.05	−0.06	−0.07	0.14	0.16	0.00	1.00	
D(Services)	0.24	0.11	0.00	−0.13	−0.04	0.05	0.08	0.19	0.02	0.11	0.05	−0.02	0.27	0.03	0.06	1.00

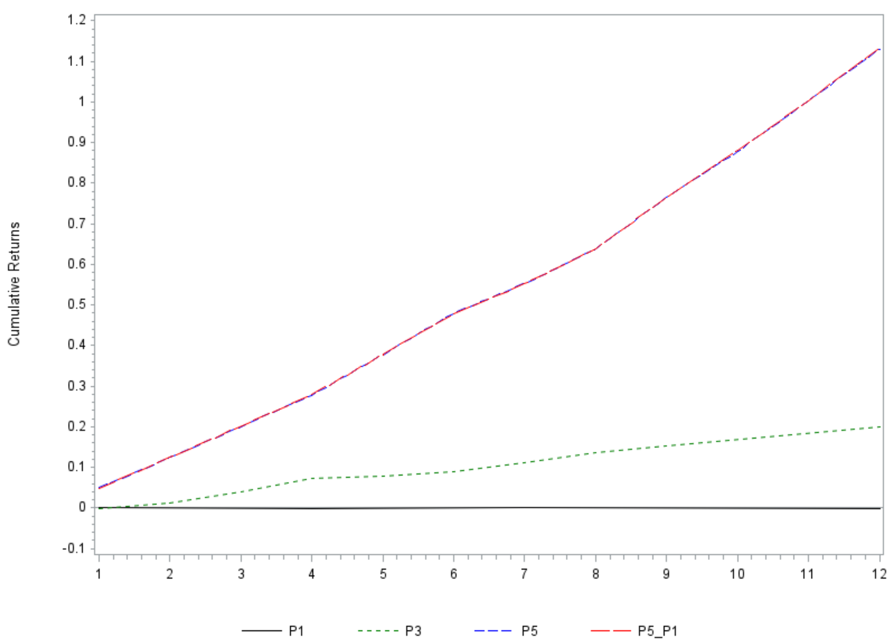
Figure 5: Long-Term Performance of Portfolios based on Failure Probability

This figure shows cumulative excess and crypto market-adjusted returns for portfolios of coins or tokens sorted on estimated failure probability (FP) after portfolio formation. The holding period is 12 weeks after portfolio formation. At the end of portfolio formation week, we assign all sample coins or tokens into five quintile portfolios based on their FP. P1, P3, and P5 includes coins or tokens with lowest, middle, and highest FP, respectively. P5_P1 buys P5 and shorts P1. The holding period is from February 2017 to December 2020 for coins and November 2017 to December 2020 for tokens.

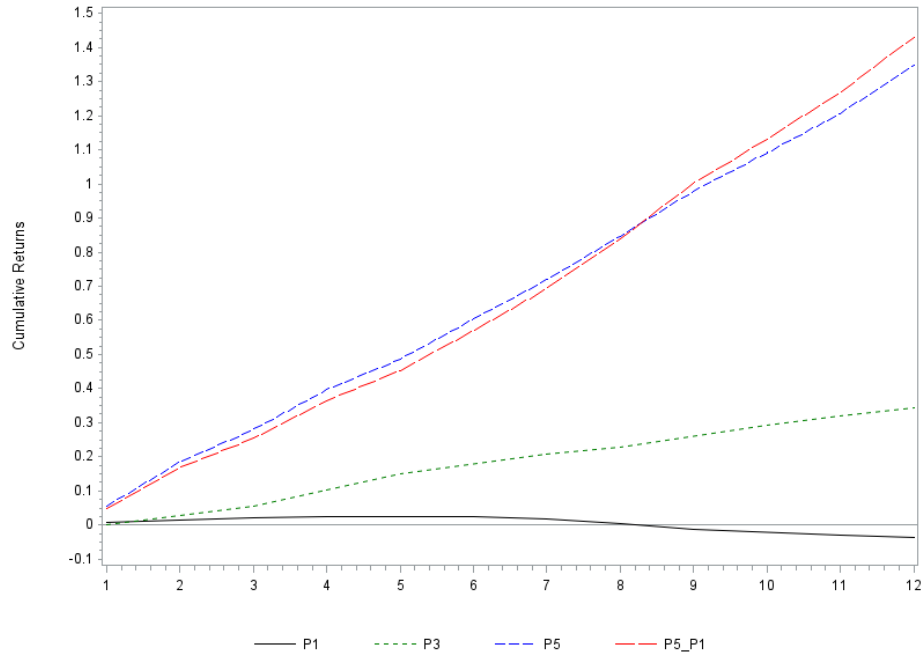
Panel A: Cumulative Excess Returns of FP Portfolios of Coins



Panel B: Cumulative CAPM Alphas of FP Portfolios of Coins



Panel C: Cumulative Excess Returns of FP Portfolios of Tokens



Panel D: Cumulative CAPM Alphas of FP Portfolios of Tokens

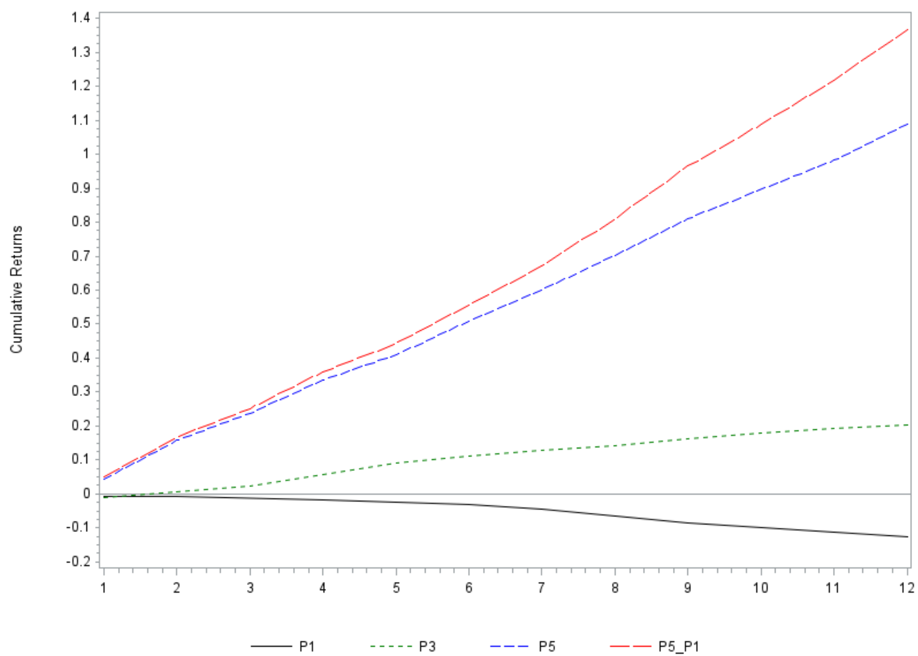
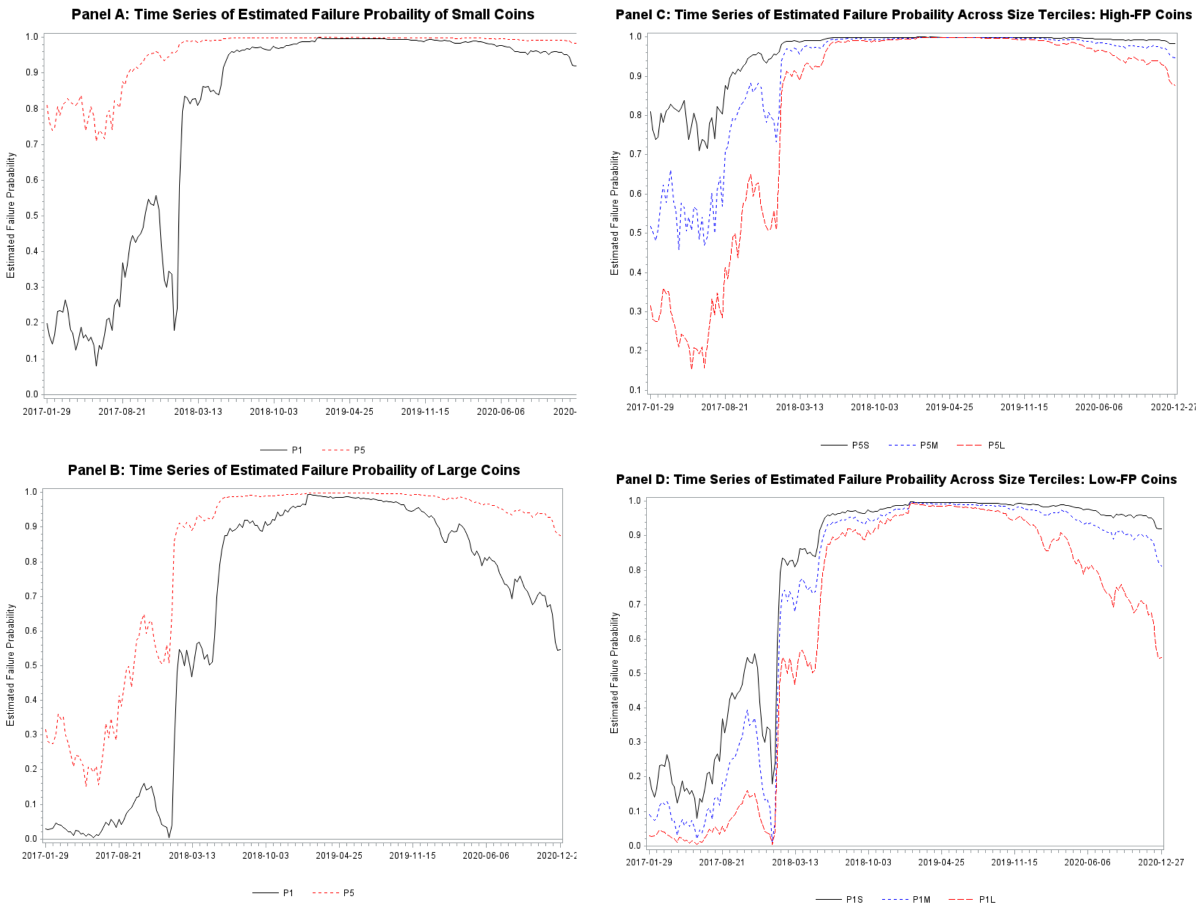
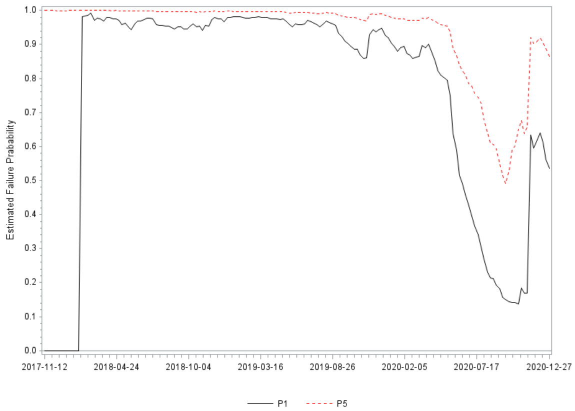


