On the Performance of Cryptocurrency Funds*

Daniele Bianchi[§] Mykola Babiak[¶]

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Abstract

We investigate the performance of funds that specialise in cryptocurrency markets. In doing so, we contribute to a growing literature that aims to understand the value of digital assets as investments. The main empirical results support the argument that cryptocurrency funds generate significantly positive alphas compared to passive benchmarks or conventional risk factors. To understand whether the fund managers have sufficient skills to more than cover their costs, we compare the actual fund alphas against the simulated values from a panel semi-parametric bootstrap approach. The analysis shows that the extreme outperformance is unlikely to be explained by the luck of fund managers. However, the significance of the alphas becomes statistically weaker after considering the cross-sectional correlation in fund returns.

Keywords: Cryptocurrency markets, Alternative investments, Fund management, Bootstrap methods.

JEL codes: G12, G17, E44, C58

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§School of Economics and Finance, Queen Mary University of London. E-mail: d.bianchi@qmul.ac.uk Web: whitesphd.com

¶Department of Accounting and Finance, Lancaster University Management School, Lancaster. E-mail: m.babiak@lancaster.ac.uk Web: sites.google.com/site/mykolababiak

1 Introduction

With the rising prices and public awareness of Bitcoin, investors have been drawn to cryptocurrency markets by the promise of significant returns compared with the paltry or negative yields on offer from cash, bonds or other traditional asset classes.[1] The hyperbolic growth of cryptocurrency markets – with a market capitalisation that stands roughly at $2 trillion at the time of writing - has led to larger investments into a new category of specialised funds, namely cryptocurrency funds. While much of the trading is still due to individual investors buying and selling their own private stashes of digital assets, the increasing adoption of cryptocurrencies as a viable form of investment drove up demand from institutional investors.[2] The goal of this paper is to shed light on the value of active asset management in the cryptocurrency space and the potential role of institutional investors in such a new and still relatively unknown market.

Beginning with Jensen (1968), the ability of fund managers to create value for investors has been studied extensively in the academic literature, especially following the growing popularity of more passive and cheaper forms of investment such as exchange-traded funds (ETFs).[3] Despite the conventional wisdom, which holds that a search for securities that could possibly outperform the market may be worth the expenses required, the empirical evidence on the value of active management is mixed at best (see Cremers et al., 2019 for an extensive review of the literature). Furthermore, such evidence is mostly focused on the US equity mutual fund industry.

We contribute to this debate by investigating the value of delegated active investment management through the lens of the new and fast-growing cryptocurrency markets. Specifically, we focus on the extent and the significance of the benchmark- and risk-adjusted performance for a representative set of funds that specialize in cryptocurrency investments. Although the depth and width of the investment management industry in the cryptocurrency space is not comparable with equity markets, cryptocurrency funds provide a peculiar context through which the value of active asset management can be further understood. The reason is threefold. First, because cryptocurrency markets have a

[1]At the time of writing there are more than 13,000 digital assets. The assets have different characteristics and features, and are traded on more than 300 exchanges worldwide (see `http://Coinmarketcap.com`).

[2]The anecdotal evidence is substantial. For instance, on June 2020 Fidelity ran a survey on more than 800 institutional investors from the EU and the US. The results showed that about a third of those investors owned digital assets. After two months, Fidelity launched its own Bitcoin fund for wealthy investors (see link here)

[3]Leading examples of this research can be found in Ippolito (1989); Gruber (1996); Wermers (2000); Davis (2001); Bogle (2005); Kacperczyk et al. (2005); Kacperczyk and Seru (2007); French (2008); Barras et al. (2010); Fama and French (2010); Amihud and Goyenko (2013); Kacperczyk et al. (2014); Berk and Van Binsbergen (2015); Moneta (2015); Pástor et al. (2015); Kacperczyk et al. (2016); and Hoberg et al. (2017) among others.

highly fragmented, multi-platform structure, which is decentralised and granular, the pricing factors for standard asset classes may not apply to cryptocurrencies (see Yermack, 2013; Liu and Tsyvinski, 2020; and Bianchi and Babiak, 2021). Such potential market segmentation may entail relatively low return correlations with more standard asset classes. The top-right panel of Figure 1 reports the sample correlation between the returns of global ETFs from equity, bond, commodity, and real estate markets, buy-and-hold returns in Bitcoin or Ethereum, an equal- and value-weight market portfolio of cryptocurrencies and a variety of anomaly-based portfolio strategies. A more detailed description of the data is provided in Section 2. The sample correlation between cryptocurrency strategies and traditional asset classes ranges between 0 and 0.2, indicating substantial diversification benefits which can ultimately attract increasing capital flows.[4]

