Survivorship and Delisting Bias in Cryptocurrency Markets*

Manuel Ammann[†], Tom Burdorf[‡], Luca J. Liebi[§], Sebastian Stöckl[¶]

November 28, 2022

ABSTRACT

This study quantifies performance measure distortions in a cryptocurrency sample truncated by survivorship and delisting bias. Previous research shows that the attrition rate in cryptocurrency markets is high. However, the survivorship and delisting bias in cryptocurrencies lacks empirical research. Using data for 3'904 cryptocurrencies during the 2014-2021 period, we estimate an annualized bias of 0.93% (62.19%) for value-weighted (equal-weighted) portfolios. After controlling for survivorship and delisting bias, we revisit the relationship between average returns, size, past performance, market β, liquidity, and downside risk. Our results confirm the size effect, but the premium is overestimated by 50% in a survival-conditioned sample. In contrast, we find no evidence of a positive relationship between average returns, one-week momentum, market β, and downside risk. Our results suggest that the survivorship and delisting bias are important biases that ought to be omitted.

Keywords: Cryptocurrency, Survivorship bias, Delisting bias, Size premium, Momentum, Downside risk, Market β

JEL Classifications: G12

---

*We are grateful for the helpful comments of Tobias Hemauer, Marlene Koch (discussant), Jonathan Chassot (discussant), Michał Bernardelli (discussant), and participants of the SFI Research Days (2022), the PiF Seminar at the University of St. Gallen (2022), the Finance Research Seminar at the University of St. Gallen (2022) and the World Finance Conference (2022).

[†]University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; Tel.: +41 71 224 70 80; E-mail address: manuel.ammann@unisg.ch.

[‡]University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; Tel.: +41 71 224 70 05; E-mail address: tom.burdorf2@unisg.ch.

[§]University of St. Gallen, Swiss Institute of Banking and Finance, Unterer Graben 21, CH-9000 St. Gallen, Switzerland; Tel.: +41 71 224 70 15; E-mail address: luca.liebi@unisg.ch.

[¶]University of Liechtenstein. Institute of Finance, Fürst-Franz-Josef-Strasse, LI-9490 Vaduz, E-mail address: sebastian.stoeckl@uni.li.

I. Introduction

The astonishing performance of a handful of cryptocurrencies attracts much interest by retail as well as institutional investors.[1] As an example, at the beginning of 2021, Shiba Inu (SHIB) was trading at \$0.000000000119. At the end of 2021, SHIB closed at \$0.00003341, which equals a return of 280'755%. Similar success stories include Terra (Luna), Axie Infinity (AXS), and Solana (SOL). However, such eye-popping returns of a few cryptocurrencies are mistakenly regarded as representative of the whole cryptocurrency market. Rialto (XRL), Bit20 (BTWTY), and Smoke (SMOKE) are three examples of unsuccessful cryptocurrencies that were delisted in 2019. The delisting of the cryptocurrencies mentioned above resulted in a total loss for investors. Importantly, delistings of cryptocurrencies are not an irregularity. The opposite is true. Overall, 39.5% of all cryptocurrencies delist with 76% incuring a total loss.

Figure 1. Number of Delisted Cryptocurrencies

This figure depicts the number of delisted (black) and currently listed cryptocurrencies (gold); 07-January-2014 to 28-December-2021, 417 weeks. During our sample period, 3'904 cryptocurrencies have been traded. 2'682 cryptocurrencies are listed at the end of the sample period. 1'222 cryptocurrencies have been delisted.

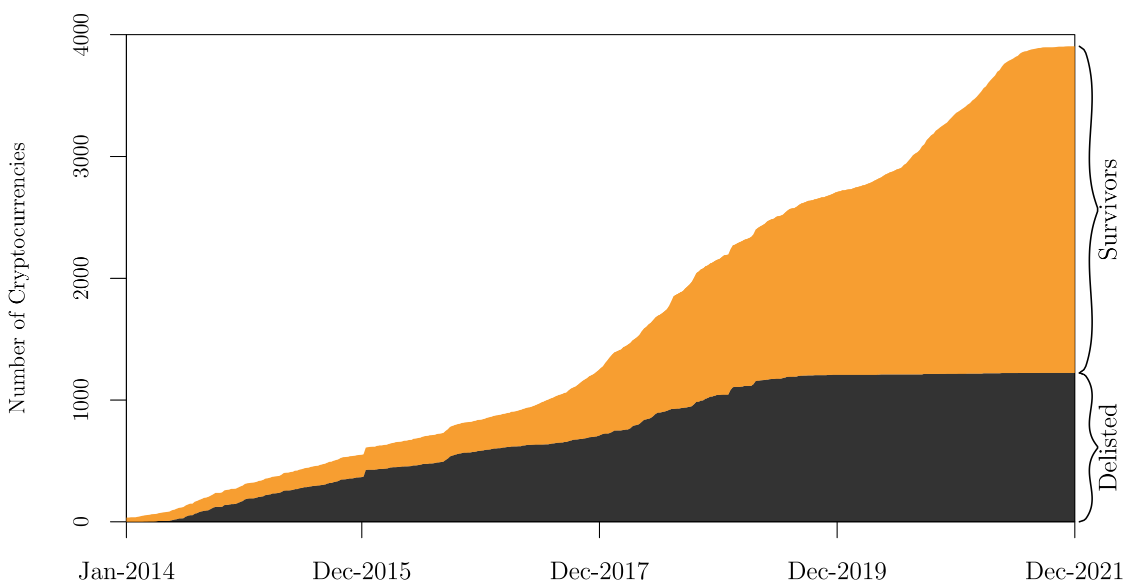


Figure 1 visualizes this frequently overlooked characteristic of the cryptocurrency market. From January 7^{th}, 2014 to December, 28^{th}, 2021 3'904 cryptocurrencies were traded.

[1]As of 2020, 45% (27%) of institutional investors in Europe (U.S.) already have exposure to cryptocurrencies, either directly or via future contracts. In the coming years, over 91% of all institutional investors surveyed by Fidelity (774 in total) are planning to invest in cryptocurrencies (Fidelity Investments (2020))

At the end of 2021, 2'682 cryptocurrencies are still listed, and 1'222 cryptocurrencies have been delisted. In other words, every third cryptocurrency dissolves. Performance measures are distorted when delisted cryptocurrencies are excluded from an index due to survivorship. This survivorship bias is widely known and well-documented in various performance studies on mutual funds, hedge funds, commodity trading advisors, and stocks.[2] To the best of our knowledge, a similar study is missing for cryptocurrencies. Obtaining a survivorship bias-free dataset is a common challenge for cryptocurrency researchers. Historical data for listed coins is readily available. However, obtaining data for delisted cryptocurrency is an issue and time-consuming. Moreover, because the ten largest cryptocurrencies account for nearly 80% of the total market capitalization, it may be legitimate to question the necessity of a survivorship-bias-free dataset for empirical studies on cryptocurrencies. Importantly, even when the sample is survivorship bias-free, the delisting bias is the second source of performance measure distortion. Cryptocurrencies do not represent ownership of a corporation or any other physical asset. Thus, the delisting of a cryptocurrency is in most cases associated with a total loss of the investment. Empirical studies on cryptocurrencies can be affected by one or both of the mentioned biases. This is of special concern since the empirical literature on cryptocurrencies is growing fast. Previous studies frequently exclude coins with a market capitalization below a prespecified threshold or focus on the largest cryptocurrencies by the end of the sample period. Both forms of survivor-only conditioning bias the results. The academic literature has not yet broached the issue of survivorship and delisting bias in cryptocurrency studies. More importantly, the characteristics of delisted cryptocurrencies remains an open question. For example, the attrition rate may vary among cryptocurrencies of different sizes. Previous studies have documented a significant size premium in cryptocurrency markets. Cryptocurrencies with a low market capitalization (small coins) outperform cryptocurrencies with a high market capitalization (big coins). Average weekly size premias range from 22.26% (Liu, Liang, and Cui, 2020) to 5.8% per week (Liu, Tsyvinski, and Wu, 2022). Liebi (2022) documents that small coins outperform large coins by 6.83% per week. However, when cryptocurrencies with smaller sizes exhibit a higher attrition rate and a lower performance, survival-conditioning leads to an inflated size premium. In the extreme case, the size effect in cryptocurrency markets is spurious and results from how researchers compile their sample. Thus, the question arises to what extent the survivorship and delisting bias affects the results of previous studies.

[2]See Malkiel (1995), Brown, Goetzmann, Ibbotson, and Ross (1992), Rohleder, Scholz, and Wilkens (2011), Rohleder et al. (2011) Armin and Hat (2003), Fung and Hsieh (1997), Davis (1996) and Elfakhani and Wei (2003).

This paper closes this gap and has three goals. First, we study the effect of survivorship and delisting bias on estimates of average performance. We can empirically shed light on this open question using a unique cryptocurrency dataset. We obtain a survivorship-bias-free dataset and manually collect delisting reason and delisting returns for all delisted cryptocurrencies. Our sample includes 3'904 cryptocurrencies from the 7^{th} of January 2014 to the 28^{th} of December 2021. We estimate the survivorship and delisting bias by comparing the weekly returns of a portfolio containing only surviving cryptocurrencies to a survivorship and delisting bias-free portfolio. We estimate a weekly value-weighted (equal-weighted) bias of 0.018% (0.934%). This equals an annualized bias of 0.93% (62.19%) for value-weighted (equal-weighted) portfolios. The first result suggests that the effect of the bias is highly weighting-scheme dependent.

Second, we determine the characteristics of delisted cryptocurrencies. Dissolved cryptocurrencies exhibit a lower market capitalization, lower trading volume, and a shorter listing age than surviving cryptocurrencies. Third, we revisit the relationship between average returns, size, momentum, and market β in cryptocurrency markets. Thereby, we test the conjecture that the size and momentum premium in cryptocurrency markets is spurious and a result of the researcher's sample compilation. We reexamine the size effect on a survivorship-bias-free dataset by univariately sorting portfolios at the end of each Tuesday. Sorted on size, we confirm a negative relation between size and average returns. The long-short portfolio, which is long in the lowest level of size and short in the highest level of size, yields an average value-weighted return of 1.89% per week. In a survivors-only conditioned sample, the size premium equals 2.84%. Thus, survivor-only conditioning inflates the size premium by 50.3%. Our results confirm the size effect in cryptocurrency markets. We are turning to performance persistence. We document momentum (reversal) within large (small) cryptocurrencies.

To the best of our knowledge, we are the first to quantify the survivorship and delisting bias in cryptocurrency markets. Overall, our results have a significant implication. The survivorship and delisting bias are important biases in cryptocurrency studies that ought to be omitted. Future research can significantly improve the robustness of their findings by using a survivorship and delisting bias-free dataset.

II. Related Literature

The survivorship bias is widely known by academics and well-documented in various performance studies on mutual funds, hedge funds, commodity trading advisors, and stocks. Exemplary, Malkiel (1995) reports an annual survivorship bias of 1.5% per year for mutual funds. The extensive literature on the survivorship bias in various asset classes stands in stark contrast to the current literature on cryptocurrencies. Lansky (2019) points towards the high attrition rate in the cryptocurrency markets. The delisting bias has also previously been investigated for stocks (Shumway and Warther, 1999). The growing literature on cryptocurrencies can be subdivided into five main strands: bubble dynamics, regulation, cyber criminality, diversification, and asset pricing studies. Below, we will focus on the empirical asset pricing studies in cryptocurrency markets, as this strand of academic literature is mostly related to our research question. Additionally, our results have the strongest implication on this strand of literature.

Considering cryptocurrencies' high attrition rate, the survivorship bias becomes a major concern for empirical studies. The bias amplifies when sampling techniques exclude coins with a minimum trading period of one year or a market capitalization above a prespecified threshold. Empirical studies on cryptocurrencies frequently rely on data from Coinmarketcap.com. However, less well known is that Coinmarketcap.com only provides historical data of currently listed cryptocurrencies, inducing the bias. To the best of our knowledge, Kaiser and Stöckl (2020) is the only empirical study on cryptocurrencies that uses a survivorship-bias-free dataset. The authors investigate 2'026 cryptocurrencies and document significant herding behavior in the crypto market. Empirical asset pricing studies in cryptocurrencies often do not consider delisted cryptocurrencies. Moreover, studies seldom provide an overview of all assets included in their analysis, making the replication of previous results difficult.[3] Moreover, paper-specific sampling methods inevitably lead to a dispersion of results. Most commonly, researchers in the cryptocurrency field try to replicate equity risk factors. The empirical asset pricing literature on cryptocurrencies is growing. See for example Zhang and Li (2020),Li, Zhang, Xiong, and Wang (2020), Liu et al. (2020),Liu and Tsyvinski (2021), and Liebi (2022). The two most frequently analyzed asset pricing regularities in stock markets are the size effect, and the momentum effect.

Panel A in Figure 2 depicts the size premium estimates of the literature. Each estimate equals the weekly return of a long position in the smallest and a short position in the largest

[3] An exception is Kaiser and Stöckl (2020).

cryptocurrencies. All studies find that small cryptocurrencies yield higher average returns than large cryptocurrencies. However, there is a considerable variation in size premium estimates ranging from 1.65% to 22.3%. The figure provides stylized evidence that paper-specific sampling techniques considerably affect size premium estimates. For example, Liu et al. (2020) investigate 78 cryptocurrencies from August 7^{th}, 2015 to December 31^{st}, 2018 and document a size premium of 22.26% per week, the highest premium in the literature known to us. The authors univariately sorted all cryptocurrencies at the end of each Tuesday (t) and held them until the consecutive Tuesday (t+1). Liebi (2022) uses the same portfolio formation day but a larger sample of 653 assets from July 4^{th}, 2017 to October 6^{th}, 2020 and reports a considerably lower size premium of 6.83% per week. Zhang and Li (2020),Li et al. (2020), and Liu et al. (2022) document size premiums of 14.4%, 6.16% and 5.80%, respectively.[4] Besides, it is noteworthy that all of the depicted studies are survivorship-biased, and the sorting methods vary from quintiles to deciles. Our survivorship-biased free size premium equals 1.89%.