Figure 6: Time Series of Estimated Failure Probability across Size Terciles

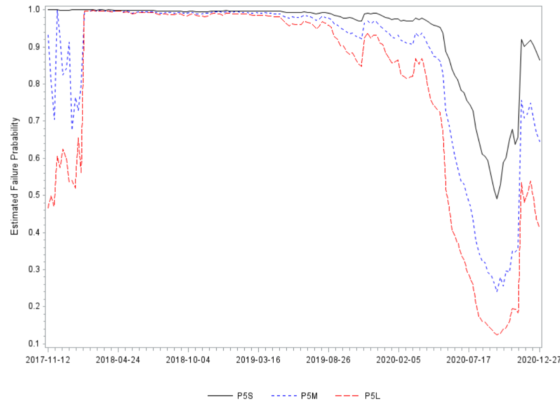
This figure shows the time series of failure probability (FP) estimated from dynamic logit models across size terciles. We first assign all sample coins or tokens into three size tercile portfolios based on their market capitalization at the end of formation week. Then within each size portfolio, we assign coins or tokens into five FP quintile portfolios based on their estimated FP. P1 (P5) refers to the portfolio of coins or tokens with the smallest (largest) FP. P5S (P1S), P5M (P1M), and P5L (P1L) refers to the portfolio including coins or tokens with the largest (smallest) estimated FP within small, middle, and large size tercile portfolio, respectively.



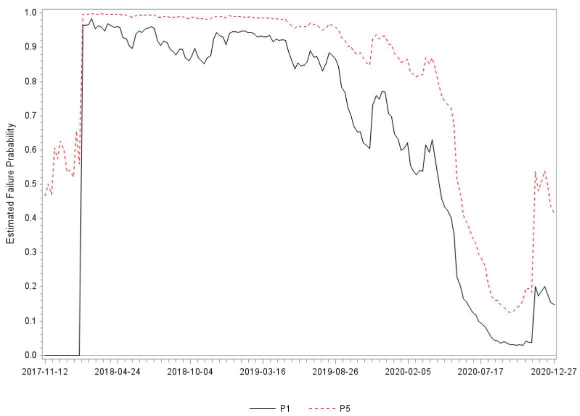
Panel E: Time Series of Estimated Failure Probaility of Small Tokens



Panel G: Time Series of Estimated Failure Probaility Across Size Terciles: High-FP Tokens



Panel F: Time Series of Estimated Failure Probaility of Large Tokens



Panel H: Time Series of Estimated Failure Probaility Across Size Terciles: Low-FP Tokens

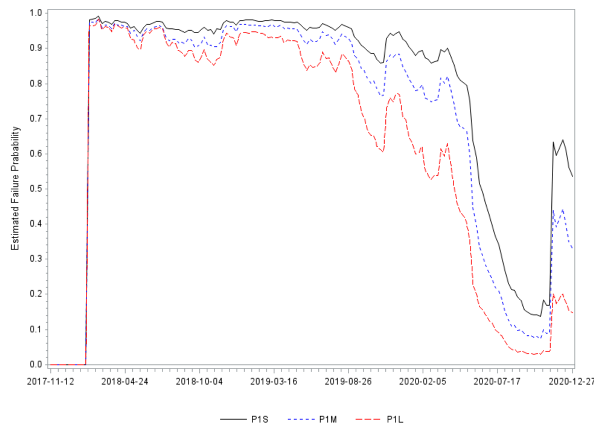
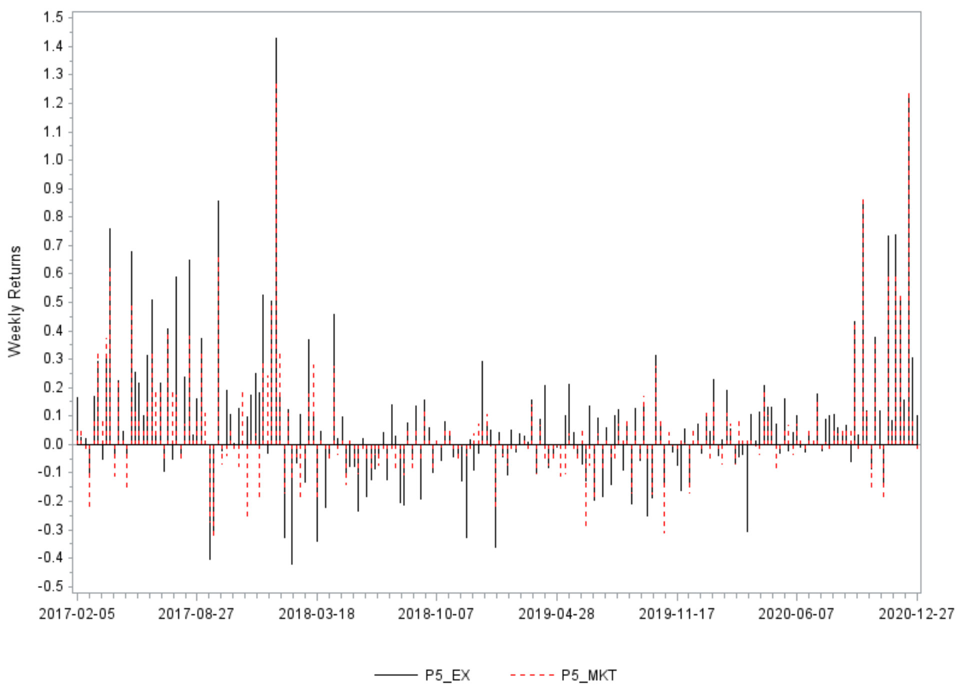


Figure 7: Time Series of Performance of High-FP Portfolios

This figure presents the time series of excess and crypto market-adjusted returns of portfolios with the highest estimated failure probability (FP). P5_EX refers to excess returns for high-FP cryptos; P5_MKT refers to crypto market-adjusted returns for high-FP cryptos. P5 refers to the quintile portfolio including top 20% of the highest FP cryptos defined in Figure 5.

Panel A: Weekly Returns of the High-FP Coin Portfolio



Panel B: Weekly Returns of the High-FP Token Portfolio

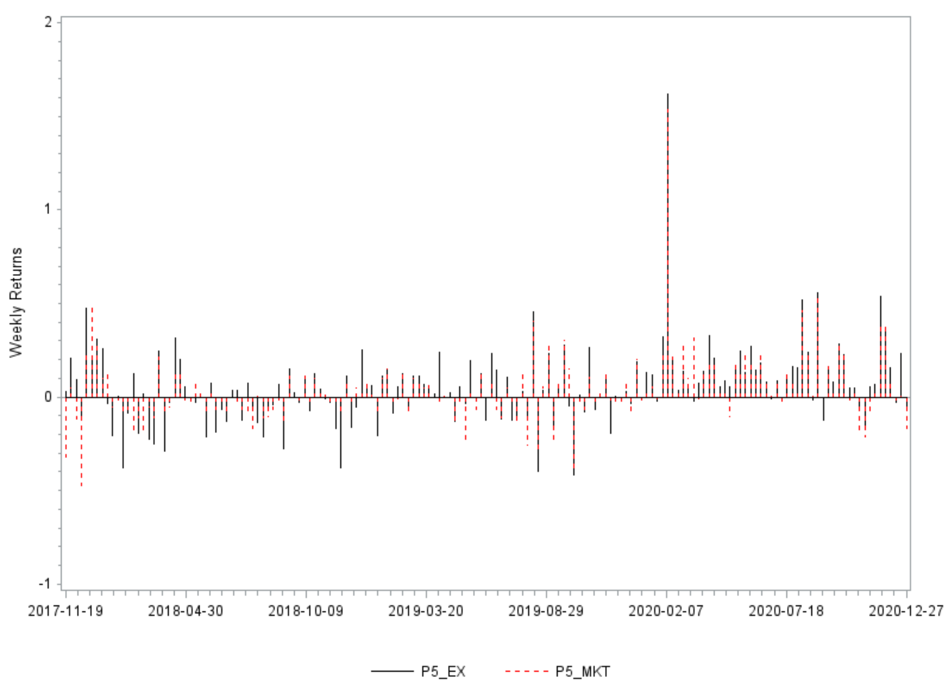


Table 1: The Number and Economic Losses of Cryptocurrency Failure

This table presents the numbers of new and total cryptocurrencies listed in CoinMarketCap, and the number of cryptocurrency failure events and their total economic losses (in millions of U.S. dollars) each year during the period of 2014 to 2020. A failure event occurs if the cryptocurrency has no trading data for at least 26 consecutive weeks during the sample period. The maximum loss for a cryptocurrency refers to its historical high of market capitalization (in millions of U.S. dollars).

Coin

Year	# of New	# of Failure	# of Total	Total Max Loss	Loss Per Coin
2014	617	202	696	1474	7.30
2015	318	243	832	52	0.22
2016	305	297	946	238	0.80
2017	389	171	1078	338	1.98
2018	349	345	1264	4949	14.34
2019	161	212	1079	2433	11.48
2020	307	100	1187	3314	33.14

Token

Year	# of New	# of Failure	# of Total	Total Max Loss	Loss Per Token
2014	52	7	52	5	0.74
2015	37	24	82	6	0.25
2016	47	29	105	66	2.27
2017	419	44	495	811	18.44
2018	835	151	1288	2962	19.62
2019	561	187	1700	4105	21.95
2020	1787	333	3314	12878	38.67

Table 2: Cryptocurrency Failure Probability

This table presents the probability that a coin or token will fail in a specified period. The rows indicate the amount of period for which the cryptocurrency is listed in CoinMarketCap. The columns indicate the time period that determines the probability of a cryptocurrency becoming delisted from CoinMarketCap. Panel A reports the ratio of the number of failed coins to the total coins in the specified period. Panel B reports the ratio of the number of failed tokens to the total tokens in the specified period. The sample period is from 2014 to 2020.

Panel A: Coins

Week	4	8	26	52	156	260
0	59/2446	136/2446	429/2446	633/2271	1116/1739	862/1075
4	77/2387	161/2387	419/2377	622/2193	1074/1678	821/1024
8	84/2310	143/2310	378/2278	591/2090	1003/1590	
26	54/2012	90/1990	218/1856	465/1727	752/1245	
52	54/1625	102/1601	257/1519	416/1459		
156	13/617	22/609	62/555			
Week	4	8	26	52	156	260
0	2.41%	5.56%	17.54%	27.87%	64.17%	80.19%
4	3.23%	6.74%	17.63%	28.36%	64.00%	80.18%
8	3.64%	6.19%	16.59%	28.28%	63.08%	
26	2.68%	4.52%	11.75%	26.93%	60.40%	
52	3.32%	6.37%	16.92%	28.51%		
156	2.11%	3.61%	11.17%			

Panel B: Tokens

Week	4	8	26	52	156	260
0	50/3711	97/3711	355/3711	332/2258	436/935	85/105
4	47/3661	100/3661	320/3412	320/2178	415/881	75/94
8	53/3614	104/3614	302/3184	317/2097	399/814	
26	84/3176	114/2996	194/2120	311/1819	267/488	
52	41/1899	53/1833	156/1664	246/1422		
156	19/485	29/444	34/255			
Week	4	8	26	52	156	260
0	1.35%	2.61%	9.57%	14.70%	46.63%	80.95%
4	1.28%	2.73%	9.38%	14.69%	47.11%	79.79%
8	1.47%	2.88%	9.48%	15.12%	49.02%	
26	2.64%	3.81%	9.15%	17.10%	54.71%	
52	2.16%	2.89%	9.38%	17.30%		
156	3.92%	6.53%	13.33%			

Table 3: Summary Statistics

This table presents summary statistics for active, distressed, and failed groups of cryptocurrencies. Panel A reports the median of the median values within each week of various variables for active, distressed, and failed groups of coins and tokens. These variables include the market capitalization (MCAP), the age (in weeks), the past 4-week return (RET_4W), the return volatility (RETVOL), the illiquidity measure (ZERO%), and the measure of downside risk (NCSKEW). Panel B reports the percentage of various dummy variables for active, distressed, and failed groups of coins and tokens. The sample period is from January 2014 to December 2020.

Panel A: Market variables

	Coin			Token		
	Active	Distress	Failure	Active	Distress	Failure
MCAP	263327	16712	11948	1055945	153799	159085
AGE	83	66	63	48	56	57
RET_4W	-0.05	-0.22	-0.21	-0.03	-0.24	-0.26
RETVOL	0.15	0.23	0.25	0.10	0.21	0.21
ZERO%	0.00	0.00	0.00	0.00	0.00	0.00
NCSKEW	-0.57	-0.68	-0.71	-0.44	-0.62	-0.63

Panel B: Crypto-specific variables

	Coin			Token		
	Active	Distress	Failure	Active	Distress	Failure
Twitter	78.97%	63.52%	61.70%	76.65%	83.34%	83.32%
Source code	46.96%	19.93%	16.64%	51.00%	44.00%	42.53%
Technical document	70.21%	39.71%	34.51%	42.00%	32.65%	32.19%
Initial offerings	7.16%	2.98%	2.75%	36.92%	40.41%	41.01%
PoW	20.71%	7.28%	5.45%			
Hybrid	16.32%	5.82%	5.31%			
Ethereum				48.82%	60.01%	59.23%
Financial	2.53%	1.56%	0.28%	12.62%	8.83%	6.79%
Infrastructure	9.15%	2.14%	1.00%	22.79%	11.17%	9.52%
Media	3.49%	0.43%	0.47%	9.98%	5.06%	5.83%
Payments	7.11%	1.73%	0.70%	13.29%	4.63%	3.51%
Services	5.36%	0.54%	0.59%	17.32%	6.76%	5.68%

Table 4: Dynamic Logit Regressions of Coin Failure Indicators on Predictor Variables

This table reports results from dynamic logit regressions of coin failure indicators on predictor variables. The sample period is from 2014 to 2020. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Distress				Failure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MCAP	-0.27***			-0.20***	-0.29***			-0.20***
	(-20.18)			(-13.13)	(-19.21)			(-12.24)
AGE	0.05			0.21***	0.11***			0.31***
	(1.28)			(4.94)	(2.67)			(6.64)
RET_4W	-0.37***			-0.38***	-0.46***			-0.49***
	(-5.67)			(-5.92)	(-6.33)			(-6.63)
RETVOL	0.97***			0.89***	1.00***			0.93***
	(7.95)			(7.42)	(7.73)			(7.25)
ZERO%	3.80***			3.06***	4.11***			3.26***
	(11.80)			(9.31)	(12.21)			(9.49)
NCSKEW	0.07			0.05	0.04			0.03
	(1.56)			(1.27)	(0.91)			(0.59)
D(Twitter)		-0.58***		-0.27***		-0.58***		-0.28***
		(-7.31)		(-3.42)		(-6.82)		(-3.19)
D(Technical doc)		-0.85***		-0.43***		-0.93***		-0.50***
		(-9.12)		(-4.46)		(-8.91)		(-4.73)
D(Source code)		-0.82***		-0.48***		-0.88***		-0.55***
		(-10.21)		(-5.77)		(-10.01)		(-6.00)
D(ICO)		-1.08***		-0.18		-1.06***		-0.15
		(-4.56)		(-0.73)		(-4.10)		(-0.57)
D(PoW)		-0.57***		-0.64***		-0.77***		-0.89***
		(-4.76)		(-5.24)		(-5.45)		(-6.17)
D(Hybrid)		-0.79***		-0.83***		-0.89***		-0.97***
		(-5.58)		(-5.76)		(-5.51)		(-5.92)
D(Financial)			0.96**	1.32***			0.09	0.37
			(2.26)	(2.78)			(0.12)	(0.48)
D(Infrastructure)			-2.02***	-0.88**			-2.28***	-1.05**
			(-5.53)	(-2.17)			(-4.82)	(-2.02)
D(Media)			-2.62***	-1.37			-2.32**	-0.90
			(-2.61)	(-1.35)			(-2.31)	(-0.88)
D(Payments)			-1.99***	-1.00**			-2.80***	-1.66**
			(-4.63)	(-2.23)			(-3.88)	(-2.26)
D(Services)			-1.64***	-0.93			-1.22**	-0.21
			(-2.78)	(-1.51)			(-2.06)	(-0.34)
Constant	-2.87***	-3.92***	-5.18***	-3.40***	-3.25***	-4.01***	-5.33***	-3.91***
	(-14.16)	(-70.78)	(-149.54)	(-15.91)	(-14.69)	(-68.56)	(-142.57)	(-16.64)
Observations	182,855	182,855	182,855	182,855	182,855	182,855	182,855	182,855
Events	856	856	856	856	728	728	728	728
Pseudo-R^2	0.096	0.071	0.023	0.119	0.103	0.080	0.024	0.133