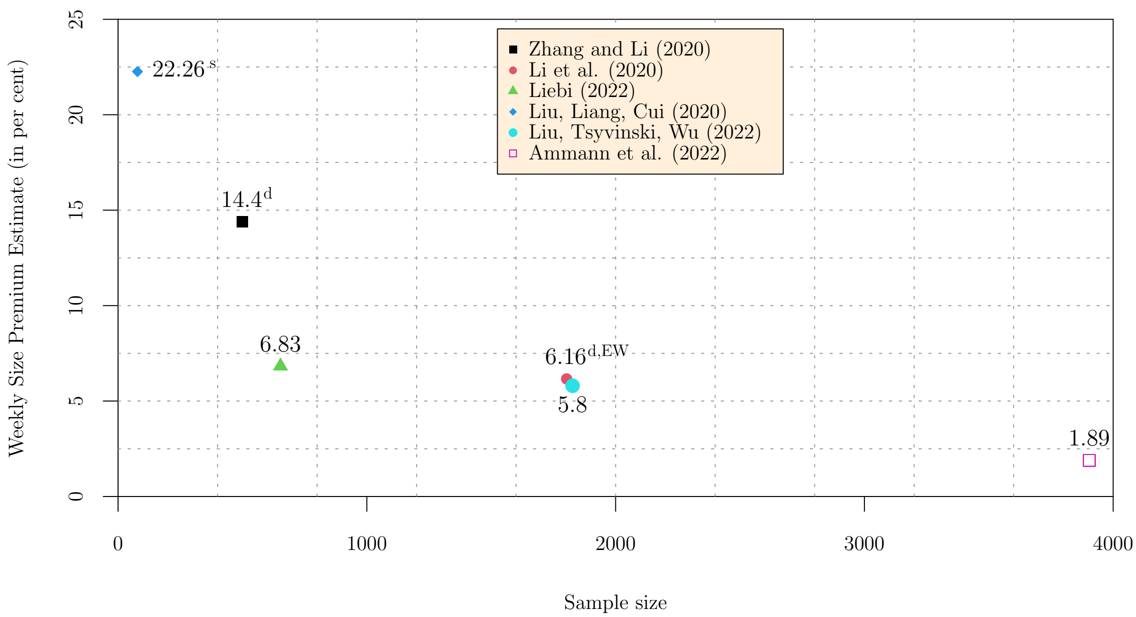
Panel B in Figure 2 depicts the average weekly momentum premium of a portfolio that is long in winners and short in loser cryptocurrencies. Contrary to the size premium, there exists no consensus if past winners outperform past losers. On the one hand, Zhang and Li (2020) and Liu et al. (2022) show that past winners outperform past losers in the consecutive week by 12% and 4.87%, respectively. Liu et al. (2022) finds a smaller one-week momentum effect of only 2.50%. Liebi (2022) documents that past winners outperform past losers by 0.98% (t=0.72) in the consecutive week. Our survivorship-biased free non-significant momentum premium is 0.13% (t=0.13).

[4] Zhang and Li (2020) sample includes 500 assets from January 2014 to September 2019. Li et al. (2020) sample comprises 1803 assets from January 2014 to May 2019.

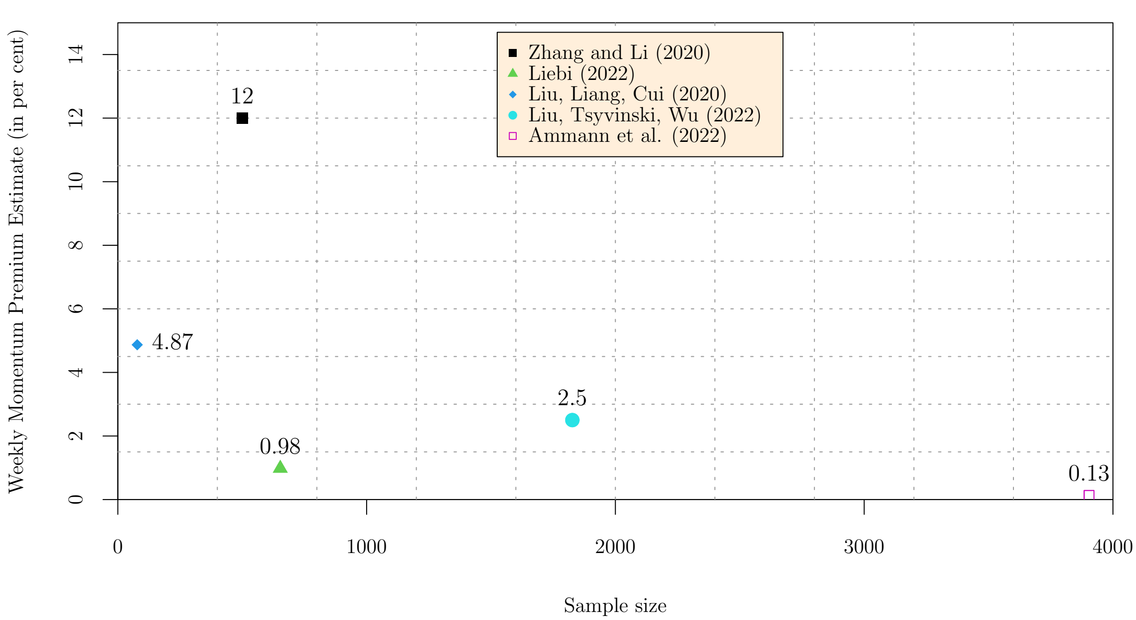
Figure 2. Size and Momentum Premium in Previous Studies

This figure depicts size premium (Panel A) and momentum premium (Panel B) estimates of previous studies. Panel A visualizes the average weekly returns of a portfolio which is long in the smallest level of size and short in the highest level of size. Panel B shows the average weekly returns of a portfolio that is long in winners and short in loser cryptocurrencies. The superscript s (d) indicates that portfolio sorts are based on sixtiles (deciles). The additional superscript EW indicates that portfolios are equal-weighted. If there is no superscript, the HML portfolio is based on value-weighted quintile sorts. From top to bottom, the legend includes Zhang and Li (2020), Li et al. (2020), Liebi (2022), Liu et al. (2020), Liu et al. (2022), and this paper.

(a) Size Premia in Previous Studies



(b) Momentum Premium in Previous Studies



III. Data and Variables

This section describes the data sources, outlines the variable construction, and provides the sample descriptive statistics.

A. *Data on Cryptocurrencies*

Coinmarketcap is one of the leading sources for cryptocurrency information. Every minute, Coinmarketcap queries the market data directly from the official APIs of 296 cryptocurrency exchanges and reports volume-weighted prices across all exchanges and cryptocurrency pairs. Coinmarketcap provides historical cryptocurrency data from April 29^{th}, 2013 onwards. The data includes open, high, low, closing prices, and market capitalization. Daily trading volume is reported since December 27^{th}, 2013. For academic research, Coinmarketcap has become a prime data source due to high data quality and historical price data.[5] Figure A1 in the Appendix provides the procedure of Coinmarketcap to decide whether to list a cryptocurrency. Most importantly, the cryptocurrency must be traded publicly and actively on at least one exchange tracked by Coinmarketcap. Moreover, the asset must be classified as a cryptocurrency, have a functional website, and have a blockchain explorer. Cryptocurrencies that do not meet all of these guidelines are classified as untracked.[6] If a cryptocurrency meets Coinmarketcaps' listing criteria and fulfills further qualitative project requirements, the cryptocurrency will be listed on the official website. Next, Coinmarketcap regularly tracks each cryptocurrency and evaluates if the asset must be delisted. Criteria that positively influence the delisting probability include low liquidity, business activity cessation, or if the project's listing resulted from false information.

What is less known about Coinmarketcap is that the official website only provides information on currently listed cryptocurrencies. This data presentation of Coinmarketcap leads to a systemic survivorship bias in empirical studies that use Coinmarketcap as the primary data source. One approach to obtain price data for delisted cryptocurrencies is through historical snapshots of the webpage.[7] Lansky (2019) uses this approach to obtain data on delisted cryptocurrencies. However, historical snapshots of the webpage are only available on a weekly basis. Overall, with the historical website approach, coins listed for several days

[5] A selection of papers that use Coinmarketcap as data source: Zhang and Li (2020), Li et al. (2020), Liu and Tsyvinski (2021), Liu et al. (2020), Gkillas and Katsiampa (2018), Liebi (2022), Hu, Parlour, and Rajan (2019), Griffin and Shams (2020),Grobys and Sapkota (2019), and Long, Zaremba, Demir, Szczygielski, and Vasenin (2020).

[6] A selection of untracked cryptocurrencies include BitBar, WorldCoin, and Mincoin. Although, these cryptocurrencies are untracked, in some cases historical data is still available.

[7] Historical snapshots are provided under a different URL: Coinmarketcap Historical Snapshots

remain excluded from the sample. Moreover, this approach is inefficient, time-consuming, and prone to errors.

We obtain historical cryptocurrency data through the official API. Thus, we retrieve price data for all coins that were listed between January 7^{st}, 2014 and December 28^{th}, 2021. The start date coincides with when Coinmarketcap reports trading volume. In our analysis, we focus on weekly returns. Returns are calculated from Tuesday's close price to Tuesday in the consecutive week. From our original sample, we apply several filters. First, we exclude all coins that are classified as *untracked* by Coinmarketcap. Second, we exclude all stablecoins that mimic real-world assets such as fiat currencies (e.g. Gemini Dollar, Binance USD, Tether, TrueUSD, and CryptoFranc), commodities (e.g. Tether Gold, and Paxos Gold), or other securities (e.g. Mirrored Google, Mirrored Netflix). Third, derivative coins (e.g. 3X Short ETH) and trading sets (e.g. ETH/BTC RSI Ratio Trading Set) are excluded from the sample. Forth, all cryptocurrencies with no reported trading volume are omitted. Importantly, we exclude Innovative Bioresearch Classic (INNBCL) and Starname (IOV) due to highly unplausible data points. The market cap of INNBCL jumps to $21'944 trillion on June 24^{th}, 2020. One week later, the market cap equals zero, which also holds true for IOV.

If historical data contains reporting gaps, we delete the following-week return as it represents a cumulative return over the reporting gap. After applying these filters, our sample includes 3'904 coins from January 7^{st}, 2014 and December 28^{th}, 2021. During the sample period, 1'222 (i.e. 39.5%) coins were delisted, and 2'682 survived until 2021.

B. Delisting Returns for Cryptocurrencies

Delisted cryptocurrencies are often not only delisted from Coinmarketcap (CMC), but also from all tracked cryptocurrency exchanges. We manually collect delisting returns for all 1'222 delisted cryptocurrencies. For 932, that is 76.3%, of all delisted coins, the delisting return equals -100%. This leads to an average delisting return of -77.8%. Comparing the delisting return of cryptocurrencies to stocks, cryptocurrencies exhibit a much lower delisting return. As a comparison, Shumway and Warther (1999) estimate a performance-related delisting return of -55% for Nasdaq listed stocks. Thus, the delisting return for cryptocurrencies is much higher compared to stocks.

Delisting from CMC is a complex process, as CMC is not an exchange itself but rather an aggregator and provider of market data gathered from other exchanges via their internet

Application Programming Interface (API). In summary, a coin is delisted from CMC, when a variety of reasons are fulfilled, which include low liquidity or fraud, cessation of development, regulatory action or other reasons not further detailed by CMC. Ìn practice, delisting often happened at the same time as when a coin was delisted from one of the major exchanges. We use a group-approach to mine several online resources such as forums and dedicated websites (e.g. bitcointalk.org) to classify delisting reasons as well as delisting returns for all cryptocurrencies that once had the status "tracked" on CMC and subsequently have been delisted (untracked or completely removed) from the platform. All individuals were either volunteers from the University of Liechtenstein or hired from an online freelancing platform. All volunteers had previous knowledge about webscraping/data search and have been trained before they started. Each delisted cryptocurrency is classified by at least 3 persons.
Fig. 3 depicts the methodology to obtain delisting returns for all cryptocurrency. We identify six delisting reasons: commitment, scam, technical issue, CMC regulatory, swaps, or not available. A detailed explanation of all delisting reasons can be found in Table A1 in the Appendix.

Table I provides summary statistics of delisting reasons and delisting returns for all cryptocurrencies in our sample. The majority of cryptocurrencies ($> 64\%$) were delisted because they were abandoned by the developers. In these cases the average delisting return equals -97%. The second most important reason for delisting is due to CMC regulatory without any further reason given (23%). The average delisting return equals -29%.

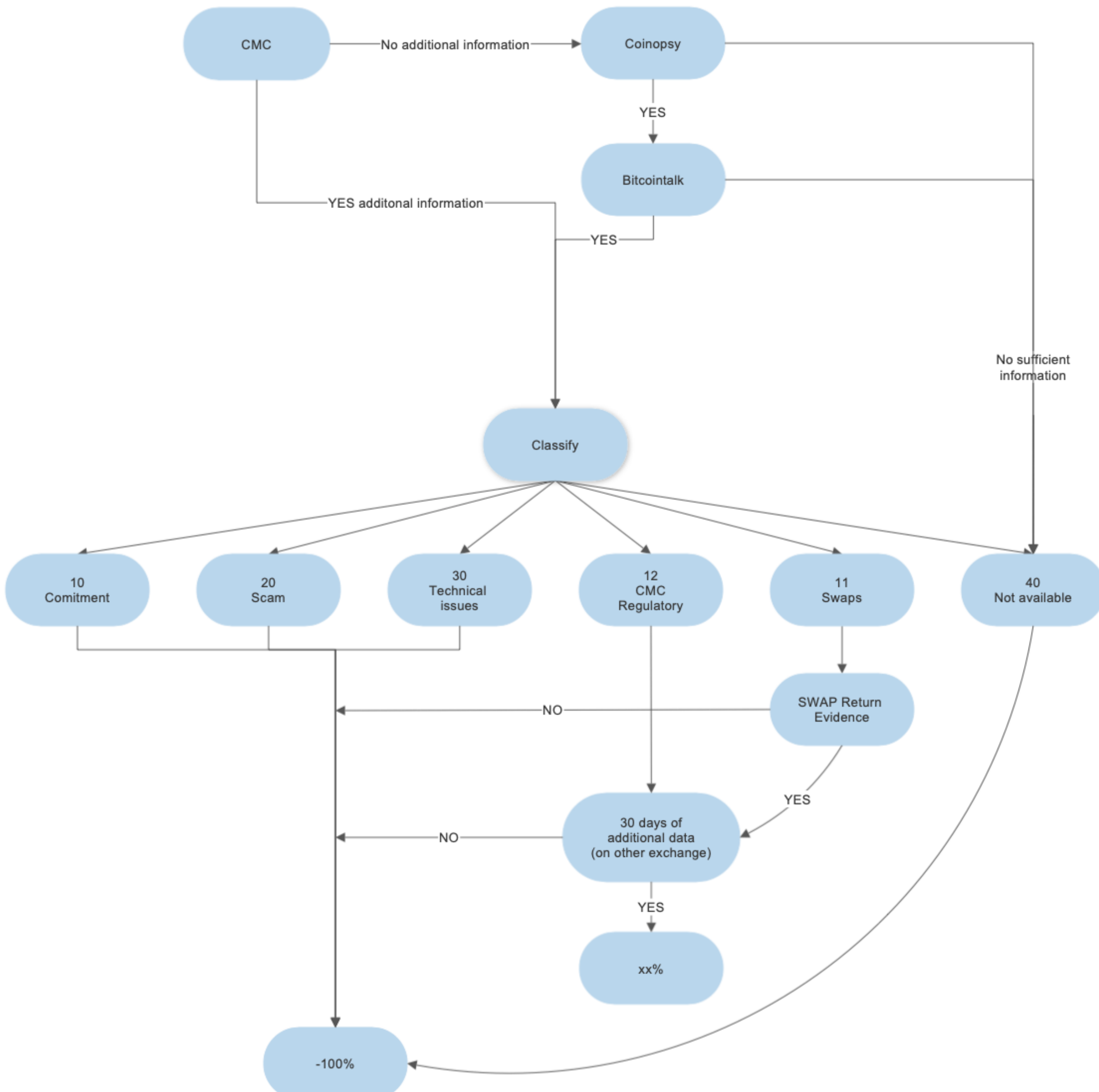
Table I Delisting Returns

This table summarizes the delisting returns. The first column indicates the delisting code and delisting reason, the second indicates the number of cryptocurrencies in that group, the third (forth) column reports the mean (median) delisting return in the group.

Delisting Reason	Number of Cryptocurrencies	Mean	Median
10 Commitment	787	-0.97	-1
12 CMC Regulatory	280	-0.29	0
11 Swap	73	-0.26	0
40 Not available	49	-1	-1
20 Scam	25	-0.92	-1
30 Technical Issue	8	-1	-1
All	1222	-0.77	-1

Figure 3. Delisting Return Methodology

This figure depicts our methodology to collect delisting returns. As a starting point, we use information provided by Coinmarketcap (CMC). If Coinmarketcap provides a delisting reason, we use this information to classify the delising into six categories. If no information is available, we use Coinopsy and Bitcointalk to obtain more information. Overall, we define six delisting reasons. The delisting return is then computed based on the delisting classification.



C. Variable Construction & Descriptive Statistics

Our primary analysis focuses on weekly cryptocurrency returns. We construct weekly returns and characteristics from daily data for each cryptocurrency on a rolling-window scheme. Table II defines the dependent and all explanatory variables. We calculate weekly returns from Tuesday's close price to Tuesday in the consecutive week, following Liu et al. (2020) and Liebi (2022). Overall, we construct five cryptocurrency-specific measures to forecast 1-week returns. The first characteristic equals the market β, which is the slope coefficient when regressing excess returns of a cryptocurrency on the excess market return. The market β is estimated on a rolling-window scheme with a window length of 365 days. The market return equals the value-weighted return of all coins in our sample. The one-month U.S. Treasury bill rate defines the risk-free rate. Size is the natural logarithm of the market capitalization at time t. Momentum equals the cumulative return in cryptocurrency returns from t-7 days to t. Trading volume equals the weekly trading volume in USD, and age equals the number of weeks the cryptocurrency has been traded since the first trading day.

Table II Variable Description

This table provides an overview of the dependent variable and all explanatory variables. The table includes notation, category, and the corresponding definition.

Variable	Notation	Category	Definition
Dependent Variable			
Excess weekly return	r_i	-	Weekly returns are measured from Tuesday's closing price at time t until Tuesday in the following week at time t+1. The excess return is defined as the weekly return minus the weekly risk-free rate (one-month U.S. Treasury bill rate).
Explanatory variables			
Market beta	β_{MKT}	Volatility	Slope coefficient in the excess returns of cryptocurrencies on the excess market return from t-365 days until t. The market return equals the value-weighted return of the 3'904 cryptocurrencies. The risk-free rate is defined by the one-month U.S. Treasury bill rate.
Size	size	Size	Natural logarithm of the market capitalisation at the portfolio formation day (=t).
Momentum	mom	Momentum	Cumulative return over the past 7 days from t-7 until portfolio formation day t (Liu and Tsyvinski, 2021), (Liebi, 2022).
Trading volume	vol	Liquidity	Weekly trading volume in USD measured over the past 7 days from t-7 until portfolio formation day t.
Age	age	Financial Visibility	Number of weeks the cryptocurrency has been traded measured from the first trading day to the portfolio formation day t.

We start our analysis with descriptive statistics of all variables for three subgroups. Table III reports means for three different samples. Each column represents a specific sample. The first column includes all 3'904 cryptocurrencies. The second column only includes cryptocurrencies that have survived until the end of the sample period. The last sample represents only coins that have been delisted during the sample period. Comparing surviving and delisted cryptocurrencies, we document a significant return difference. The average weekly return of the surviving (delisted) sample equals 2.24% (0.56%). Moreover, delisted cryptocurrencies tend to have a significantly lower market cap and trading volume, momentum, and a shorter listing age. Surviving coins have a 393 times bigger weekly trading volume and an almost 145 times greater weekly market cap than delisted coins. Age equals the number of weeks passed from the first listing until the delisting or end of the sample period. Delisted coins are, on average, listed for 75 weeks. In short, delisted cryptocurrencies are characterized by low performance, low market capitalization, low trading volume, and tend to be young in terms of trading history.

Table III Summary Statistics by Group

Averages of the overall sample, the survivorsip-biased sample, and the delisted sample, 07-January-2014 to 28-December-2021, 417 weeks, 3'904 cryptocurrencies. Variables include weekly returns (in per cent), size (natural logarithm of market cap), market beta (estimated from t-365 days until t on a rolling-window), momentum (cumulative return from t-7 days until t), weekly trading volume (in million USD), and market capitalization (in million USD), age (number of trading weeks), and number of coins. Weekly returns are trimmed at the 99% level.

	All Cryptocurrencies	Surviving Cryptocurrencies	Delisted Cryptocurrencies
Weekly Return (in %)	1.96	2.24	0.56
Size	13.89	14.50	10.87
Market Beta	0.87	0.86	1.02
Momentum (in %)	2.19	2.26	1.85
Volume (in Million USD)	241.46	286.54	0.73
Market Cap (in Million USD)	334.54	401.47	2.77
Age (in weeks)	120.61	141.22	75.37
Number of Coins	3904	2682	1222

We calculate the attrition rate in cryptocurrency markets each year to get a clear picture of the number of delistings. Table A2 tabulates the number of cryptocurrencies listed at the start and end of each year. The number of cryptocurrencies at the end of the year equals the number of coins listed at the beginning of the year, plus the newly listed assets, minus all dissolutions. Note that year-end equals the last Tuesday of the year. The year start equals the first Tuesday of the year. Thus, the number of assets at the start does not necessarily have to equal the number at the end of the previous year. The sixth column reports the number of cryptocurrencies listed and delisted in the same year. The attrition rate in year t equals the ratio of the number of delisted cryptocurrencies in year t minus the number of coins that were listed/ delisted in the same year t, divided by the number of coins at the beginning of the year. For example, at the beginning (end) of 2019, 1'290

(1'516) cryptocurrencies exist. 166 coins dissolved during 2019, of which three were listed and delisted in the same year. Thus, the attrition rate for 2019 equals $\frac{166-3}{1'290} = 12.64\%$. For 2014 the attrition rate equals zero because the total number of dissolutions equals the number of listed and delisted coins in 2014. Looking at the attrition rate column, we document that the attrition rate was especially high between 2015 and 2018. For 2018, the attrition rate in cryptocurrency markets equals 32.44%. Interestingly, the attrition rate has become extremely low after 2019. In the year 2020 (2021), the rate is 0.46% (0.23%). Altogether, the average attrition rate over the analyzed eight years equals 14.65%. This number is considerably lower compared to the attrition rate over the whole sample period of 31%. The discrepancy arises since Table A2 only incorporates coins that are listed and delisted in the same year. We have already pointed out that delisted cryptocurrencies tend to have a short life cycle. 332 coins are listed and delisted within the same year. Table A4 in the Appendix provides a more granular analysis of the number of weeks coins are listed. We document that 51% of all dissolved coins delist within the first 60 weeks of trading.

Table IV presents the dissolution in cryptocurrency markets differently. Similarly to Fung and Hsieh (1997), we calculate dissolution rates of cryptocurrencies for multi-year intervals. As the endpoint, we specify the December 28^{th}, 2021. The starting points equal the last Tuesday of each year from 2014 until 2020. The mortality rate for year t equals the ratio of the number of cryptocurrencies that did not survive until the end of 2021, divided by the number of cryptocurrencies that existed at the end of year t. As an example, 511 cryptocurrencies were traded at the end of 2014, and 127 are still listed at the end of 2021. The mortality rate for year 2014 equals $\frac{511-127}{511} = 75.15\%$. In other words, only every fourth cryptocurrency that existed in 2014 is still listed today. From 2014 until 2020, the average mortality rate of cryptocurrencies is 37.06%. The mortality rate is lower than the average mortality rate in CTA funds of 52.3% during 1989 until 1994 (Fung and Hsieh (1997)). Mechanically, mortality rates are higher than attrition rates as the latter are dissolution rates over a single year. Nevertheless, the results presented in Table A2 and IV show that cryptocurrencies dissolve frequently.

In this Section, we have shown that cryptocurrencies dissolve frequently. Only every fourth cryptocurrency that existed in 2014 is still listed today. To what extent excluding delisted cryptocurrencies distort performance measures are part of the next Section.

Table IV Mortality Rate of Cryptocurrencies by Year

This table mortality rates of cryptocurrencies for each year; 07-January-2014 to 28-December-2021, 417 weeks. For each year, the mortality rate is calculated by dividing the number of cryptocurrencies that did not survive until the end of 2021 with the number of listed cryptocurrency at the end of each year

Year End	Number of Cryptocurrencies	Number of Cryptocurrencies surviving until 2021	Mortality rate (%)
2014	511	127	75.15
2015	592	184	68.92
2016	584	255	56.34
2017	968	539	44.32
2018	1285	1111	13.54
2019	1516	1504	0.79
2020	2150	2143	0.33
Average			37.06

IV. Findings

A. Survivorship & Delisting Bias

Table V quantifies the survivorship bias in cryptocurrency markets. We report the average weekly returns of three portfolios. The first (second) column reports weekly returns of a portfolio containing all (only surviving) cryptocurrencies. As a reference point, column three equals the average Bitcoin return. We quantify the survivorship bias by comparing the weekly returns of the surviving portfolio with a portfolio that contains all cryptocurrencies.[8] Considering the portfolio containing all 3'904 cryptocurrencies, the average weekly value-weighted (equal-weighted) return equals 1.40% (1.60%) per week. In contrast, the average return of a value-weighted (equal-weighted) survivorship-biased portfolio equals 1.42% (2.53%). Thus, survivor only conditioning positively biases performance measures. The return difference between the surviving portfolio and the portfolio including all cryptocurrencies quantifies the survivorship and delisting bias in cryptocurrency markets. The weekly survivorship bias is reported in column four. We estimate a weekly bias of 0.018% (0.934%) for a value-weighted (equal-weighted) weighting scheme, which equals an annualized survivorship bias of 0.93% for value-weighted portfolios. For value-weighted portfolios, the survivorship bias plays a minor role. In contrast, the annualized bias for equal-weighted portfolios equals 62.19%.

Table V Estimates of the Survivorship & Delisting Bias

This table compares the average weekly returns (in per cent) from 2014 through 2021 of all cryptocurrencies in existence with the returns for all cryptocurrencies that survived until the end of 2021; 07-January-2014 to 28-December-2021, 417 weeks. Column 3 reports the average weekly Bitcoin return. The estimated survivorship and delisting bias is reported in column 4. The bias equals the average return difference between the surviving and all ever existing cryptocurrencies. The last column reports the annualized bias. The bias is estimated using value-weighted and equal-weighted portfolios.

	All Cryptocurrencies in Existence (%)	Cryptocurrencies that survived until 2021 (%)	Bitcoin (%)	Weekly Bias (%)	Annualised Bias (%)
Value-weighted:	1.402	1.419	1.515	0.018	0.933
Equal-weighted:	1.595	2.53	1.515	0.934	62.188
Number of Coins:	3904	2682	1	1222	

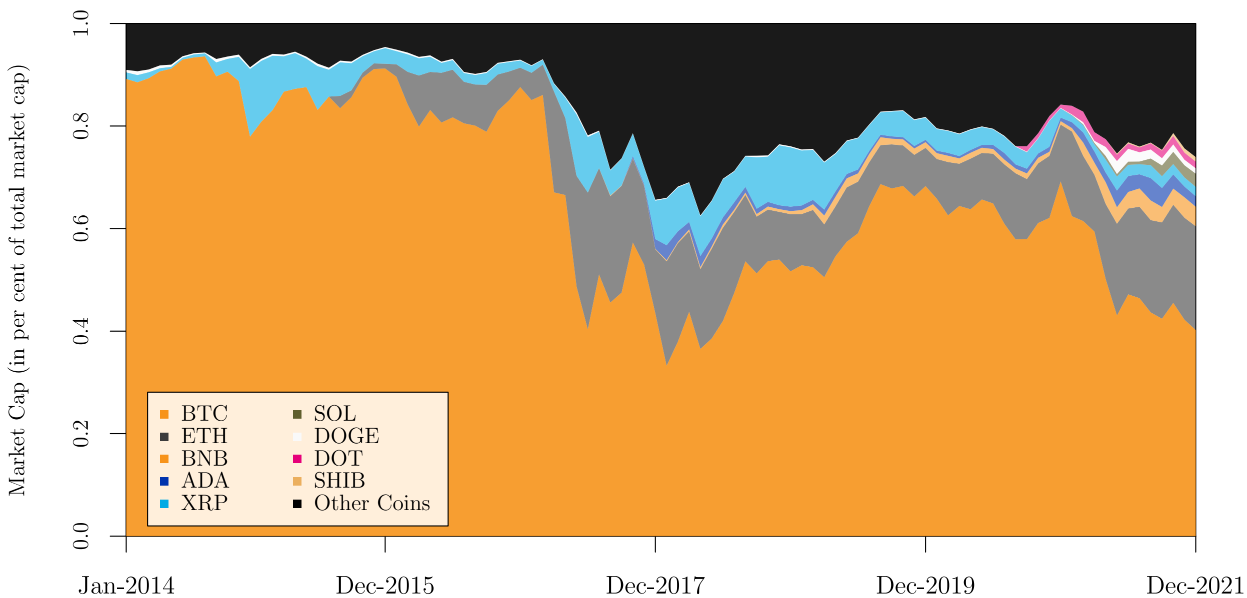
We conclude that performance measures distortion in a cryptocurrency sample truncated by survivorship is weighting-scheme dependent. The survivorship bias only slightly distorts returns for value-weighted portfolios but significantly affects equal-weighted portfolios. The bias is highly weighting-scheme-dependent due to the market structure of cryptocurrencies. Figure 4 depicts the market concentration of cryptocurrencies. The market is highly concentrated around a few cryptocurrencies with high market capitalization. At the end of 2021,

[8]This definition is in line with Goetzmann, Ibbotson, and Brown (1999), and Fung and Hsieh (2000).

Bitcoin (Ether) alone accounts for 40% (20%) of the total market capitalization of the cryptocurrency market. The market dominance of Bitcoin fluctuated around 90% before 2016. Thus, it is unsurprising that survivor-only conditioning results in an economically small performance measure distortion in value-weighted portfolios. As soon as the weighting scheme in portfolios is changed, the exclusion of the 1'222 delisted cryptocurrencies significantly biases performance measures.