Table 5: Dynamic Logit Regressions of Token Failure Indicators on Predictor Variables

This table reports results from dynamic logit regressions of token failure indicators on predictor variables. The sample period is from 2014 to 2020. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Distress				Failure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
MCAP	-0.28***			-0.27***	-0.30***			-0.28***
	(-13.87)			(-12.30)	(-14.24)			(-12.66)
AGE	0.24***			0.26***	0.29***			0.32***
	(-3.26)			(-3.55)	(-3.87)			(-4.13)
RET_4W	-0.05			-0.05	-0.05			-0.06
	(-0.49)			(-0.53)	(-0.54)			(-0.56)
RETVOL	1.63***			1.55***	1.63***			1.56***
	(5.00)			(4.76)	(4.86)			(4.64)
ZERO%	4.77***			4.71***	4.94***			4.90***
	(6.67)			(5.69)	(6.87)			(5.83)
NCSKEW	0.19***			0.18***	0.20***			0.19***
	(2.89)			(2.86)	(2.95)			(2.91)
D(Twitter)		0.09		0.38		0.04		0.34
		(0.39)		(1.53)		(0.18)		(1.33)
D(Technical doc)		-0.39***		-0.10		-0.43***		-0.13
		(-3.46)		(-0.84)		(-3.77)		(-1.10)
D(Source code)		-0.43***		-0.40***		-0.41***		-0.38***
		(-3.89)		(-3.55)		(-3.63)		(-3.27)
D(ICO)		-0.09		0.14		-0.05		0.20
		(-0.84)		(1.21)		(-0.39)		(1.63)
D(Ethereum)		-0.22*		-0.12		-0.21		-0.10
		(-1.66)		(-0.81)		(-1.51)		(-0.68)
D(Financial)			-0.30	0.05			-0.37*	0.01
			(-1.53)	(0.26)			(-1.72)	(0.05)
D(Infrastructure)			-0.59***	-0.16			-0.64***	-0.20
			(-3.34)	(-0.85)			(-3.45)	(-0.99)
D(Media)			-0.39**	-0.08			-0.30	0.01
			(-2.00)	(-0.40)			(-1.57)	(0.06)
D(Payments)			-1.02***	-0.69**			-1.18***	-0.83***
			(-3.71)	(-2.44)			(-3.82)	(-2.63)
D(Services)			-0.50***	-0.12			-0.54***	-0.15
			(-2.80)	(-0.64)			(-2.85)	(-0.74)
Constant	-3.64***	-5.52***	-5.80***	-3.89***	-3.77***	-5.56***	-5.85***	-4.00***
	(-8.89)	(-27.96)	(-94.58)	(-8.17)	(-8.86)	(-27.61)	(-92.80)	(-8.12)
Observations	163,240	163,240	163,240	163,240	163,240	163,240	163,240	163,240
Events	359	359	359	359	336	336	336	336
Pseudo-R^2	0.071	0.008	0.014	0.076	0.078	0.008	0.016	0.084

Table 6: Forecasting at Long Horizons

This table reports results from dynamic logit regressions of coin and token failure indicators on lagged predictor variables. The sample period is from 2014 to 2020. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Coin Failure			Token Failure		
Lag (Weeks)	1	4	8	1	4	8
MCAP	-0.20***	-0.17***	-0.15***	-0.28***	-0.24***	-0.22***
	(-12.24)	(-10.04)	(-8.94)	(-12.66)	(-10.27)	(-9.16)
AGE	0.31***	0.22***	0.30***	0.32***	0.27***	0.36***
	(6.64)	(4.85)	(5.70)	(4.13)	(3.59)	(4.24)
RET_4W	-0.49***	-0.25***	-0.38***	-0.06	0.06	0.07
	(-6.63)	(-3.87)	(-5.09)	(-0.56)	(0.72)	(0.79)
RETVOL	0.93***	0.71***	0.58***	1.56***	0.84**	1.40***
	(7.25)	(4.80)	(3.06)	(4.64)	(2.37)	(4.06)
ZERO%	3.26***	3.06***	2.38***	4.90***	5.05***	4.63***
	(9.49)	(8.44)	(5.58)	(5.83)	(5.88)	(4.99)
NCSKEW	0.03	-0.002	-0.04	0.19***	0.05	-0.03
	(0.59)	(-0.05)	(-0.90)	(2.91)	(0.80)	(-0.45)
D(Twitter)	-0.28***	-0.29***	-0.21**	0.34	0.53**	0.29
	(-3.19)	(-3.43)	(-2.26)	(1.33)	(2.04)	(1.15)
D(Technical doc)	-0.50***	-0.54***	-0.61***	-0.13	-0.15	-0.07
	(-4.73)	(-5.16)	(-5.88)	(-1.10)	(-1.23)	(-0.62)
D(Source code)	-0.55***	-0.58***	-0.57***	-0.38***	-0.30***	-0.31***
	(-6.00)	(-6.56)	(-6.31)	(-3.27)	(-2.59)	(-2.75)
D(ICO)	-0.15	-0.23	-0.27	0.20	0.06	0.09
	(-0.57)	(-0.89)	(-1.06)	(1.63)	(0.49)	(0.75)
D(PoW)	-0.89***	-0.91***	-0.94***			
	(-6.17)	(-6.40)	(-6.68)			
D(Hybrid)	-0.97***	-1.03***	-1.09***			
	(-5.92)	(-6.30)	(-6.74)			
D(Ethereum)				-0.10	-0.23	-0.25*
				(-0.68)	(-1.59)	(-1.73)
D(Financial)	0.37	0.04	-0.53	0.01	0.02	0.17
	(0.48)	(0.05)	(-0.50)	(0.05)	(0.09)	(0.87)
D(Infrastructure)	-1.05**	-0.95**	-1.15**	-0.20	-0.33*	-0.36*
	(-2.02)	(-2.05)	(-2.32)	(-0.99)	(-1.70)	(-1.86)
D(Media)	-0.90	-1.16	-1.10	0.01	-0.08	0.02
	(-0.88)	(-1.14)	(-1.08)	(0.06)	(-0.41)	(0.09)
D(Payments)	-1.66**	-1.01*	-1.32**	-0.83***	-0.75**	-1.06***
	(-2.26)	(-1.91)	(-2.22)	(-2.63)	(-2.57)	(-3.33)
D(Services)	-0.21	-0.49	-0.36	-0.15	-0.33	-0.44**
	(-0.34)	(-0.80)	(-0.59)	(-0.74)	(-1.62)	(-2.16)
Constant	-3.91***	-3.74***	-4.14***	-4.00***	-4.21***	-4.72***
	(-16.64)	(-15.89)	(-15.39)	(-8.12)	(-8.36)	(-8.92)
Observations	182,855	177,861	165,432	163,240	157,734	145,054
Events	728	735	677	336	343	349
Pseudo-R^2	0.133	0.113	0.101	0.084	0.063	0.067

Table 7: The Impact of Bitcoin Futures on Cryptocurrency Failure

This table reports results from dynamic logit regressions of coin or token failure indicators on predictor variables including the interactions between the initial Bitcoin futures offerings (IFO) and predictors. The sample period is from January 2016 to December 2019. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Coin				Token			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
IFO	0.42***				-0.22			
	(-3.82)				(-0.99)			
MCAP		-0.25***		-0.11***		-0.17***		-0.07
		(-6.90)		(-2.83)		(-3.29)		(-0.83)
AGE		0.25**		0.43***		0.05		-0.16
		(2.40)		(3.85)		(0.24)		(-0.67)
RET_4W		-0.56***		-0.57***		-1.07**		-1.03**
		(-3.09)		(-3.17)		(-2.05)		(-2.03)
RETVOL		0.21		0.48		2.40**		2.36**
		(0.45)		(1.03)		(2.52)		(2.34)
ZERO%		3.86***		2.62***		3.93***		3.33**
		(5.34)		(3.50)		(2.61)		(2.16)
NCSKEW		0.25*		0.21		0.57*		0.54*
		(1.86)		(1.57)		(1.77)		(1.65)
MCAP * IFO		-0.06		-0.20***		-0.13**		-0.22***
		(-1.53)		(-4.44)		(-2.42)		(-2.64)
AGE * IFO		0.26**		0.38***		0.36*		0.57**
		(2.50)		(3.52)		(1.89)		(2.33)
RET_4W * IFO		0.52**		0.52**		0.96*		0.90*
		(2.51)		(2.52)		(1.80)		(1.72)
RETVOL * IFO		1.07*		0.58		0.77		0.78
		(1.70)		(0.91)		(0.73)		(0.70)
ZERO% * IFO		3.02***		3.84***		3.01		3.57*
		(3.28)		(4.03)		(1.60)		(1.85)
NCSKEW * IFO		-0.07		-0.04		-0.37		-0.34
		(-0.43)		(-0.27)		(-1.10)		(-1.01)
D(Twitter)			-0.32*	-0.10			0.30	-0.02
			(-1.93)	(-0.53)			(0.81)	(-0.05)
D(Technical doc)			-1.82***	-1.53***			-16.16	-15.66
			(-3.50)	(-2.90)			(-0.04)	(-0.04)
D(Source code)			-2.13***	-1.94***			-0.91	-0.53
			(-6.73)	(-6.02)			(-1.18)	(-0.63)
D(ICO)			-10.46	-9.51			-15.91	-15.57
			(-0.06)	(-0.05)			(-0.03)	(-0.03)