Figure 4. Market Share of the Largest Cryptocurrencies

This figure depicts the market share of the largest cryptocurrencies in percent of the total market capitalization; 27-January-2014 to 27-December-2021, 96 months. The visualized coins include Bitcoin (BTC), Ether (ETH), Binance Coin (BNB), Cardano (ADA), Ripple (XRP), Solana (SOL), Doge Coin (DOGE), Polkadot (DOT), Shiba (SHIB), and all other cryptocurrencies (Other coins).



B. Characteristics of Delisted Cryptocurrencies

Subsequently, we use logistic regressions to determine the characteristics of cryptocurrencies that precipitate a delisting. Eq. 1 represents the full model:

$$P_{i,T}(Delist = 1) = \alpha + \beta_1 Age_{i,T} + \beta_2 Return_{i,T-1} + \beta_3 Size_{i,T-1} + \beta_4 ln(Volume)_{i,T-1} + \epsilon_{i,T} \quad (1)$$

where, $Delist = 1$ if cryptocurrency i is delisted and $Delist = 0$ if the cryptocurrency i is still listed at the end of 2021. $Age_{i,T}$ equals the number of weeks a cryptocurrency has been traded, $Ret_{i,T-1}$ is the lagged weekly return (in percent) of cryptocurrency i measured from Tuesday (T-2) to Tuesday (T-1). $Size_{i,T-1}$ equals the natural logarithm of the market capitalization of cryptocurrency i at time T-1. $ln(Volume)_{T-1}$ equals the one-week lagged weekly natural logarithm of the trading volume of cryptocurrency i. The cryptocurrency characteristics are regressed on the binary $Delist$ variable.

Table VI reports the results from logistic regressions. We specify five models. In models one to four, the characteristics are regressed individually. Model 5 equals the full model from Eq. 1. In the first column of each model, we report coefficients and standard errors in parentheses below the coefficients. The second column of each model, reports the marginal effects. The marginal effect equals the partial effect of the explanatory variable on the probability of delisting. In model one, the age variable is negative and significant at the 1% level (coefficient = -0.011; standard error = 0.001). This confirms the negative relationship between age and the probability of delisting. The marginal effect of the size variable equals -0.002, implying that a unit increase in size decreases the delisting probability by 0.2%, on average. The magnitude of the effect is economically large as the age variable equals the number of weeks the cryptocurrency is listed. Model two shows that smaller coins exhibit a higher probability of being delisted. The size coefficient equals -0.535 (SE=0.019). Models three and four equally exhibit high significance for the lagged return and trading volume variables. The coefficients are -1.037 (SE=0.144) and -0.238 (SE=0.010), respectively. Model five represents the full model. The coefficients for trading age, weekly trading volume and market capitalization are significant and the 1% level. The weekly return becomes insignificant. The marginal effect of the age variable in the full model, as a discrete variable, equals 0.11%. This means that the delisting probability decreases by 1.1% with a ten weeks increase in listing age, all other factors being constant. The marginal effects of the volume and size variables, as continuous variables, are -0.013 and -0.030, which means that a 1% increase in trading volume and market capitalization decreases the delisting probability by 1.3% and

3%, respectively.

Overall, the regression results imply that a cryptocurrency that has a longer trading history, higher trading volume, and a larger market capitalization exhibit a lower probability of being delisted. Our findings are similar to Kashefi Pour and Lasfer (2013) who analyze equity characteristics at the IPO and ex-post at the delisting date for stocks, with a logistic regression. (Kashefi Pour and Lasfer (2013)) find that continuing high leverage, low trading volume, growth opportunities, and profitability are defining factors for voluntary delistings of companies.

Table VI Factors Determining Delistings

This table depicts results of a logistic regression where the dependent variable equals 1 for delisted coins and is 0 otherwise; 07-January-2014 to 28-December-2021, 417 weeks. Model 5 is defined as follows:

$$P_{i,T}(Delist = 1) = \alpha + \beta_1 Age_{i,T} + \beta_2 Return_{i,T-1} + \beta_3 Size_{i,T} + \beta_4 ln(Volume)_{i,T-1} + \epsilon_{i,T}$$

Standard errors (S.E) are reported below the coefficient estimates in parentheses. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels respectively, using Wald test.

	Dependent variable:									
	Delist Dummy									
	(1)		(2)		(3)		(4)		(5)	
	Coefficient (S.E)	Marginal Effect	Coefficient (S.E)	Marginal Effect	Coefficient (S.E)	Marginal Effect	Coefficient (S.E)	Marginal Effect	Coefficient (S.E)	Marginal Effect
Age	-0.011^{***} (0.001)	-0.002							-0.013^{***} (0.001)	-0.001
$Size_{t-1}$			-0.535^{***} (0.019)	-0.065					-0.394^{***} (0.026)	-0.030
$Return_{t-1}$					-1.037^{***} (0.144)	-0.194			-0.287 (0.181)	-0.022
$ln(Volume)_{t-1}$							-0.238^{***} (0.010)	-0.031	-0.167^{***} (0.017)	-0.013
Constant	0.310^{***} (0.061)		5.585^{***} (0.233)		-1.076^{***} (0.039)		0.850^{***} (0.088)		6.565^{***} (0.313)	
Observations	3,904		3,586		3,571		3,434		3,387	
Nagelkerke R^2	0.171		0.499		0.023		0.307		0.570	
Note:									*p<0.1; **p<0.05; ***p<0.01	

V. Revisiting previous Findings

This section revisits the relationship between average returns, size, past performance, and market β using a survivorship and delisting bias-free dataset. Specifically, we aim to answer if size, momentum, and market β carry a positive return premium or if these premiums are spurious and the result of how researchers compile their data.

A. *Size Premium*

We revisit the magnitude of a size premium in cryptocurrency markets using a survivorship and delisting bias-free dataset. At the end of each Tuesday (t), we rank cryptocurrencies into five size groups and calculate portfolio returns from Tuesday (t) to Tuesday in the consecutive week (t+1) (Liu et al., 2020), (Liebi, 2022). Table VII reports value-weighted (Panel A) and equal-weighted (Panel B) weekly returns for quintile portfolios sorted on size. For each weighting scheme, we compare the results when all cryptocurrencies are considered and compare the results to a survivorship-biased dataset. The small-minus-big (SMB) row reports average weekly returns of a portfolio that is long in the first and short in the fifth size quintile. Additionally, Table VII shows portfolio returns adjusted for systematic risk. The alpha equals the intercept from regressing the excess SMB returns on the excess cryptocurrency market return.

Table VII Survivorship Bias and the Size Premium

Averages of weekly percent excess returns for value-weighted (Panel A: VW) and equal-weighted (Panel B: EW) portfolios formed on size; 07-January-2014 to 28-December-2021, 417 weeks. At the end of each Tuesday (=t), cryptocurrencies are sorted into quintiles based on size. Then, value-weighted and equal-weighted portfolio returns are calculated from t to t+1. The small-minus-big (SMB) row reports the average weekly return of the 1-5 portfolio. The alpha is the intercept obtained from a regression of SMB returns on the excess market return. T-statistics are reported in parenthesis below the coefficients. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels, respectively.

Panel A: VW	Return (in per cent)		Panel B: EW	Return (in per cent)	
Size	All Cryptocurrencies	Surviving Cryptocurrencies	Size	All Cryptocurrencies	Surviving Cryptocurrencies
Small	3.30***	4.26***	Small	4.63***	5.88***
	(5.74)	(6.63)		(7.78)	(8.98)
2	1.38**	2.12***	2	1.62***	2.36***
	(2.40)	(3.56)		(2.72)	(3.87)
3	0.72	1.72***	3	0.75	1.92***
	(1.24)	(2.68)		(1.28)	(2.96)
4	0.55	1.25**	4	0.66	1.45**
	(0.91)	(2.02)		(1.07)	(2.31)
Big	1.41***	1.42***	Big	0.82	1.19*
	(2.70)	(2.73)		(1.35)	(1.93)
SMB	1.89***	2.84***	SMB	3.81***	4.69***
	(4.75)	(5.79)		(8.95)	(9.07)
Alpha	2.15***	3.09***	Alpha	3.99***	4.88***
	(5.50)	(6.36)		(9.39)	(9.43)

Looking at Panel A in Table VII, we find that within each quintile portfolio, average returns of the survivorship bias-free dataset are lower compared to the survivorship biased sample. For the smallest size quintile, the average return difference between the surviving and the unbiased sample equals 0.36% per week. Except for the 5^{th} quintile, average returns are decreasing from the first to the fifth quintile. Thus, smaller coins tend to outperform large coins. This result is independent of the sample. However, the unbiased sample's value-weighted SMB return equals 1.89% (t=4.75). The survivorship and delisting biased SMB portfolio yields an average weekly return of 2.84% (t=5.79). The average return difference of the SMB portfolios equals 0.95% per week. Economically, this is a large bias. The value-weighted size premium is overestimated by 50.3% per week in a survivorship biased sample. The risk-adjusted alpha of the unbiased (biased) SMB size portfolio equals 2.15% (3.09%) for value-weighted portfolios. Importantly, both samples confirm a size premium in cryptocurrency markets. Panel B of Table VII reports equal-weighted returns. Overall, we find a similar picture. Average returns are smaller for the unbiased sample than the biased sample within each size quintile. Average returns decrease with increasing size. Interestingly, the size premium is underestimated for equal-weighted portfolios in a biased sample due to the large bias in the largest size quintile, where the return difference equals 0.34% per week.

Overall, Table VII confirms the findings of previous studies. Small cryptocurrencies yield higher average returns than big cryptocurrencies. Importantly, this result holds when a survivorship and delisting bias-free dataset is used. We conclude that the size premium is not spurious. Comparing our estimated size premium to other studies, we find that our estimate is considerably lower than previously documented. The value-weighted size premium equals 1.89%. Liu et al. (2020) document a size premium of 22.26% per week. The authors use sixtile sorts, which might be a potential explanation for the higher premium. Liebi (2022) finds a size premium of 6.53%, and Liu et al. (2022) estimate a premium of 3.4% per week. Both authors use quintile portfolio sorts. Li et al. (2020) and Zhang and Li (2020) use decile sorts resulting in a size premium of 6.16 and 14.4%, respectively.

Besides the portfolio sorting technique, two other reasons might explain the large variation in estimated size premiums. The first one is different cryptocurrency samples, and the second reason is the sample period. Next, we want to evaluate if size filters may drive the variation in the estimated size premiums. As an example, Liu et al. (2022) and Liebi (2022) use a size filter of $1 Million. We examine the dependence of the size premium and the size filter. We rank all cryptocurrencies on survival dummy and the market capitalization at the end of 2021. We start with a sample of 100 cryptocurrencies with the highest market capitalization at the end of 2021. Then, we sort these cryptocurrencies into size quintiles and calculate the weekly SMB return. This portfolio sorting method is iterated by sequentially adding 200 cryptocurrencies to the sample. Importantly, we add surviving coins with the highest market capitalization at the end of the sample period first. In a second phase, we add delisted cryptocurrencies. Again, delisted cryptocurrencies with a high market capitalization at the last trading day are added first. This method provides insights into how size filters and sample sizes affect the size premium.

Figure 5. Selection Bias and the Size Premium

This figure depicts the size premium for different sample sizes. The size premium is defined as the high-minus-low quintile portfolio that is long in the lowest level of size and short in the highest level of size. At the end of each Tuesday (t), coins are sorted on size and held until the consecutive Tuesday (t+1). Portfolio returns are value-weighted and portfolios are weekly rebalanced. The sample size starts with 100 coins and is step-wise increased by 200 coins. First, only surviving coins are added to the sample. Second, we add the delisted coins. Importantly, we add coins sequentially according to their market capitalization on the last trading day. Thus, larger coins are always added first within the surviving and delisted group. We label the maximum, the survivorship-biased, and the true estimate of the size premium. T-statistics are reported in parentheses below the coefficients. The darkgray area between the dashed lines represents 95% confidence intervals.

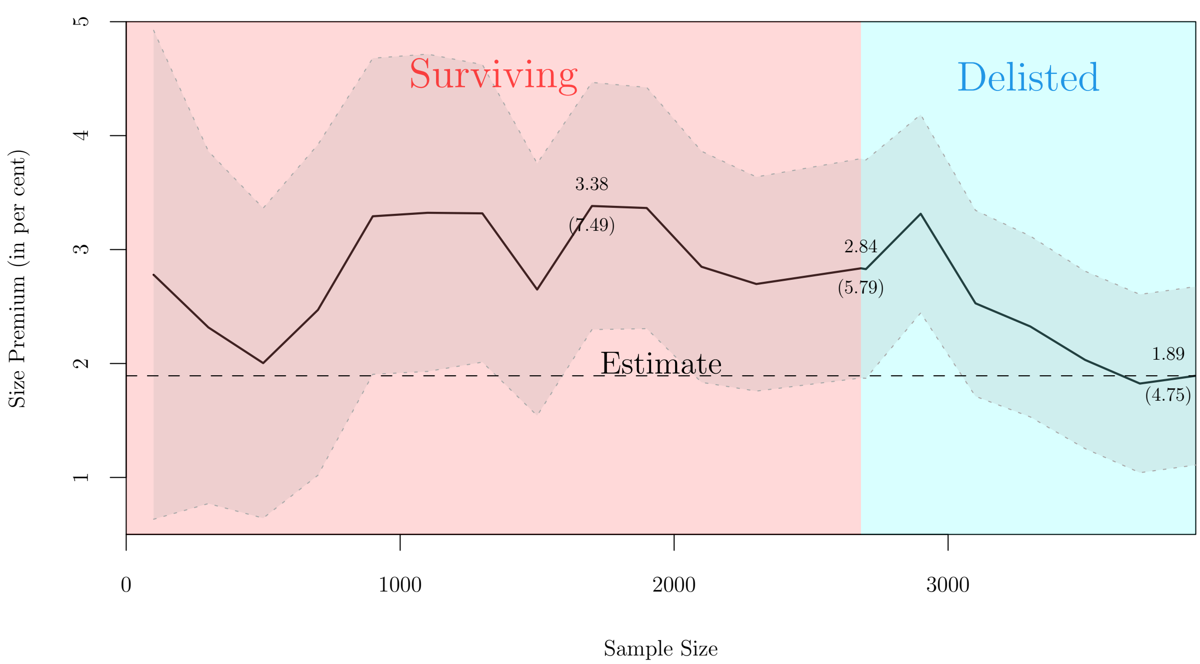
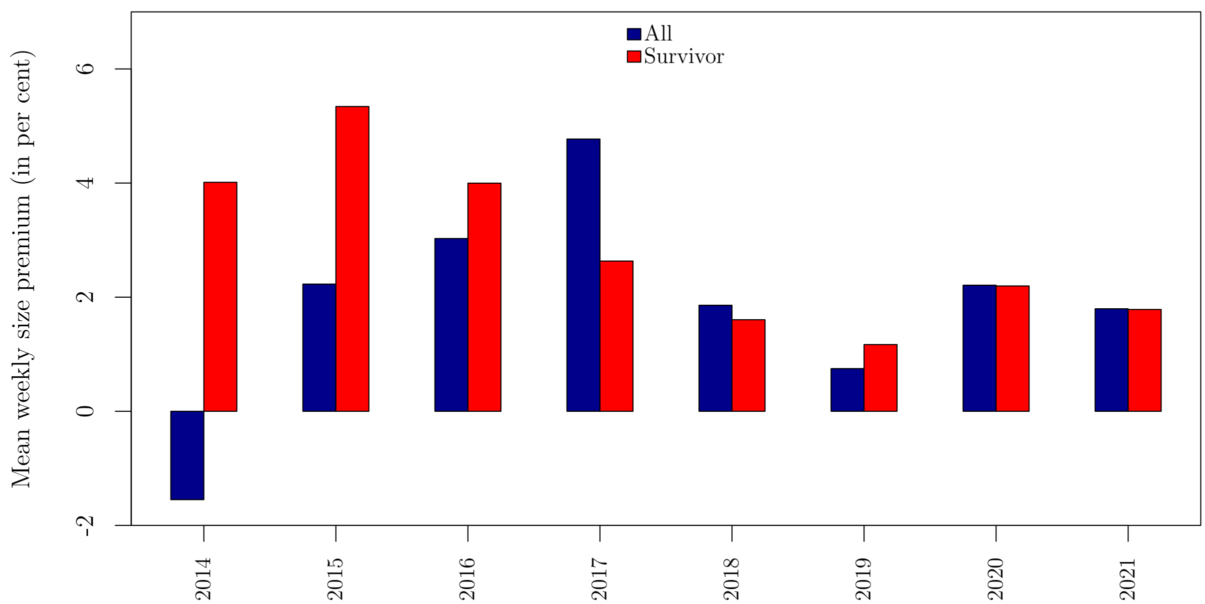


Figure 5 depicts the sample size on the x-axis and the weekly value-weighted SMB return on the y-axis. In the light red area, only survivors are added to the sample. In the light blue area, we sequentially add delisted cryptocurrencies. Three specific points are labeled in Figure 5. The first equals the highest SMB return. The second point equals the SMB return in the survivorship-biased sample. The last point equals the SMB return in a survivorship-bias free sample, including all cryptocurrencies. T-values are reported in parenthesis below the coefficients. Note that the second and third labels are consistent with Panel A in Table VII. Figure 5 depicts that the size premium is positive in all subsamples. The highest size premium of 3.38% (t=7.46) results when the 1700 largest cryptocurrencies are in the sample. Including all surviving cryptocurrencies, the size premium equals 2.84% (t=5.79). Including also delisted cryptocurrencies, the size premium falls to 1.89% (t=4.75). Since we sequentially add cryptocurrencies with smaller market capitalization, one might expect that the value-weighted SMB return might not change significantly. Delisted coins are characterized by large losses at the delisting date and small with respect to market capitalization. Hence, when sorting on size, the delisted coins end up in the small quintile, resulting in a lower return than without delisted coins. Thus, it is not surprising that with increasing sample size, the size premium decreases. Overall, Figure 5 indicates that the size premium is strongly dependent on the way researchers compile their data. The size premium can be inflated by one percentage point per week. This result should raise awareness of the survivorship and delisting bias in cryptocurrency studies.

Finally, we ask if the sample period may cause the large variety of documented size premiums in previous studies. Figure 6 visualizes the average value-weighted SMB return for each year. We report the returns for the whole as well as a survivorship-biased sample. The first finding is that the size premium inflation due to survivorship bias is especially profound in 2014. The size premium is overestimated by 5 percentage points, which similarly holds for 2015. During the ICO boom, the effect of the bias reverses. The size premium is larger in the whole sample than the biased one. In more recent years, survivorship bias does not result in a large difference between the two samples, mainly due to the small number of delistings in 2020 and 2021.

Figure 6. Average Weekly Size Premium by Year

This figure reports average value-weighted weekly returns per year of a SMB portfolio that is long in the smallest and short in the highest size quintile.



B. *Momentum*

Similarly, we revisit the momentum effect in cryptocurrency markets. We use one-week momentum in cryptocurrency returns, i.e. the cumulative return from t-7 days to t for each cryptocurrency. The one-year horizon is chosen according to Jegadeesh and Titman (1993), Carhart (1997), and Liu and Tsyvinski (2021). At the end of each Tuesday (t), cryptocurrencies are sorted for momentum into quintile portfolio. Each portfolio is held for one week. Thus, portfolio returns are calculated from Tuesday (t) until Tuesday in the consecutive week (t+1).

Table VIII reports value-weighted (Panel A) and equal-weighted (Panel B) weekly returns for quintile portfolios sorted on one-week momentum. Independent of the weighting scheme and the dataset, we cannot confirm that past winners outperform past losers in the consecutive week. The HML portfolio yields negative returns, long in past winners and short in past losers. For value-weighted returns, the average return difference is indistinguishable from zero. Regarding equal-weighted portfolios, the HML portfolio yields -11.46% (t=-32.91) per week for all cryptocurrencies. These results suggest no momentum effect in cryptocurrency markets and stand in contrast to previous findings. Surprisingly, no momentum effect is documented even when a survivorship-biased sample is used.

Table VIII Survivorship Bias and Momentum

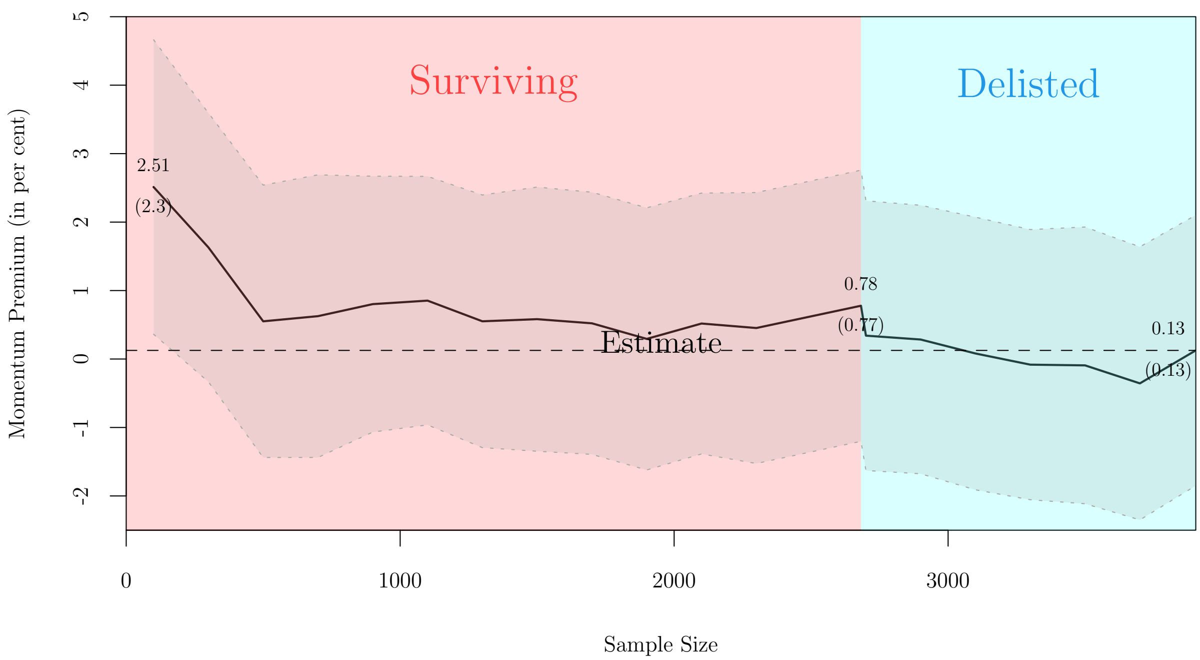
Averages of weekly percent excess returns for value-weighted (Panel A: VW) and equal-weighted (Panel B: EW) portfolios formed on one-week momentum; 07-January-2014 to 28-December-2021, 417 weeks. At the end of each Tuesday (=t), cryptocurrencies are sorted into quintiles based on momentum. In the sort time t, momentum equals the cumulative weekly return over the previous 7 days. Then, value-weighted and equal-weighted portfolio returns are calculated from t to t+1. The high-minus-low (HML) column reports the average weekly returns of the 5-1 portfolio. The alpha is the intercept obtained from a regression of HML returns on the excess market return. T-statistics are reported in parenthesis below the coefficients. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels, respectively.

Panel A: VW	Return (in per cent)		Panel B: EW	Return (in per cent)	
Momentum	All Cryptocurrencies	Surviving Cryptocurrencies	Momentum	All Cryptocurrencies	Surviving Cryptocurrencies
Low	1.38	1.04	Low	8.53***	8.04***
	(1.69)	(1.33)		(13.72)	(12.27)
2	1.08	1.07	2	2.18***	2.34***
	(1.51)	(1.56)		(3.72)	(3.79)
3	0.79	1.02	3	1.46**	1.82***
	(1.32)	(1.62)		(2.46)	(3.10)
4	1.93***	1.88***	4	1.42**	2.24***
	(2.99)	(3.02)		(2.41)	(3.57)
High	1.51	1.82*	High	-2.93***	-0.36
	(1.64)	(1.92)		(-5.13)	(-0.59)
HML	0.13	0.78	HML	-11.46***	-8.40***
	(0.13)	(0.77)		(-32.91)	(-19.19)
Alpha	-0.06	0.61	Alpha	-11.32***	-8.24***
	(-0.06)	(0.60)		(-32.56)	(-18.81)

Figure 7 displays that the resulting momentum premium depends significantly on the way researchers may compile their data. If the entire sample is considered, the momentum effect is only 0.13%, which is in line with Table VIII. Considering all surviving cryptocurrencies, the momentum premia is 0.78%. Within the surviving cryptocurrencies, there is considerable variation of the momentum premium. The sample of the largest 100 surviving cryptocurrencies exhibits the greatest momentum effect with 2.51%.

Figure 7. Selection Bias and the Momentum Premium

This figure depicts the momentum premium for different sample sizes. The momentum premium is defined as a high-minus-low portfolio that is long in the highest quintile coins and short in the lowest momentum quintile. Momentum equals the cumulative return over the past 7 days. At the end of each Tuesday (t), coins are sorted on size and held until the consecutive Tuesday (t+1). Portfolio returns are value-weighted and portfolios are weekly rebalanced. The sample size starts with 100 coins and is step-wise increased by 200 coins. First, only surviving coins are added to the sample. Second, we add the delisted coins. Importantly, we add coins sequentially according to their market capitalization at the last trading day. Thus, larger coins are always added first within the surviving and delisted group. We label the maximum, the survivorship-biased, and the true estimate of the momentum premium. T-statistics are reported in parentheses below the coefficients. The darkgray area between the dashed lines represents 95% confidence intervals.



Finally, Figure 8 demonstrates that there is a momentum premium for the years 2014, 2017, and 2021 and a momentum reversal effect for the years 2015 and 2016. This considerable difference could help explain the unsettled consensus of the literature regarding the momentum effect.

Figure 8. Average Weekly Momentum Premium by Year

This figure reports average weekly returns per year of a HML portfolio that is long in the highest and short in the lowest momentum quintile.

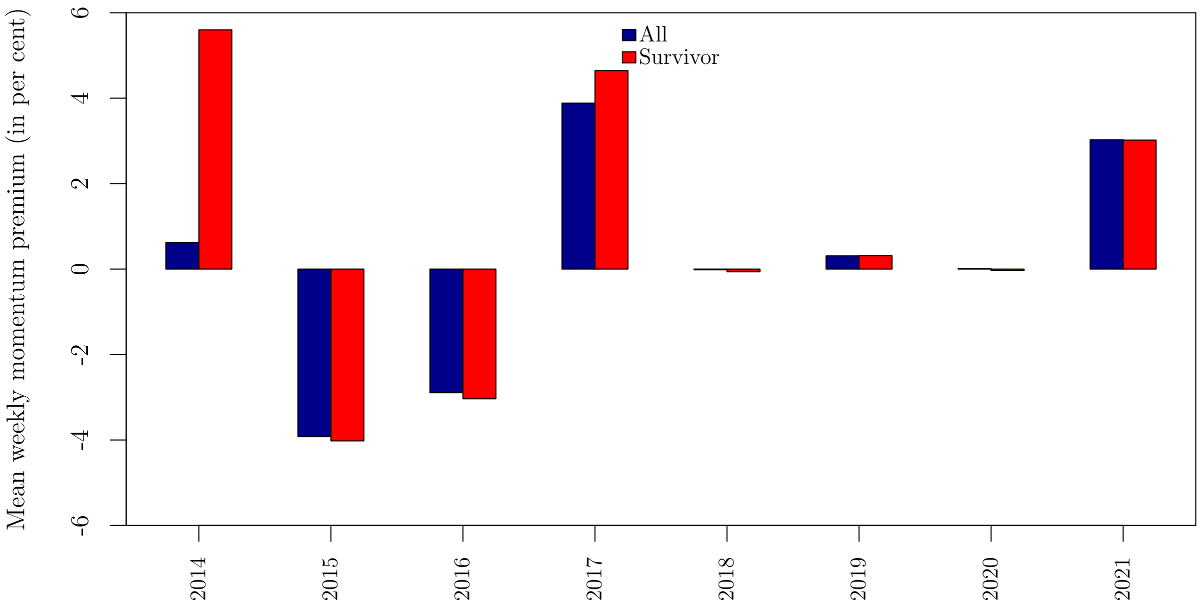


Table IX Two-dimensional Sorts on Momentum and Size

Averages of weekly percent excess returns for value-weighted (Panel A: VW) and equal-weighted (Panel B: EW) portfolios formed on size; 07-January-2014 to 28-December-2021, 417 weeks. At the end of each Tuesday, crypotcurrencies are allocated into terciles portfolios on momentum. Cryptocurrencies are allovated independently to terciles portfolios based on size. The intersections of the two sorts results in nine portfolios. Panel A (B) reports value-weighted (equal-weighted) weekly percent returns in excess of the one-month Treasury bill rate. Excess returns are calculated from Tuesday (t) until Tuesday in the following week (t+1). The HML column (row) is a long-short portfolio, which is long in the third column (row) and short in the first column (row). T-statistics are reported in paranthesis below the coefficients. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels, respectively.