D(PoW)			-1.59***	-1.59***				
			(-3.07)	(-3.05)				
D(Hybrid)			-1.94***	-1.81**				
			(-2.68)	(-2.48)				
D(Ethereum)							1.34**	1.53**
							(2.54)	(2.10)
D(Twitter) * IFO			-0.28	0.10			-0.12	0.38
			(-1.46)	(0.42)			(-0.34)	(0.66)
D(Technical doc) * IFO			1.12**	1.17**			15.62	15.31
			(2.09)	(2.15)			(0.04)	(0.04)
D(Source code) * IFO			1.73***	1.86***			0.51	0.29
			(5.10)	(5.29)			(0.65)	(0.34)
D(ICO) * IFO			9.47	9.69			15.69	15.76
			(0.05)	(0.05)			(0.03)	(0.04)
D(PoW) * IFO			1.30**	0.71				
			(2.40)	(1.28)				
D(Hybrid) * IFO			1.49**	0.82				
			(1.99)	(1.09)				
D(Ethereum) * IFO							-1.80***	-1.88**
							(-3.29)	(-2.51)
Constant	-5.94***	-4.31***	-4.19***	-5.21***	-5.85***	-4.23***	-5.19***	-4.18***
	(-62.47)	(-11.16)	(-41.85)	(-12.22)	(-27.40)	(-7.86)	(-22.29)	(-6.50)
Observations	116,955	116,955	116,955	116,955	95,586	95,586	95,586	95,586
Events	412	412	412	412	224	224	224	224
Pseudo-R^2	0.003	0.094	0.072	0.137	0.000	0.105	0.027	0.119

Table 8: The Impact of the COVID-19 Pandemic on Cryptocurrency Failure

This table reports results from dynamic logit regressions of coin or token failure indicators on predictor variables including the interactions between the outbreak of the COVID-19 Pandemic (COVID19) and predictors. The sample period is from July 2019 to June 2020. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Coin				Token			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
COVID19	-1.13***				-1.55***			
	(-4.61)				(-5.35)			
MCAP		-0.46***		-0.50***		-0.39***		-0.38***
		(-10.00)		(-9.60)		(-9.10)		(-8.46)
AGE		0.48***		0.98***		0.40**		0.43**
		(2.90)		(4.05)		(2.09)		(2.02)
RET_4W		-0.48		-0.44		-0.30		-0.30
		(-1.60)		(-1.47)		(-1.00)		(-1.00)
RETVOL		1.39*		1.34*		3.38***		3.29***
		(1.93)		(1.84)		(4.32)		(4.12)
ZERO%		-108.01		-209.07		-125.25		-179.66
		(-0.01)		(-0.00)		(-0.01)		(-0.00)
NCSKEW		-0.12		-0.11		0.35**		0.35**
		(-0.97)		(-0.94)		(2.42)		(2.42)
MCAP * COVID19		0.11		0.17		-0.04		-0.05
		(1.24)		(1.50)		(-0.37)		(-0.46)
AGE * COVID19		-0.50**		-1.08***		-0.09		-0.12
		(-2.56)		(-2.90)		(-0.30)		(-0.24)
RET_4W * COVID19		0.55		0.47		0.48		0.49
		(1.09)		(0.93)		(0.77)		(0.80)
RETVOL * COVID19		2.07		1.80		-6.01***		-6.20***
		(1.35)		(1.10)		(-2.81)		(-2.88)
ZERO% * COVID19		-0.44		-3.59		-6.99		-13.94
		(-0.00)		(-0.00)		(-0.00)		(-0.00)
NCSKEW * COVID19		0.30		0.28		-0.58*		-0.57**
		(1.10)		(1.06)		(-1.92)		(-1.97)
D(Twitter)			0.20	0.88**			14.58	14.47
			(0.48)	(2.14)			(0.04)	(0.03)
D(Technical doc)			-0.59***	-0.17			-0.25	-0.06
			(-2.60)	(-0.72)			(-1.09)	(-0.27)
D(Source code)			-0.14	0.18			-0.03	0.10
			(-0.47)	(0.59)			(-0.12)	(0.39)
D(ICO)			-1.56***	0.03			-0.47**	-0.12
			(-2.62)	(0.04)			(-2.05)	(-0.51)

D(PoW)			-0.24	-0.97**				
			(-0.67)	(-2.34)				
D(Hybrid)			0.14	-0.48				
			(0.45)	(-1.34)				
D(Ethereum)							-0.26	-0.23
							(-0.88)	(-0.73)
D(Twitter) * COVID19			-1.10*	-0.48			-0.22	1.95
			(-1.90)	(-0.48)			(-0.33)	(0.79)
D(Technical doc) * COVID19			-0.65	-0.36			-0.07	-0.17
			(-1.28)	(-0.66)			(-0.11)	(-0.29)
D(Source code) * COVID19			0.43	2.73			-1.62**	-1.80**
			(0.73)	(1.56)			(-2.34)	(-2.53)
D(ICO) * COVID19			-12.3	-13.76			-0.04	-0.22
			(-0.04)	(-0.03)			(-0.06)	(-0.36)
D(PoW) * COVID19			0.39	1.71**				
			(0.60)	(2.15)				
D(Hybrid) * COVID19			-0.66	0.35				
			(-0.82)	(0.39)				
D(Ethereum) * COVID19							-0.88	-0.91
							(-1.39)	(-1.39)
Constant	-5.54***	-3.22***	-5.19***	-5.84***	-6.03***	-3.46***	-19.92	-17.86
	(-50.69)	(-3.72)	(-12.73)	(-4.78)	(-53.51)	(-3.82)	(-0.05)	(-0.03)
Observations	38,043	38,043	38,043	38,043	60,259	60,259	60,259	60,259
Events	105	105	105	105	93	93	93	93
Pseudo-R^2	0.018	0.145	0.044	0.160	0.028	0.144	0.048	0.158

Table 9: Size Effect

This table reports results from dynamic logit regressions of coin and token failure indicators on predictor variables in different size subsamples. We first equally divide sample coins or tokens into two subsamples of large and small coins or tokens based on their market capitalizations at the end of formation period. The sample period is from 2014 to 2020. T-statistics are in parentheses. ***, **, * denote significant at 1%, 5%, or 10%, respectively.

	Coin		Token	
	Large	Small	Large	Small
MCAP	-0.05	-0.15***	0.03	-0.23***
	(-0.71)	(-6.94)	(0.30)	(-8.25)
AGE	0.71***	0.20***	0.61***	0.28***
	(4.89)	(3.98)	(2.60)	(3.37)
RET_4W	-0.16	-0.53***	-0.45	-0.03
	(-0.94)	(-6.51)	(-1.20)	(-0.30)
RETVOL	0.44	0.89***	4.11***	1.27***
	(0.83)	(6.59)	(4.08)	(3.62)
ZERO%	5.43***	3.10***	-225.71	5.32***
	(5.11)	(8.54)	(-0.02)	(6.34)
NCSKEW	0.00	0.03	0.58**	0.15**
	(-0.01)	(0.66)	(2.52)	(2.17)
D(Twitter)	-0.83***	-0.23**	-0.46	0.34
	(-3.06)	(-2.56)	(-0.75)	(1.22)
D(Technical doc)	-0.82***	-0.45***	0.03	-0.16
	(-2.77)	(-3.93)	(0.10)	(-1.26)
D(Source code)	-0.86***	-0.55***	-0.53	-0.34***
	(-3.01)	(-5.76)	(-1.60)	(-2.72)
D(ICO)	-0.90	0.14	0.34	0.14
	(-1.22)	(0.52)	(0.95)	(1.11)
D(PoW)	-1.52***	-0.76***		
	(-3.14)	(-4.98)		
D(Hybrid)	-1.34***	-0.85***		
	(-2.77)	(-4.87)		
D(Ethereum)			-0.59	-0.08
			(-1.57)	(-0.47)
D(Financial)	0.25	0.60	0.23	-0.17
	(0.20)	(0.58)	(0.58)	(-0.61)
D(Infrastructure)	-1.40	-0.03	-0.29	-0.02
	(-1.61)	(-0.04)	(-0.75)	(-0.10)
D(Media)	-13.8	0.98	-0.13	0.07
	(-0.03)	(0.95)	(-0.29)	(0.29)
D(Payments)	-0.67	-13.27	-0.90	-0.92**

	(-0.83)	(-0.07)	(-1.58)	(-2.34)
D(Services)	0.05	-0.24	-1.43**	0.13
	(0.06)	(-0.21)	(-2.30)	(0.63)
Constant	-7.40***	-3.91***	-9.65***	-4.27***
	(-8.44)	(-15.22)	(-4.56)	(-7.87)
Observations	92,943	89,912	82,608	80,632
Events	90	638	40	296
Pseudo-R^2	0.156	0.084	0.063	0.048

Table 10: Returns on Failure Probability-Sorted Portfolios

This table reports the average equal-weighted and value-weighted returns to portfolios of coins or token sorted on their estimated failure probability (FP). Excess returns refer to raw returns in excess of risk-free T-bill rates. CAPM alphas refer to cryptocurrency market-adjusted returns. 3-factor alphas refer to three-factor (market returns (CMKT), size (CSMB), and momentum (CMOM)) adjusted returns. At the end of each week, we divide all sample coins or tokens into five quintile portfolios based on each cryptocurrency's estimated failure probability. P1 (P5) includes coins or tokens with lowest (highest) FP. The portfolios are hold for 1 week. The holding period is from February 2017 to December 2020 for coins and November 2017 to December 2020 for tokens. We use the Bitcoin's returns to measure the crypto market returns. This table also reports the mean estimated failure probability (FP) in percentage, market capitalization (MCAP) in millions of U.S. dollars, mean age (AGE) in weeks, mean return standard deviation (STD) and downside risk (NCSKEW) for each portfolio. Newey and West (1987) adjusted t-statistics are in parentheses.