A: VW					B: EW				
Mom-size	Loser	Neutral	Winner	HML	Mom-size	Loser	Neutral	Winner	HML
Small	8.09***	4.92***	2.02***	-6.07***	Small	10.98***	5.64***	2.7***	-8.28***
	(12.10)	(7.53)	(2.59)	(-9.09)		(16.35)	(8.71)	(3.98)	(-19.50)
Neutral	2.95***	2.17***	1.79***	-1.16***	Neutral	4.14***	2.28***	1.56**	-2.58***
	(4.52)	(3.38)	(2.99)	(-2.65)		(6.45)	(3.54)	(2.38)	(-6.11)
Big	-1.68***	-0.63	2***	3.68***	Big	-1.6***	-0.99	1.28*	2.89***
	(-2.76)	(-0.96)	(2.72)	(5.69)		(-2.68)	(-1.58)	(1.89)	(6.18)
HML	-9.77***	-5.54***	-0.02		HML	-12.58***	-6.63***	-1.42***	
	(-22.39)	(-14.00)	(-0.03)			(-33.43)	(-18.23)	(-4.01)	

C. Market β

Subsequently, we analyse the relationship between market betas and the survivorship bias. At the end of each Tuesday (=t), cryptocurrencies are sorted into quintiles based on the market beta. Market beta equals the slope coefficient when regressing excess returns of cryptocurrencies on the excess market return from t-365 days until t. The market return equals the value-weighted return of all cryptocurrencies in our sample. Table X reports value-weighted (Panel A) and equal-weighted (Panel B) weekly returns for quintile portfolios sorted one-year market betas. Depending on the weighting scheme, the HML portfolio has a positive return for the value-weighted and a negative return for the equal-weighted. The HML portfolio is long in high market beta cryptocurrencies and short in low market beta cryptocurrencies. Our findings are not significant, which is consistent with the existing literature, for example, Liu and Tsyvinski (2021).

Table X Market Beta and Survivorship Bias

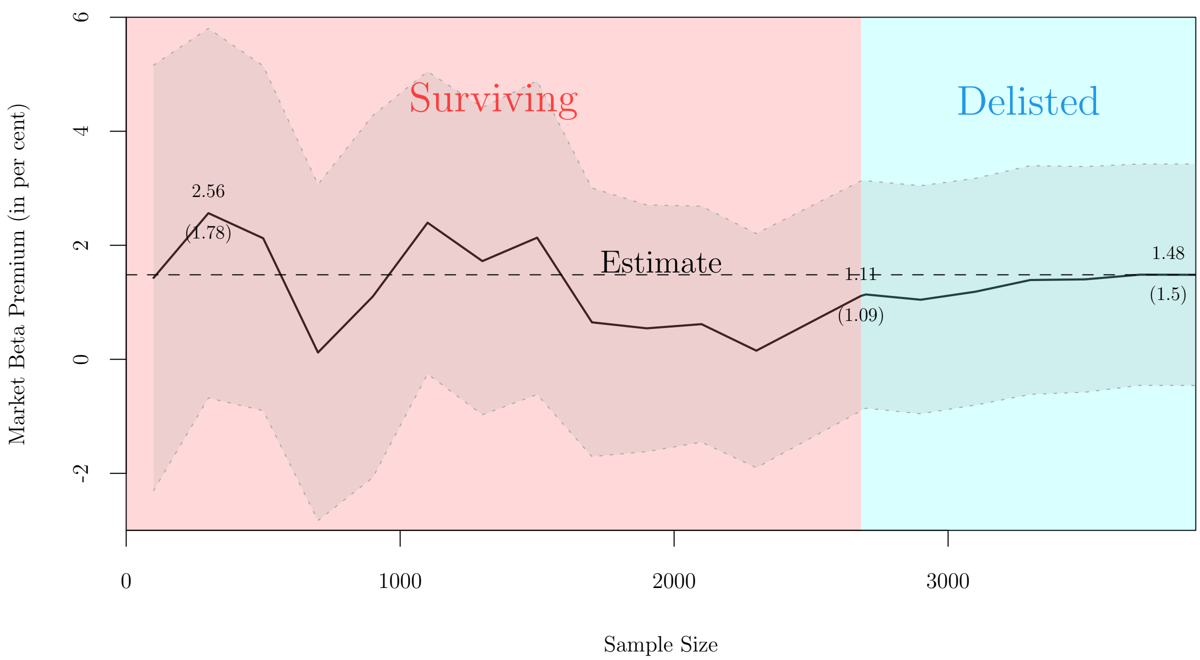
Averages of weekly percent excess returns for value-weighted (Panel A: VW) and equal-weighted (Panel B: EW) portfolios formed on market beta; 07-January-2014 to 28-December-2021, 417 weeks. At the end of each Tuesday (=t), cryptocurrencies are sorted into quintiles based on market beta. In the sort time t, market beta is estimated from t-365 days until t. Then, value-weighted and equal-weighted portfolio returns are calculated from t to t+1. The high-minus-low (HML) row reports the average weekly return of the 5-1 portfolio.The alpha is the intercept obtained from a regression of HML returns on the excess market return. T-statistics are reported in parenthesis below the coefficients. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels, respectively.

Panel A: VW	Return (in per cent)		Panel B: EW	Return (in per cent)	
Market beta	All Cryptocurrencies	Surviving Cryptocurrencies	Market beta	All Cryptocurrencies	Surviving Cryptocurrencies
Low	0.31	0.69	Low	2.40***	3.08***
	(0.37)	(0.80)		(3.19)	(3.62)
2	1.69*	1.39	2	2.97***	2.28***
	(1.87)	(1.46)		(3.44)	(2.63)
3	1.38	1.55*	3	2.15***	2.63***
	(1.62)	(1.84)		(2.61)	(2.96)
4	1.84*	2.43**	4	2.53***	2.91***
	(1.94)	(2.39)		(2.97)	(3.13)
High	1.79**	1.81**	High	3.25***	2.93***
	(2.01)	(2.08)		(3.73)	(3.30)
HML	1.48	1.11	HML	0.85	-0.15
	(1.50)	(1.09)		(1.07)	(-0.17)
Alpha	0.72	0.42	Alpha	0.52	-0.36
	(0.74)	(0.41)		(0.65)	(-0.41)

As before for the size and momentum premium, Figure 9 displays that the resulting market betas depend on the way researchers compile their sample. The weekly market beta premium for the total sample is 1.48%. Considering all surviving cryptocurrencies, it is 1.11%. The largest market beta premium in our case exists with a sample size of 300 surviving cryptocurrencies with 2.56%.

Figure 9. Selection Bias and Market β

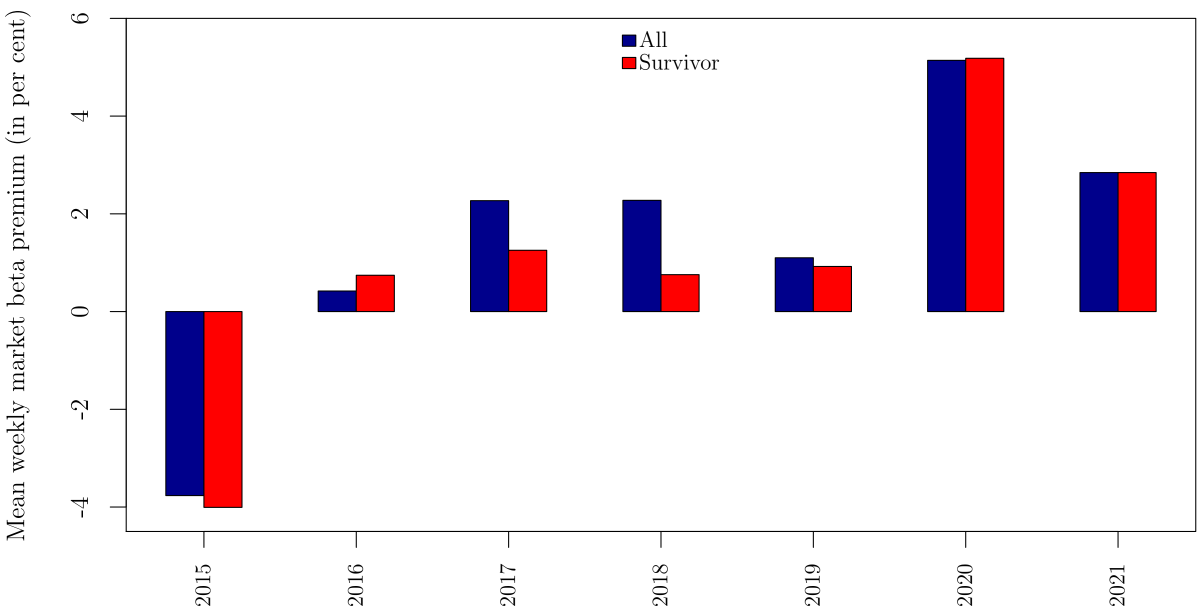
This Figure depicts the market beta premium for different sample sizes. The market beta premium is defined as a high-minus-low portfolio that is long in the highest quintile coins and short in the lowest market beta quintile. Market beta equals the slope coefficient when regressing excess returns of cryptocurrencies on the excess market return from t-365 days until t. At the end of each Tuesday (t), coins are sorted on size and held until the consecutive Tuesday (t+1). Portfolio returns are value-weighted and portfolios are weekly rebalanced. The sample size starts with 100 coins and is step-wise increased by 200 coins. First, only surviving coins are added to the sample. Second, we add the delisted coins. Importantly, we add coins sequentially according to their market capitalization at the last trading day. Thus, larger coins are always added first within the surviving and delisted group. We label the maximum, the survivorship-biased, and the true estimate of the market β premium. T-statistics are reported in parentheses below the coefficients. The darkgray area between the dashed lines represents 95% confidence intervals.



In Figure 10 we exhibit the market beta premium by year; again, no consistent pattern occurs. The premium is highly negative for 2015, then for 2016-2019, the premium is mostly smaller than 2%, while for 2020 and 2021, the average weekly market beta premiums are large; greater than 5% and 2%, respectively.

Figure 10. Average Weekly Market Beta Premium by Year

This figure reports average weekly returns per year of a HML portfolio that is long in the highest and short in the lowest market β quintile.



D. *Other Cross-Sectional Return Predictors*

Table XI revisits additional cross-sectional return predictors. Importantly, all predictors investigated have been examined in previous studies. Each predictor is classified into one of four categories: momentum (MOM), downside risk (DOWN), upside risk (UP), liquidity (LIQ), or volatility (VOL). In Sec. 7, we show that one-week momentum premium only exists within large cryptocurrency portfolios. Liu et al. (2022) document that also for two-, three-, and four-week momentum strategies, average returns are monotonically increasing. Table XI confirms this result for two-week and four-week momentum. Importantly, for these two predictors, the relationship is almost in all cases monotonic increasing. The average return difference between the highest and lowest level of two-week (four-week) momentum equals 2.87% (2.43%) per week. Liu et al. (2022) document a similar return difference of 3.1% (2.2%) for two-week (four-week) momentum. In short, we confirm the existence of profitable momentum strategies for two and four-week return measures. We do not find a statistically significant relationship between 1-year momentum and future returns. We turn to downside risk as a cross-sectional return predictor. Zhang, Li, Xiong, and Wang (2021) find a positive cross-sectional relation between downside risk and cryptocurrency returns. This result is consistent with loss aversion preferences according to Kahneman and Tversky (1979). If investors dislike losses more than gains, an asset with a higher downside risk must exhibit higher expected returns than an asset with a low downside risk. However, when cryptocurrency investors prefer risky assets a higher downside risk would be associated with a lower expected return (see Conlon and McGee (2020) and Pelster, Breitmayer, and Hasso (2019)). Following Zhang et al. (2021), we measure downside risk using the value-at-risk. The 5%VaR is estimated from t-90 days until t and equals the 5^{th} percentile of daily returns multiplied by 1. Thus, a higher 5%VaR implies a higher downside risk. We find a negative relationship between downside risk and future returns. The average value-weighted return difference between cryptocurrencies with the highest, and cryptocurrencies with the lowest level of 5%VAR equals -3.01% (t=-3.48). When downside risk is measured using the 1%VAR, the return difference equals -2.71% (t=-3.04).[9] The preference of cryptocurrency investors for risk investments is also reflected in the upside risk and volatility row. Cryptocurrencies with a higher level of upside risk have lower expected returns. Finally, we turn to illiquidity measures as cross-sectional return predictors for cryptocurrencies. We use the amihud (Amihud (2002)) and EDGE (Ardia, Guidotti, and Kroencke (2021)) to estimate illiquidity. For both measures, we do not find that higher illiquidity is associated with higher returns.

[9]A similar relationship has been documented in equity markets: Atilgan, Bali, Demirtas, and Gunaydin (2019), Atilgan, Bali, Demirtas, and Gunaydin (2020a), and Atilgan, Demirtas, and Gunaydin (2020b)

Table XI One-dimensional weekly sorts

Averages of weekly percent excess return for value-weighted portolios fromed on the past two-week, three-week, four-week, five-week 52-week return measures, 5% Value at Risk, 1% Value at Risk, Amihud illiquidity measure, standard deviation of daily returns in the portfolio formation week (RETVOL) maximum return in the portfolio formation week (MAXRET); 07-January-2014 to 28-December-2021, 417 weeks. At the end of each Tuesday (=t), crypotcurrencies are sorted into quintiles based on corresponding variable. In the sort time t, Value at Riks is estimated from t-90 days until t and EDGE is estimated from t-60 days until t. Then, value-weighted portfolio returns are calculated from t to t+1. The high-minus-low (HML) column reports average weekly returns of the 5-1 portfolio. The alpha is the intercept obtained from regression of HML returns on the market return. T-statistics are reported in parenthesis below the coefficients. *, **, *** indicate statistical significance levels at the 10%, 5%, 1% levels, respectively.

Category	Predictor	Low	2	3	4	High	HML	α	Reference	Confirm
MOM	2-week MOM	-0.01	0.43	1.09	2.17	2.86	2.87***	2.75***	Liu et al. (2022)	✓
		(-0.01)	(0.66)	(1.79)	(3.37)	(3.49)	(2.85)	(2.71)		
MOM	3-week MOM	0.93	0.62	0.97	2.17	2.65	1.72*	1.58	Liu et al. (2022)	✓
		(1.03)	(0.88)	(1.47)	(3.27)	(3.42)	(1.72)	(1.57)		
MOM	4-week MOM	0.1	0.43	1.04	2.19	2.62	2.52***	2.43***	Liu et al. (2022)	✓
		(0.12)	(0.61)	(1.67)	(3.29)	(3.55)	(2.89)	(2.76)		
MOM	5-week MOM	0.64	1.48	0.98	2.1	1.61	0.97	0.93		-
		(0.76)	(2.04)	(1.53)	(3.07)	(2.21)	(1.14)	(1.08)		
MOM	6-week MOM	0.72	1.49	1.07	1.62	2.22	1.51*	1.27		-
		(0.90)	(2.21)	(1.58)	(2.53)	(3.04)	(1.87)	(1.57)		
MOM	1-year MOM	1.45	1.35	1.22	2.18	2.31	0.87	0.68	Cong, Karolyi, Tang, and Zhao (2022)	✓
		(1.74)	(1.85)	(1.84)	(3.27)	(3.07)	(1.03)	(0.80)		
DOWN	5% VAR	1.68	1.52	0.02	-0.1	-1.71	-3.39***	-3.01***	Zhang et al. (2021)	✗
		(3.19)	(2.08)	(0.02)	(-0.10)	(-1.82)	(-3.92)	(-3.48)		
DOWN	1% VAR	1.56	1.06	0.6	1.31	-1.21	-2.77***	-2.71***	Zhang et al. (2021)	✗
		(3.03)	(1.41)	(0.79)	(1.31)	(-1.22)	(-3.15)	(-3.04)		
UP	95% VAR	1.69	1.83	0.96	-0.17	-2.28	-3.97***	-3.75***		-
		(3.21)	(2.41)	(1.06)	(-0.20)	(-2.24)	(-4.27)	(-3.99)		
UP	99% VAR	1.65	1.93	0.89	0.83	-1.81	-3.46***	-3.42***		-
		(3.12)	(2.70)	(1.12)	(0.87)	(-1.78)	(-3.77)	(-3.68)		
LIQ	Amihud	1.51	0.31	0.93	0.04	-0.36	-1.87**	-1.63*	Wei (2018)	✓
		(2.89)	(0.42)	(1.32)	(0.05)	(-0.36)	(-2.07)	(-1.79)		
LIQ	EDGE	1.31	1.65	2.29	-0.05	0.44	-0.87	-0.71		-
		(2.28)	(2.32)	(3.02)	(-0.08)	(0.53)	(-1.23)	(-0.99)		
VOL	RETVOL	1.55	1.71	1.75	-0.77	-5.18	-6.73***	-6.53***	Liu et al. (2022) and Ang, Hodrick, Xing, and Zhang (2006)	✓
		(2.88)	(2.36)	(1.97)	(-0.91)	(-4.74)	(-6.61)	(-6.37)		
VOL	MAXRET	1.45	1.92	1.59	0.24	-4.14	-5.59***	-5.38***	Liu et al. (2022) and Bali, Cakici, and Whitelaw (2011)	✗
		(2.58)	(2.67)	(2.17)	(0.26)	(-3.67)	(-5.13)	(-4.90)		

VI. Conclusion

Cryptocurrencies vanish frequently. Every third cryptocurrency listed between 2014 and 2021 delisted before the end of 2021. Hence, empirical studies on cryptocurrencies that exclude delisted coins are biased. Survival-only conditioning can occur in many forms but is present in nearly every cryptocurrency study. The survivorship and delisting bias leads to distorted performance measures and results. Notably, cryptocurrencies do not represent ownership of a corporation or any other physical asset. Therefore, the delisting of a cryptocurrency is frequently associated with a total loss for investors. The combination of survivorship and delisting bias in empirical studies raises several concerns. In this paper, we address three major issues. First, we quantify the effect of survivorship and delisting bias on estimates of average cryptocurrency market performance. Thereby, we manually collect delisting return of all delisted cryptocurrencies and classify their delisting reason. Second, we determine the characteristics of delisted cryptocurrencies. Third, we revisit previous findings that document a relationship between size, momentum, downside risk and average returns. Quantifying the magnitude of the survivorship and delisting bias, we find that the annualized value-weighted (equal-weighted) bias equals 0.933% (62.188%). The estimate equals the average return difference between the surviving and all ever existing cryptocurrencies. Analyzing delisted cryptocurrencies closer, we find they are characterized by low trading volume, small market capitalization, and young trading age. After controlling for the survivorship and delisting bias, we revisit the relationship between average returns, size, momentum, and market β. Our results confirm the existence of a size premium in cryptocurrency markets. However, there exists a high variation of reported size premiums in the cryptocurrency literature. Size premium estimates range from 5.8% (Liu et al. (2022)) to 22.3% (Liu et al. (2020)) per week. Importantly, we find that survival-only conditioning overestimates the size premium by 50%. In contrast, we find no evidence of a one-week momentum effect. Neither the complete sample nor a survivorship-biased sample displays past winners outperforming past losers. However, we confirm two- and four-week momentum. A higher market β is not associated with higher expected returns, which is in line with existing literature. Unlike Zhang et al. (2021), we find a negative relationship between downside risk and expected returns. This negative relationship also exists between upside risk and expected return. These results imply that cryptocurrency investors have a preference for risky investments.

Empirical studies that use portfolio sorts based on cryptocurrency characteristics are significantly affected by the survivorship and delisting bias. The extraordinary high number of delistings in cryptocurrency markets makes it particularly important to correct for both biases and avoids spurious findings.

REFERENCES

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Ardia, David, Emanuele Guidotti, and Tim Alexander Kroencke, 2021, Efficient Estimation of Bid-Ask Spreads from Open, High, Low, and Close Prices, *Working paper, University of Neuchatel* .

Armin, Gaurav S, and Harry M. Hat, 2003, Welcome to the Dark Side, *The Journal of Alternative Investments* 6, 57–73.

Atilgan, Yigit, Turan G. Bali, K. Ozgur Demirtas, and A. Doruk Gunaydin, 2019, Global downside risk and equity returns, *Journal of International Money and Finance* 98, 102065.

Atilgan, Yigit, Turan G Bali, K Ozgur Demirtas, and A Doruk Gunaydin, 2020a, Left-tail momentum: Underreaction to bad news, costly arbitrage and equity returns, *Journal of Financial Economics* 135, 725–753.

Atilgan, Yigit, K. Ozgur Demirtas, and A. Doruk Gunaydin, 2020b, Downside beta and the cross section of equity returns: A decade later, *European Financial Management* 26, 316–347.

Bali, Turan G., Nusret Cakici, and Robert F. Whitelaw, 2011, Maxing out: Stocks as lotteries and the cross-section of expected returns, *Journal of Financial Economics* 99, 427–446.

Brown, Stephen J., William Goetzmann, Roger G. Ibbotson, and Stephen A. Ross, 1992, Survivorship Bias in Performance Studies, *Review of Financial Studies* 5, 553–580.

Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cong, Lin William, George Andrew Karolyi, Ke Tang, and Weiyi Zhao, 2022, Value Premium, Network Adoption, and Factor Pricing of Crypto Assets, *Working Paper, Cornell University* .

Conlon, Thomas, and Richard J. McGee, 2020, Betting on Bitcoin: Does gambling volume on the blockchain explain Bitcoin price changes?, *Economics Letters* 191, 108727.

Davis, James L., 1996, The cross-section of stock returns and survivorship bias: Evidence from delisted stocks, *Quarterly Review of Economics and Finance* 36, 365–375.

Elfakhani, Said, and Jason Wei, 2003, The survivorship bias, share price effect, and small firm effect in Canadian markets, *Review of Financial Economics* 12, 397–411.

Fidelity Investments, 2020, Growing Number of Institutional Investors Believe That Digital Assets Should Be a Part of Their Investment Portfolios.

Fung, William, and David A. Hsieh, 1997, Survivorship bias and investment style in the returns of CTAs, *Journal of Portfolio Management* 24, 30–41.

Fung, William, and David A. Hsieh, 2000, Performance Characteristics of Hedge Funds and Commodity Funds: Natural vs. Spurious Biases, *The Journal of Financial and Quantitative Analysis* 35, 291.

Gkillas, Konstantinos, and Paraskevi Katsiampa, 2018, An application of extreme value theory to cryptocurrencies, *Economics Letters* 164, 109–111.

Goetzmann, William N., Roger G. Ibbotson, and Stephen J. Brown, 1999, Offshore Hedge Funds: Survival & Performance 1989-1995, *Journal of Business* 72, 91–117.

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

Grobys, Klaus, and Niranjan Sapkota, 2019, Cryptocurrencies and momentum, *Economics Letters* 180, 6–10.

Hu, Albert S., Christine A. Parlour, and Uday Rajan, 2019, Cryptocurrencies: Stylized facts on a new investible instrument, *Financial Management* 48, 1049–1068.

Ince, Ozgur S., and R. Burt Porter, 2006, Individual Equity Return Data from Thomson Datastream: Handle with Care!, *Journal of Financial Research* 29, 463–479.

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

Kahneman, Daniel, and Amos Tversky, 1979, Prospect theory: An analysis of decision under risk, *Econometrica* 47, 363–391.

Kaiser, Lars, and Sebastian Stöckl, 2020, Cryptocurrencies: Herding and the transfer currency, *Finance Research Letters* 33, 101214.

Kashefi Pour, Eilnaz, and Meziane Lasfer, 2013, Why do companies delist voluntarily from the stock market?, *Journal of Banking & Finance* 37, 4850–4860.

Lansky, Jan, 2019, Cryptocurrency Survival Analysis, *The Journal of Alternative Investments* 22, 55–64.

Li, Yi, Wei Zhang, Xiong Xiong, and Pengfei Wang, 2020, Does size matter in the cryptocurrency market?, *Applied Economics Letters* 27, 1141–1149.

Liebi, Luca J., 2022, Is there a value premium in cryptoasset markets?, *Economic Modelling* 109, 105777.

Liu, Weiyi, Xuan Liang, and Guowei Cui, 2020, Common risk factors in the returns on cryptocurrencies, *Economic Modelling* 86, 299–305.

Liu, Yukun, and Aleh Tsyvinski, 2021, Risks and Returns of Cryptocurrency, *The 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.

Long, Huaigang, Adam Zaremba, Ender Demir, Jan Jakub Szczygielski, and Mikhail Vasenin, 2020, Seasonality in the Cross-Section of Cryptocurrency Returns, *Finance Research Letters* 35, 101566.

Malkiel, Burton G., 1995, Returns from Investing in Equity Mutual Funds 1971 to 1991, *Journal of Finance* 50, 549–572.

Pelster, Matthias, Bastian Breitmayer, and Tim Hasso, 2019, Are cryptocurrency traders pioneers or just risk-seekers? Evidence from brokerage accounts, *Economics Letters* 182, 98–100.

Rohleder, Martin, Hendrik Scholz, and Marco Wilkens, 2011, Survivorship Bias and Mutual Fund Performance: Relevance, Significance, and Methodical Differences, *Review of Finance* 15, 441–474.

Schmidt, Peter S., Urs von Arx, Andreas Schrimpf, Alexander F. Wagner, and Andreas Ziegler, 2019, Common risk factors in international stock markets, *Financial Markets and Portfolio Management* 33, 213–241.

Shumway, Tyler, and Vincent A. Warther, 1999, The Delisting Bias in CRSP's Nasdaq Data and Its Implications for the Size Effect, *Journal of Finance* 54, 2361–2379.

Wei, Wang Chun, 2018, Liquidity and market efficiency in cryptocurrencies, *Economics Letters* 168, 21–24.

Zhang, Wei, and Yi Li, 2020, Is idiosyncratic volatility priced in cryptocurrency markets?, *Research in International Business and Finance* 54, 101252.

Zhang, Wei, Yi Li, Xiong Xiong, and Pengfei Wang, 2021, Downside risk and the cross-section of cryptocurrency returns, *Journal of Banking & Finance* 133, 106246.

VII. Appendix

Figure A1. Coinmarketcap Listing Criterias

This table provides an overview of Coinmarketcap listing criteria. Panel A depicts the guidelines for an asset to be classified as a cryptocurrency. Panel B reports the possible project status. Panel C documents how Coinmarketcap decides on delisting a project.

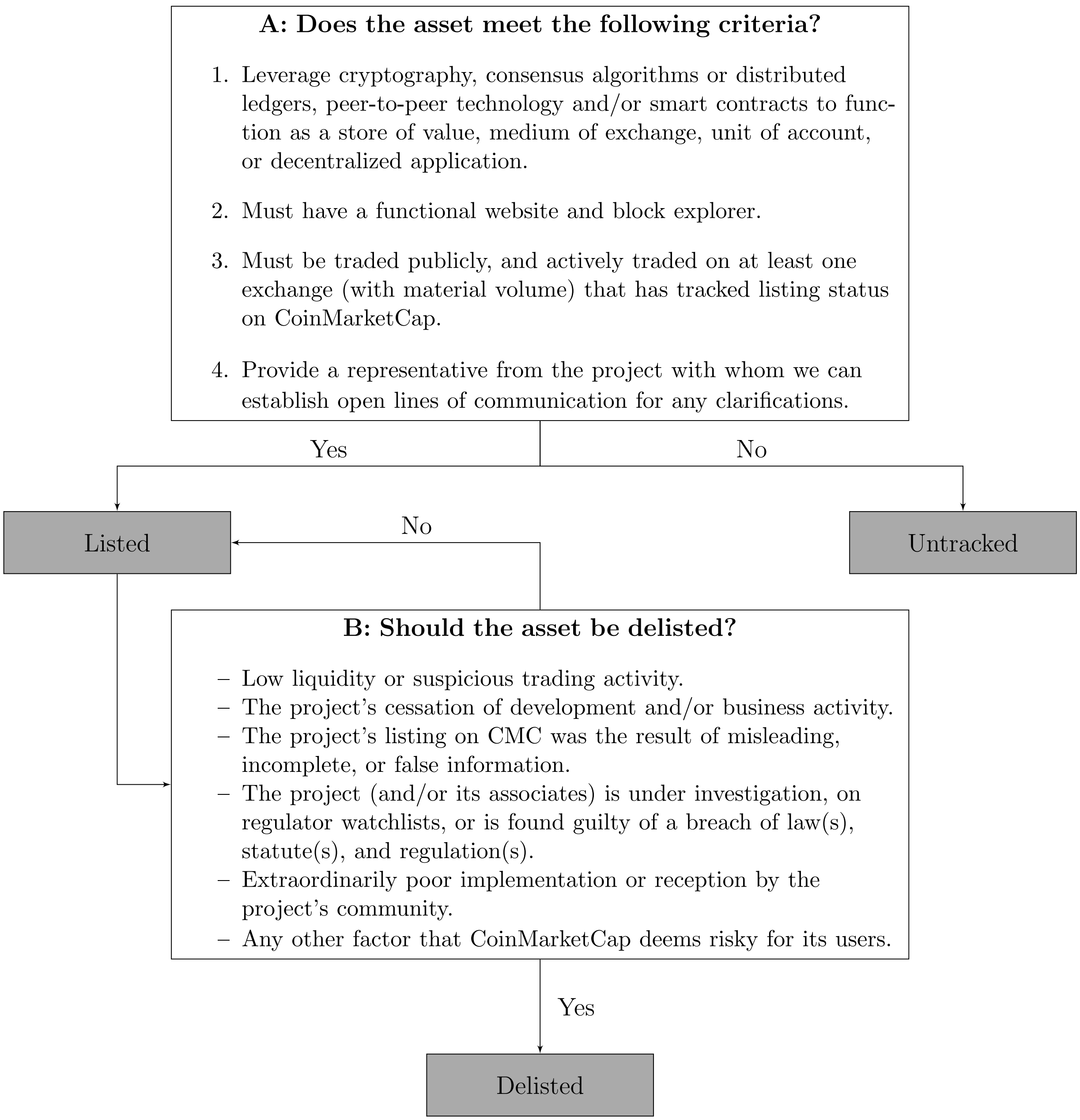


Table A1 Delisting Classification

This table summarizes all delisting reasons and the corresponding classification. Overall, we identify six delisting reasons a cryptocurrency can be delisted. For each reasons, we provide the id, classification, description and the delisting return.