Panel A: Coin

FP Portfolios	P1	P2	P3	P4	P5	P5-P1
Equal-weighted Returns						
Excess return	2.75	4.10	5.79	7.66	13.88	11.13
	(1.71)	(2.61)	(3.42)	(4.24)	(6.43)	(9.02)
CAPM alpha	0.59	1.84	3.73	5.40	11.55	10.97
	(0.45)	(1.56)	(2.60)	(3.61)	(6.25)	(8.48)
3-factor alpha	-1.13	0.32	1.88	3.45	9.88	11.01
	(-1.81)	(0.59)	(2.78)	(5.71)	(8.13)	(8.66)
Equal-weighted Portfolio Three-factor Regression Coefficients						
CMKT	0.96	0.99	0.91	1.00	1.02	0.07
	(13.29)	(18.96)	(13.64)	(14.8)	(11.17)	(0.83)
CSMB	0.76	0.67	0.82	0.86	0.74	-0.02
	(12.39)	(9.86)	(12.39)	(7.29)	(4.32)	(-0.12)
CMOM	-0.03	-0.09	-0.11	-0.09	-0.09	-0.06
	(-0.31)	(-1.33)	(-1.91)	(-1.27)	(-1.01)	(-0.40)
Value-weighted Returns						
Excess return	2.29	3.56	1.99	3.27	7.56	5.28
	(2.26)	(1.78)	(1.54)	(1.86)	(3.47)	(3.05)
CAPM alpha	0.05	1.02	-0.14	1.13	4.97	4.92
	(0.13)	(0.74)	(-0.13)	(0.76)	(2.78)	(2.96)
3-factor alpha	-0.26	0.39	-1.06	-0.24	3.27	3.53
	(-0.93)	(0.28)	(-1.22)	(-0.20)	(2.21)	(2.39)
Value-weighted Portfolio Three-factor Regression Coefficients						
MKT	0.97	1.11	0.93	0.94	1.14	0.17
	(20.12)	(8.12)	(9.41)	(11.06)	(8.95)	(1.65)
SMB	0.14	0.26	0.39	0.60	0.76	0.62
	(4.43)	(1.75)	(3.49)	(5.47)	(5.51)	(4.49)
MOM	-0.01	-0.30	-0.23	-0.16	0.04	0.05
	(-0.18)	(-1.34)	(-2.06)	(-1.56)	(0.38)	(0.46)

Portfolio Characteristics						
FP	0.69	0.76	0.81	0.87	0.93	
MCAP	1484.40	87.37	13.74	1.83	0.41	
AGE	112	127	132	122	128	
STD	0.13	0.14	0.18	0.21	0.24	
NCSKEW	-0.72	-0.62	-0.64	-0.64	-0.60	

Panel B: Token

Portfolios	P1	P2	P3	P4	P5	P5-P1
Equal-weighted Returns						
Excess return	1.08	1.00	2.22	4.26	13.17	12.08
	(0.68)	(0.65)	(1.37)	(2.37)	(6.14)	(7.74)
CAPM alpha	-0.35	-0.41	0.93	2.90	11.83	12.18
	(-0.28)	(-0.34)	(0.65)	(1.87)	(6.13)	(8.06)
3-factor alpha	0.27	-0.20	0.64	2.78	10.96	10.69
	(0.18)	(-0.14)	(0.44)	(1.74)	(6.02)	(6.62)
Equal-weighted Portfolio Three-factor Regression Coefficients						
MKT	0.94	0.90	0.80	0.84	0.80	-0.14
	(10.42)	(11.39)	(7.83)	(10.31)	(6.39)	(-1.36)
SMB	-0.06	0.10	0.31	0.30	0.53	0.59
	(-0.34)	(0.62)	(1.46)	(1.00)	(1.70)	(3.47)
MOM	0.37	0.25	0.11	0.22	-0.06	-0.43
	(1.25)	(1.01)	(0.45)	(0.72)	(-0.36)	(-2.29)
Value-weighted Returns						
Excess return	0.64	0.23	0.15	2.63	5.49	4.86
	(0.43)	(0.17)	(0.11)	(1.73)	(2.74)	(2.73)
CAPM alpha	-0.63	-1.01	-1.07	1.59	4.29	4.92
	(-0.56)	(-0.99)	(-0.86)	(1.17)	(2.35)	(2.95)
3-factor alpha	0.60	-0.60	-0.90	1.27	3.95	3.35
	(0.38)	(-0.50)	(-0.67)	(0.88)	(2.05)	(1.83)
Value-weighted Portfolio Three-factor Regression Coefficients						
MKT	0.92	0.83	0.80	0.68	0.76	-0.15
	(10.81)	(11.55)	(8.22)	(7.76)	(5.14)	(-1.05)
SMB	-0.61	-0.11	0.02	0.05	0.17	0.78
	(-2.11)	(-0.74)	(0.17)	(0.65)	(1.16)	(2.94)
MOM	0.23	0.18	0.14	-0.17	-0.07	-0.30
	(0.78)	(1.13)	(0.83)	(-1.29)	(-0.52)	(-1.07)
Portfolio Characteristics						
FP	0.66	0.72	0.75	0.80	0.91	
ME	109.57	22.66	15.06	8.60	6.93	
AGE	55	62	63	64	67	
STD	0.10	0.10	0.12	0.17	0.26	
NCSKEW	-0.73	-0.53	-0.47	-0.49	-0.70	

Table 11: Performance of Failure Probability-Sorted Portfolios in Event Time

This table reports the value-weighted cryptocurrency market-adjusted alphas for portfolios of coins or tokens sorted on their estimated failure probability (FP) in each week following the formation week. We assign sample coins or tokens into five quintile portfolios based on each cryptocurrency's estimated failure probability. P1 (P5) includes coins or tokens with lowest (highest) FP. P5-P1 refers to the zero-investment portfolio that buys coins or tokens in P5 and sells coins or tokens in P1. Week t is the week after portfolio formation. The holding period is from February 2017 to December 2020 for coins and November 2017 to December 2020 for tokens. Newey and West (1987) adjusted t-statistics are in parentheses.

Panel A: Coin

Week *t*	P1	P2	P3	P4	P5	P5-P1
1	0.05	1.02	-0.14	1.13	4.97	4.92
	(0.13)	(0.74)	(-0.13)	(0.76)	(2.78)	(2.96)
2	-0.05	1.65	1.41	4.64	7.09	7.15
	(-0.15)	(1.22)	(1.24)	(1.46)	(4.07)	(4.41)
3	-0.05	1.30	2.68	3.22	6.85	6.90
	(-0.14)	(1.07)	(1.74)	(1.54)	(3.67)	(3.86)
4	-0.04	1.78	3.26	1.91	6.39	6.43
	(-0.11)	(1.61)	(1.19)	(1.28)	(3.73)	(4.02)
5	0.09	1.58	0.52	4.50	7.80	7.71
	(0.24)	(1.26)	(0.47)	(2.02)	(3.47)	(3.59)
6	0.08	1.55	0.91	6.90	7.40	7.32
	(0.20)	(1.30)	(0.72)	(1.93)	(3.29)	(3.39)
7	-0.02	1.93	1.96	3.83	4.95	4.97
	(-0.04)	(1.63)	(1.17)	(2.21)	(3.20)	(3.53)
8	-0.07	1.11	2.32	3.83	5.46	5.53
	(-0.20)	(0.85)	(1.45)	(1.89)	(3.42)	(3.83)
9	-0.01	1.36	1.51	3.09	7.78	7.79
	(-0.04)	(1.00)	(1.32)	(1.93)	(2.69)	(2.90)
10	-0.08	1.20	1.34	4.27	6.39	6.47
	(-0.20)	(0.84)	(1.09)	(2.17)	(3.60)	(3.94)
11	0.04	0.69	1.33	5.25	6.64	6.60
	(0.10)	(0.54)	(1.07)	(2.34)	(2.85)	(3.05)
12	-0.06	0.32	1.38	1.47	6.38	6.44
	(-0.16)	(0.30)	(1.05)	(1.11)	(3.54)	(3.99)

Panel B: Token

Week *t*	P1	P2	P3	P4	P5	P5-P1
1	-0.63	-1.01	-1.07	1.59	4.29	4.92
	(-0.56)	(-0.99)	(-0.86)	(1.17)	(2.35)	(2.95)
2	-0.23	-0.59	1.75	3.66	10.99	11.23
	(-0.20)	(-0.56)	(1.28)	(3.05)	(4.16)	(4.25)
3	-0.42	1.84	1.54	3.77	6.87	7.29
	(-0.37)	(1.27)	(1.22)	(2.69)	(4.19)	(4.70)
4	-0.57	0.11	3.40	3.22	7.96	8.53
	(-0.53)	(0.10)	(2.19)	(2.77)	(3.83)	(3.93)
5	-0.71	0.45	3.19	6.91	5.50	6.20
	(-0.65)	(0.35)	(2.21)	(2.87)	(3.31)	(3.88)
6	-0.74	0.17	1.96	3.82	7.10	7.84
	(-0.72)	(0.17)	(1.56)	(2.85)	(3.95)	(4.56)
7	-1.31	0.44	1.54	3.90	6.06	7.38
	(-1.70)	(0.39)	(1.55)	(3.07)	(3.27)	(3.97)
8	-1.93	0.84	0.99	4.05	6.41	8.34
	(-2.65)	(0.84)	(1.20)	(2.79)	(3.65)	(4.82)
9	-2.26	-0.30	1.84	2.76	6.31	8.57
	(-2.87)	(-0.46)	(1.58)	(2.59)	(3.94)	(5.34)
10	-1.47	-0.07	1.47	3.79	4.74	6.21
	(-1.72)	(-0.10)	(0.77)	(3.23)	(3.65)	(4.94)
11	-1.71	-0.04	1.29	3.15	4.52	6.23
	(-2.23)	(-0.05)	(1.52)	(2.69)	(3.20)	(4.52)
12	-1.42	0.21	0.69	2.22	5.33	6.75
	(-1.55)	(0.27)	(0.97)	(2.64)	(2.77)	(3.68)

Table 12: Failure Risk-Return Tradeoff for Different Characteristics

This table reports the value-weighted cryptocurrency market-adjusted alphas for portfolios of coins or tokens sorted on their estimated failure probability (FP) within each characteristic portfolio. We first assign all sample coins or tokens into three tercile portfolios based on each crypto characteristic. Then within each characteristic portfolio, we assign coins or tokens into five quintile portfolios based on their FP. P1 (P5) includes coins or tokens with lowest (highest) FP. The portfolios are hold for 1 week. The holding period is from February 2017 to December 2020 for coins and November 2017 to December 2020 for tokens. We use the Bitcoin's returns to measure the crypto market returns. Failure probability for each portfolio is in percentage. Newey and West (1987) adjusted t-statistics are in parentheses.

Panel A: Coin

	Portfolio Returns						Estimated Failure Probability				
	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5
Market Capitalization											
Small	4.86	6.55	6.41	9.64	11.88	7.02	0.79	0.85	0.89	0.92	0.96
	(3.49)	(3.97)	(3.83)	(5.27)	(5.17)	(3.82)					
Middle	2.36	1.74	3.40	3.12	5.30	2.93	0.73	0.78	0.81	0.85	0.91
	(1.46)	(1.19)	(1.91)	(2.07)	(3.88)	(2.63)					
Large	0.08	0.26	0.84	-0.47	-1.28	-1.36	0.65	0.70	0.73	0.77	0.82
	(0.22)	(0.22)	(0.62)	(-0.50)	(-1.20)	(-1.63)					
Age											
Young	0.61	0.56	-1.45	-0.05	3.73	3.11	0.68	0.76	0.82	0.88	0.94
	(0.45)	(0.52)	(-1.33)	(-0.03)	(2.77)	(1.78)					
Middle	0.59	1.72	-0.35	0.36	7.88	7.29	0.70	0.77	0.82	0.88	0.94
	(0.47)	(1.19)	(-0.29)	(0.26)	(2.17)	(1.94)					
Old	-0.12	0.93	0.26	4.23	3.28	3.40	0.69	0.76	0.79	0.84	0.91
	(-0.55)	(0.56)	(0.19)	(1.39)	(2.29)	(2.41)					
Momentum											
Low	-1.10	-0.86	3.03	10.66	15.16	16.25	0.72	0.79	0.84	0.89	0.95
	(-0.97)	(-0.85)	(2.94)	(2.58)	(6.92)	(7.02)					
Middle	0.29	1.49	-0.71	0.95	3.44	3.15	0.69	0.76	0.80	0.86	0.92
	(0.39)	(1.12)	(-0.56)	(0.63)	(1.77)	(1.75)					
High	0.48	-0.68	-1.89	-3.52	0.11	-0.38	0.68	0.74	0.79	0.84	0.91
	(0.59)	(-0.44)	(-1.68)	(-2.77)	(0.05)	(-0.18)					
Standard Deviation											
Low	0.26	0.90	1.24	-0.48	0.43	0.17	0.66	0.73	0.77	0.81	0.90
	(0.65)	(0.71)	(1.03)	(-0.58)	(0.34)	(0.17)					
Middle	-0.53	-0.26	0.40	-0.25	0.75	1.28	0.70	0.76	0.81	0.86	0.92
	(-0.43)	(-0.23)	(0.40)	(-0.18)	(0.51)	(0.90)					
High	-3.84	-1.07	3.32	7.78	10.79	14.62	0.73	0.80	0.85	0.90	0.95
	(-2.25)	(-0.76)	(1.43)	(3.53)	(4.64)	(6.05)					

Panel B: Token

	Portfolio Returns						Estimated Failure Probability				
	P1	P2	P3	P4	P5	P5-P1	P1	P2	P3	P4	P5
Market Capitalization											
Small	0.65	2.40	5.54	9.97	17.61	16.96	0.76	0.79	0.82	0.90	0.94
	(0.48)	(1.51)	(3.18)	(4.83)	(5.49)	(5.30)					
Middle	-0.03	-0.26	0.20	1.58	2.41	2.44	0.70	0.73	0.75	0.77	0.86
	(-0.02)	(-0.19)	(0.16)	(1.29)	(2.20)	(2.33)					
Large	-0.59	-1.42	1.89	-1.37	-1.39	-0.80	0.62	0.67	0.69	0.72	0.79
	(-0.46)	(-1.34)	(0.50)	(-1.47)	(-1.18)	(-0.76)					
Age											
Young	-1.12	2.28	-0.31	2.91	9.11	10.23	0.64	0.70	0.74	0.78	0.88
	(-0.91)	(0.54)	(-0.21)	(1.08)	(3.87)	(4.69)					
Middle	-1.18	-1.85	1.56	3.60	7.46	8.64	0.68	0.74	0.77	0.80	0.90
	(-1.10)	(-1.46)	(0.89)	(1.62)	(2.77)	(3.28)					
Old	-0.40	-0.88	-1.24	-0.08	0.93	1.33	0.67	0.72	0.76	0.85	0.90
	(-0.36)	(-0.81)	(-1.21)	(-0.06)	(0.69)	(1.21)					
Momentum											
Low	-1.44	1.64	4.55	7.32	20.20	21.65	0.68	0.74	0.77	0.83	0.93
	(-0.95)	(1.11)	(1.98)	(3.74)	(5.88)	(5.76)					
Middle	-1.47	-0.60	-0.69	-0.96	1.90	3.36	0.65	0.71	0.74	0.78	0.89
	(-1.51)	(-0.48)	(-0.69)	(-0.91)	(1.25)	(2.81)					
High	-0.18	-0.51	-4.68	-0.85	-5.62	-5.44	0.65	0.71	0.75	0.80	0.90
	(-0.15)	(-0.32)	(-2.93)	(-0.52)	(-4.09)	(-4.19)					
Standard Deviation											
Low	-0.57	-0.13	-0.38	-0.20	-0.10	0.47	0.64	0.69	0.72	0.75	0.87
	(-0.62)	(-0.11)	(-0.39)	(-0.27)	(-0.11)	(0.96)					
Middle	-0.79	-0.93	-0.21	1.05	1.34	2.13	0.66	0.72	0.75	0.78	0.88
	(-0.62)	(-0.75)	(-0.17)	(0.73)	(1.10)	(1.89)					
High	-1.15	0.49	0.99	3.93	13.84	14.99	0.71	0.77	0.80	0.87	0.94
	(-0.29)	(0.20)	(0.57)	(2.40)	(4.39)	(2.99)					

Table 13: Asset Allocation: CER and Sharpe ratio

This table reports the CER gains, Sharpe ratios, and portfolio weights of a mean-variance investor with risk-aversion A = 3, 9, or 15 by allocating her wealth weekly into crypto assets (coins or tokens), the stock market and the risk-free asset relative to allocating wealth into the stock market and the risk-free asset. CER gain is the annualized CER difference between the three-asset portfolio including crypto assets, the stock market, and the risk-free asset, and the two-asset benchmark portfolio including the stock market and the risk-free asset. The portfolio weights for two risky assets in the three-asset portfolio are estimated recursively using data available at the forecast formation week t. Sharpe ratio is the annualized average portfolio excess return divided by its standard deviation. Transaction cost for the benchmark (three-asset including coins or tokens) portfolio is fixed at 50 (500) bps per week. The out-of-sample evaluation period for coins and tokens is from January 2019 to December 2020.