Id	Classification	Description	Delisting Return
10	Commitment (abandoned)	Neither the developer nor anyone else does want to continue maintaining and developing the cryptoasset. Reasons might either be, that the contract is not very well designed, the payoff does not compensate the amount of work or generally no one is interested in the cryptoasset. This leads to abandonment of the project and eventual delisting from exchanges	-1
11	Swap	Another reason is, that a contract is not well designed and needs to be changed or upgraded, which makes a relaunch necessary - possibly on a new blockchain (e.g. summercoin $\longrightarrow$ summercoin2 $\longrightarrow$ navajocoin). In this case the developers will announce the relaunch (usually this involves the emission of a new cryptoasset with its own symbol) and offer holders of the coin a swap to the new contract. Depending on the reach of this announcement, the time allowed for the swap as well as the difficulty of the swapping procedure, some asset holders with swap their contract and potentially not lose money (depending on the design and marketing of the new contract this might actually be generating a profit for the swapping party). Others might not notice the limited swapping time, or fail with the procedure. Eventually, once the original cryptoasset is abandoned by the developers, the asset will be delisted and whoever did not swap might lose his investment. The delisting return assigned by us depends crucially on whether the swapped asset is available on CMC latest 30 days after the delisting (delisting return of 0), available elsewhere (if data is available calculate detailed delisting return using 30 days of data. If no data is available, we set the delisting return to a careful 0%. In case of no further listing we depict a delisting return of -1.	Coin dependant
12	CMC Regulatory	The developers keep a cryptoasset active but it still is delisted from CMC for various reasons. In this case, the cryptoasset can still be bought and sold on other (potentially smaller) exchanges. We check on other data collection portals and, if not available, on other exchanges for the price of the crypto asset on the 30 days after delisting from CMC. Given, that volume on the alternative exchange is large enough, we use the average 30-day price after delisting to calculate a delisting return. In case of no data availability we depict a delisting return of 0%).	Coin dependant
20	Scam	The developer is gone unannounced with all available funds and leaves the project abandoned. We only classify delisting returns if the scam can be proven (e.g. dedicated article on medium or lawsuit evidence).	-1
30	Technical issue	Technical issues equal a broken contract (e.g. that allows to mine an infinite amount of coins like Dimcoin, which was a possible scam at the same time. In this case, trading will cease and not pick up again. Exchanges will delist the cryptoasset.	-1
40	Not available	If the delisting reason is not available, we classify this coin as "not available". The delisting return equals -100%.	-1

Table A2 Entry, Dissolution and Attrition Rates of Cryptocurrencies

This table reports the number of listed cryptocurrency at the beginning and end of each year; 07-January-2014 to 28-December-2021, 417 weeks. The entry (dissolution) column reports the number of cryptocurrencies that entered (dissolved) within each year. The number of cryptocurrencies that are listed and delisted in the same year are reported in the sixth column. The attrition rate equals the number of dissolutions minus cryptocurrencies that are listed and delisted in the same year divided by the number of cryptocurrencies at the beginning of each year. In the last row, we report the average attrition rate across the seven years.

Year	Year Start	Entry	Dissolution	Year End	Listed & Delisted in the same year	Attrition Rate (%)
2014	74	607	170	511	170	0
2015	499	289	196	592	79	23.45
2016	592	208	216	584	24	32.43
2017	585	506	123	968	32	15.56
2018	971	650	336	1285	21	32.44
2019	1290	392	166	1516	3	12.64
2020	1520	638	8	2150	1	0.46
2021	2159	530	7	2682	2	0.23
Average						14.65

Table A3 Summary Statistics

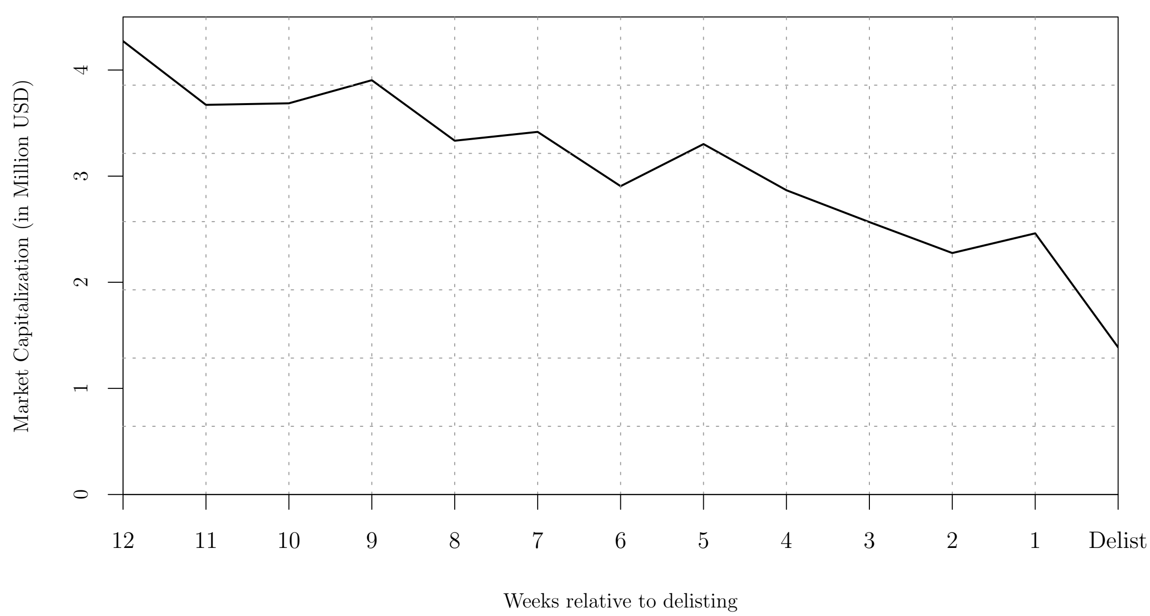
Summary statistics (number of observations (N), Mean, standard deviation (Sd), minimum (min), 25% quantile (Q1), median, 75% quantile (Q3), and maximum (max)) of weekly observations; 07-January-2014 to 28-December-2021, 417 weeks, 3'904 cryptocurrencies. Summary statistics contain weekly returns, market return, size (natural logarithm of market cap), market beta (estimated from t-365 days until t), momentum (cumulative return from t-7 until t), weekly trading volume (in million USD), and market capitalization (in million USD) Weekly returns are trimmed at the 99% level. Note that for the size variable we replaced -Inf values with NAs.

	N	Mean	Sd	Min	Q1	Median	Q3	Max
Return	440217	0.02	0.33	-1.00	-0.14	-0.01	0.12	2.26
Market Return	416	0.01	0.11	-0.35	-0.05	0.01	0.07	0.39
Size	445977	13.89	3.24	6.43	11.58	14.03	16.17	21.55
Market Beta	38825	0.87	0.33	0.01	0.65	0.93	1.10	1.59
Momentum	439258	0.02	0.33	-1.00	-0.14	-0.01	0.12	2.26
Volume (in million USD)	436619	241.46	5753.99	0.00	0.00	0.09	2.71	669947.06
Market Cap (in million USD)	446791	334.54	11121.91	0.00	0.11	1.23	10.52	1263667.11

Figure A2. Average Market Cap and Trading Volume around Delistings

This figure depicts average market capitalization (Panel A), and average weekly trading volume (Panel B) for delisted cryptocurrencies. Averages are reported 12 weeks before delisting.

(a) Average market cap around delistings



(b) Average trading volume around delistings

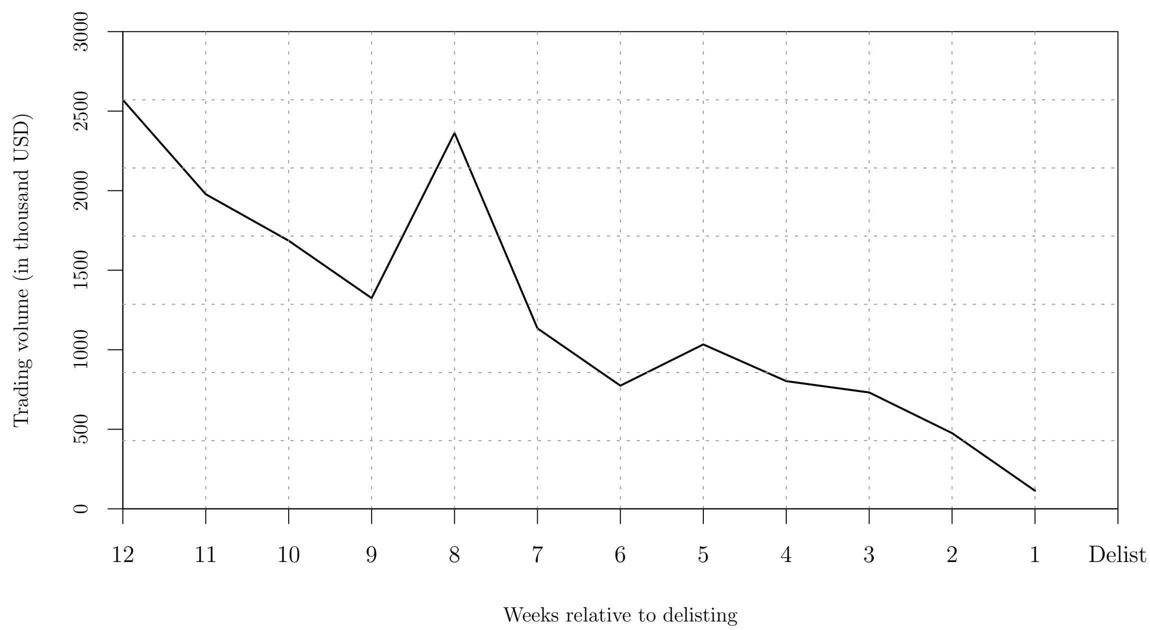


Table A4 Number of Cryptocurrencies by Their Trading Period

This table provides an overview of the number of cryptocurrencies according to their trading period; 07-January-2014 to 29-December-2021, 417 weeks.

Trading Weeks	Number of Cryptocurrencies	Trading Weeks	Number of Cryptocurrencies	Trading Weeks	Number of Cryptocurrencies
Panel A: Delisted					
0-20 weeks	270	141-160 weeks	43	281-300 weeks	3
21-40 weeks	208	161-180 weeks	34	341-360 weeks	3
41-60 weeks	141	181-200 weeks	22		
61-80 weeks	159	201-220 weeks	31		
81-100 weeks	115	221-240 weeks	27		
101-120 weeks	93	241-260 weeks	21		
121-140 weeks	42	261-280 weeks	10		
Panel B: Survived					
0-20 weeks	30	141-160 weeks	150	281-300 weeks	36
21-40 weeks	310	161-180 weeks	271	301-320 weeks	16
41-60 weeks	331	181-200 weeks	166	321-340 weeks	29
61-80 weeks	345	201-220 weeks	228	341-360 weeks	23
81-100 weeks	145	221-240 weeks	123	361- or more	130
101-120 weeks	107	241-260 weeks	51		
121-140 weeks	169	261-280 weeks	22		

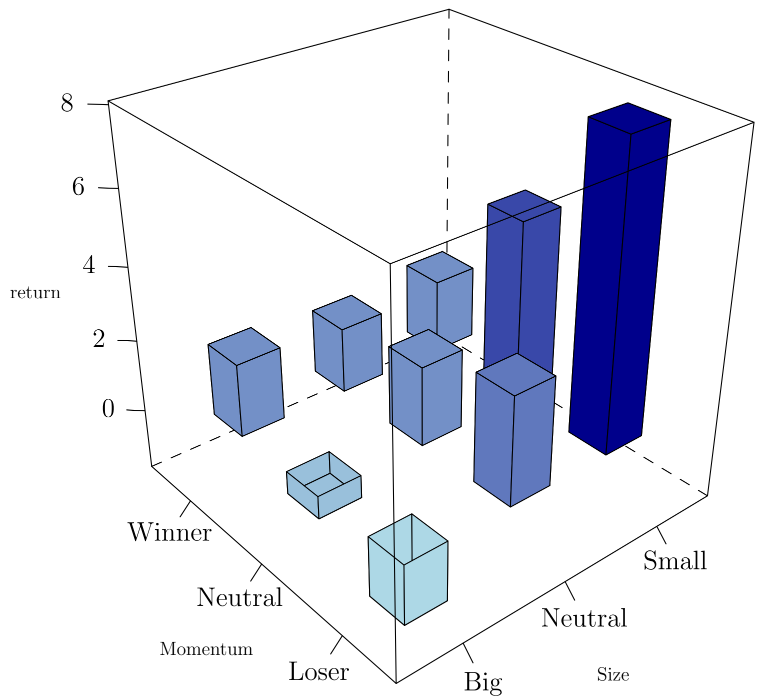


Figure A3. 3x3 Independent momentum-size sort

Averages of weekly percent excess returns for value-weighted portfolios formed on 7-day momentum and size; 07-January-2014 to 29-December-2021, 417 weeks. At the end of each Tuesday (=t), cryptocurrencies are allocated independently into three momentum and three size groups. The intersection of the two sorts produces nine portfolios. Then, value-weighted returns are calculated from Tuesday (t) to Tuesday in the consecutive week (t+1).

Table A5 Static Screens

Screen Identifier	Short Description	Variable Involved
SS01	We exclude cryptocurrencies that are marked as untracked by Coinmarketcap. Untracked coins are identified by a value of -1 in the is_active column.	Type
SS02	We exclude all stablecoins from the sample. Stablecoins mimic real-world assets such as fiat currencies (e.g. Gemini Dollar, Binance USD, Tether, TrueUSD, and CryptoFranc), commodities (e.g. Tether Gold, and Paxos Gold), or other securities (e.g. Mirrored Google, Mirrored Netflix)	Type
SS03	We exclude derivative coins using name filters for cryptocurrencies. As an example, all coins that include (i.e. 1X Long, 2X Long, 3X Long, 1X Short, 2X Short, 3X Short) in their name are removed.	Type
SS04	All trading sets are removed. Trading sets represent trading strategies on other cryptocurrencies. We exclude tokens that include the substring "Trading Set" in their name.	Type
SS05	We exclude all coins for which no trading volume is reported at any point in time.	Volume
SS06	We exclude all coins for which no market cap is reported at any point in time.	Market Cap

Table A6 Dynamic Screens

Screen Identifier	Short Description	Variable Involved
DS01	We only keep observations since January 7^{th}, 2014. The start date coincides with when Coinmarketcap reports trading volume.	Beginning and end dates
DS02	We treat returns for which R_t or R_{t1} is greater than 1000% and $(1+R_t)(1+R_{t1})1$ is less than 100% as zero returns (this is similar to Schmidt et al. (2019) and Ince and Porter (2006)).	Return
DS03	We set all returns to missing, for which R_t is greater than 1000%.	Return
DS04	We set the market cap at time t to missing for which $\frac{\text{Market Cap}_t}{\text{Market Cap}_{t-1}} - 1$ is greater than 1000%.	Market Cap
DS05	When trading days of a cryptocurrency are missing, we forward fill price and market cap. For all missing days, R_t is set to missing. The first R_t that follows non-filled values is also set to missing as it represents the cumulative return over the missing period. Also the market cap is set to missing at this day.	Missing days