Panel A: Portfolio including coins, the stock market, and the risk-free asset

Risk aversion	CER gains (%)	Sharpe ratio	Crypto weight	Stock weight
3	58.01	2.03	0.34	0.86
9	19.41	1.84	0.11	0.40
15	11.60	1.84	0.07	0.24

Panel B: Portfolio including tokens, the stock market, and the risk-free asset

Risk aversion	CER gains (%)	Sharpe ratio	Crypto weight	Stock weight
3	73.94	2.74	0.15	0.71
9	25.07	2.5	0.05	0.27
15	15.03	2.5	0.03	0.16

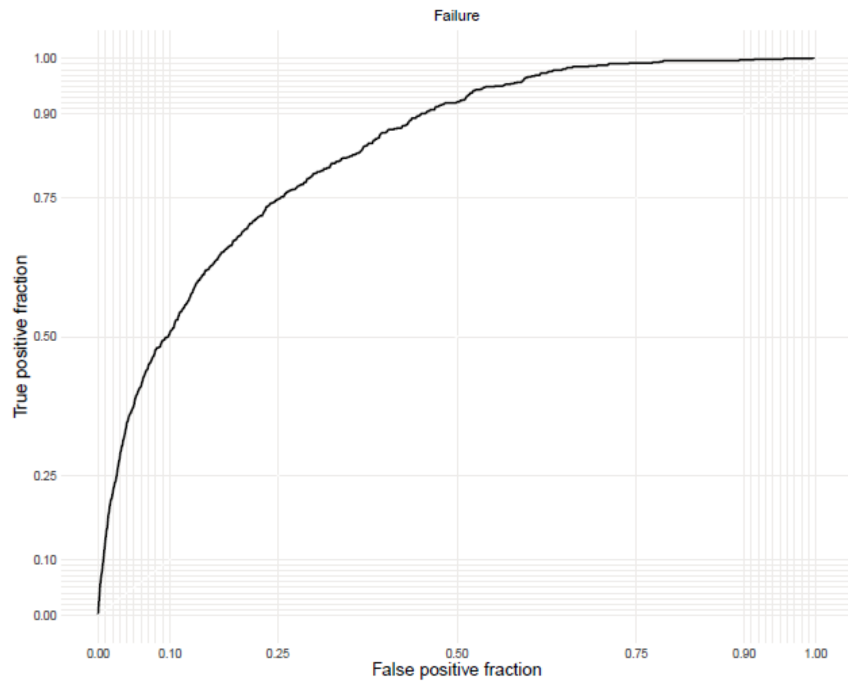
Table A1: Variable Definitions

Variables	Definition
MCAP	Market capitalization is measured by the natural logarithm of the total market value of a cryptocurrency (a cryptocurrency's price times circulating supply) at the end of week t-1.
AGE	Age is measured by the natural logarithm of the number of weeks since the cryptocurrency is newly listed in CoinMarketCap at the end of week t-1.
RET_4W	The cumulative return over the week t-4 to week t-1.
RETVOL	Total return volatility is estimated using the daily returns over the week t-4 to week t-1.
ZERO%	The illiquidity measure is the ratio of the number of days without trading data to the total number of days during week t-4 to t-1.
NCSKEW	Following Chen, Hong, and Stein (2001), the downside risk is calculated by taking the negative of the third moment of daily returns, and dividing it by the standard deviation of daily returns raised to the third power.
D(Twitter)	A dummy variable that takes a value of 1 if a cryptocurrency has a twitter and 0 otherwise. Information about twitter is obtained from ’twitter username’ in metadata.
D(Technical doc)	A dummy variable that takes a value of 1 if a cryptocurrency has a technical document (e.g., white paper or yellow paper) and 0 otherwise. Information about technical document is obtained from ’urls/technical doc’ in metadata.
D(Source code)	A dummy variable that takes a value of 1 if source code of project is available and 0 otherwise. The availability of source code is obtained from ’urls/source code’ in metadata.
D(ICO)	A dummy variable that takes a value of 1 if the cryptocurrency has the experience of offerings and 0 otherwise.
D(PoW)	A dummy variable that is equal to 1 when the consensus algorithm of blockchain beneath coin is Proof-of-Work (PoW) and 0 otherwise. PoW is obtained from ’tags’ in metadata.
D(Hybrid)	A dummy variable that is equal to 1 when the blockchain beneath coin allows for both PoW and PoS as consensus algorithm and 0 otherwise. Hybrid-pow-pos is obtained from ’tags’ in metadata.
D(Ethereum)	A dummy variable that is equal to 1 if Ethereum is listed as token platform and 0 otherwise. Information about platform is obtained from ’platform’ in metadata.
D(Finance)	A dummy variable that is equal to 1 when the property tag is categorized as finance industry based on methodology of Messari Classifications and 0 otherwise. Property tags of infrastructure applications are obtained from ’tags’ in metadata.
D(Infrastructure)	A dummy variable that is equal to 1 when the property tag is categorized as infrastructure industry based on methodology of Messari Classifications and 0 otherwise.
D(Media)	A dummy variable that is equal to 1 when the property tag is categorized as media industry based on methodology of Messari Classifications and 0 otherwise.
D(Payments)	A dummy variable that is equal to 1 when the property tag is categorized as payment industry based on methodology of Messari Classifications and 0 otherwise.
D(Services)	A dummy variable that is equal to 1 when the property tag is categorized as services industry based on methodology of Messari Classifications and 0 otherwise.

Figure A1: The Accuracy Ratio

This figure shows the dynamic logit model's accuracy in predicting crypto failures. The ROC curve is the graph that shows the true positive rate against the false positive rate at various classification thresholds. The AUC (Area Under Curve) represents the area under the ROC curve. AUC ranges from 0 to 1. The bigger the AUC, the more accurate the classification model.

Panel A: The ROC Curve for Coin Failure Events



Panel B: The ROC Curve for Token Failure Events

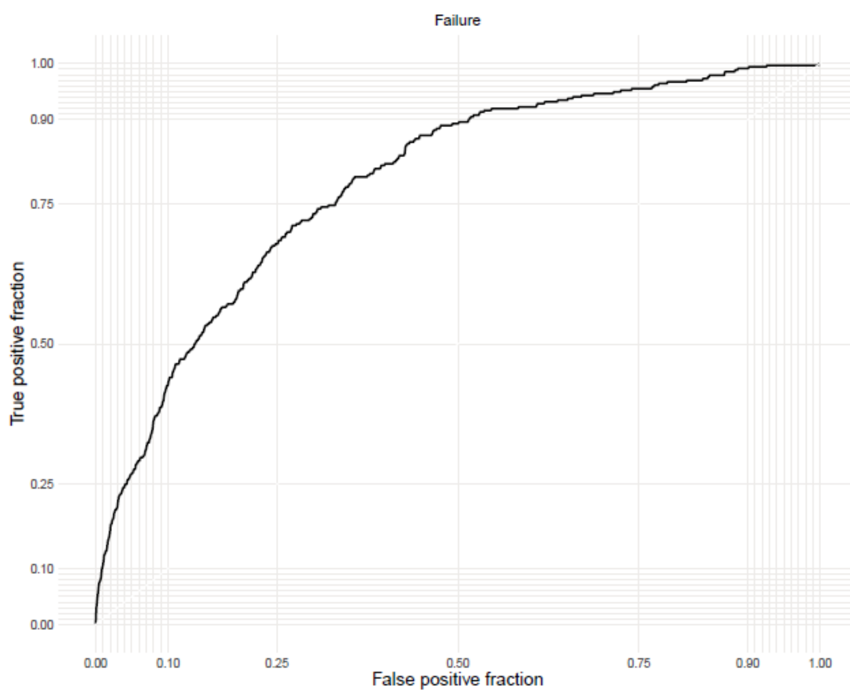
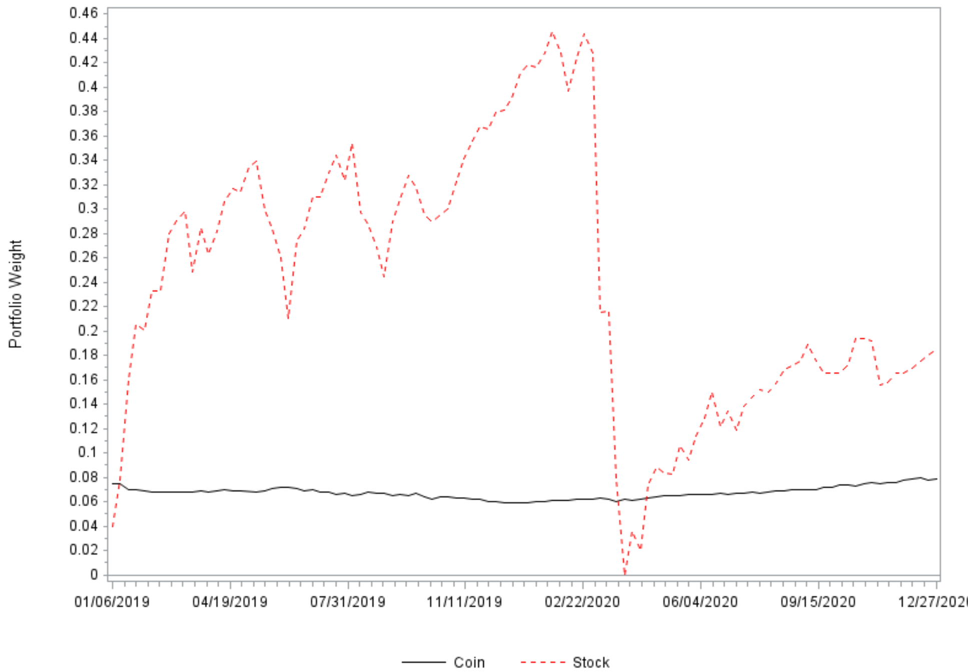


Figure A2: Portfolio Weights

This figure shows the optimal portfolio weights of coins, tokens, and the stock market for a mean-variance investor with a risk aversion of 15 as in Table 13.

Panel A: Time Series of Weights on Coins and the Stock Market



Panel B: Time Series of Weights on Tokens and the Stock Market