Second, competition in the crypto fund space is quite low compared to the traditional equity fund industry. Assets under management (AUM) are highly concentrated in a few funds. The top-left panel of Figure 1 shows the Lorenz curve, a visual representation of the Gini concentration index, for the size of cryptocurrency funds. The top 10% of the funds own roughly 90% of total assets; that is, the bottom 90% of the funds own only 10% of the AUM in the industry. Further, the top 1% of the funds manage more than 50% of the total AUM. Therefore, the crypto fund industry is far from being perfectly competitive, as perfect competition would correspond to the Lorenz curve having the 45 degree slope, and resembles an oligopoly where a few funds dominate the industry in terms of size.[5] In the empirical analysis, we document that managers of crypto funds are able to generate large and economically significant alphas, which may be explained by low competition in the cryptocurrency market. Further, we demonstrate that this performance is not dominated by a given strategy over others. Instead, we find that a fraction of fund managers outperform others irrespective of the investment strategy adopted.

Third, there is generally rather lax regulatory oversight on funds that specialise in cryptocurrency investments. The bottom panels of Figure 1 show that, although around half of the funds in our sample are based in the US, only 8% of all funds are actually SEC registered and regulated. In

[4]For instance, on May 2, 2019, Fidelity released the results of a large-scale survey and found that nearly half of traditional institutional investors surveyed found digital assets' low correlation to be a highly appealing characteristic. Surveyed participants acknowledged such property could spark more investments in the cryptocurrency space. Fidelity's report on the survey can be found here.

[5]The straight diagonal line with a slope of 1 represents perfect equality in distribution for the variable of interest; the Lorenz curve lies beneath it, showing the observed or estimated distribution. The area between the straight line and the curved line, expressed as a ratio of the area under the straight line, is the Gini coefficient, a scalar measurement of inequality.

addition, within the other half of the funds that are not based in the US, a relevant fraction of these is based in jurisdictions which do not regulate cryptocurrencies as securities or risky investments. These include some European countries and fiscal paradises. The lack of regulation could affect the managers' decisions and risk-taking behaviors. For instance, Novy-Marx and Rauh (2011) and Andonov et al. (2017) show that the regulation of US public pension funds links their liability discount rate to the expected return on assets, affecting the risk-taking by US public funds.

Among others, these three aspects jointly make institutional investing in cryptocurrencies quite unique. We argue that such a setting could help shed further light on the value of active asset management above and beyond the exposure to market trends, risk factors and the inevitable random component in the realised returns. The latter is particularly relevant in the context of cryptocurrency markets, characterised by an incredibly high volatility in returns, which may make disentangling *skill* versus *luck* more difficult. Throughout the paper we look at *skill* at the fund level, as we do not keep track of changing managers. In other words, within our context the definition of manager and fund coincide. The relatively short average length of the funds' life allows us to conjecture, to some extent, that there is not much turnover within groups of funds. Also, by *skill* we follow the definition of Kosowski et al. (2006) and Fama and French (2010), namely that a given fund's performance net of fees and exposure to sources of risk cannot simply reconciled by the random sampling variation of the returns.

Empirically, we look at the performance of 250 funds that specialise in cryptocurrency investments and have been actively managed from March 2015 to June 2021. To avoid survivorship bias, the sample includes not only currently active funds, but also funds that have been closed before the end of the sample. Although the sample size is limited, it is fairly representative of all market phases as is illustrated in Figure 2. The left panel shows the compounded returns, assuming a $1 initial investment in March 2015, of a value-weight market portfolio of the top 100 cryptocurrencies, sorted on average market capitalisation. The cryptocurrency market experienced a significant boom until December 2017, a major collapse from January 2018 to April 2018 – the so-called ICO bubble burst – and then traded sideways until mid-2020. After a major market drop in the early stage of the COVID-19 pandemic, the market soared with Bitcoin, Ethereum and all other major cryptocurrencies reaching record high prices by early 2021. Furthermore, the sample period covers major regulatory and institutional changes, from the ban by the Chinese government on crypto exchanges and trading to the introduction of tradable Bitcoin futures contracts on the Chicago Mercantile Exchange (CME). The right panel of Figure 2 further shows that the average crypto fund significantly outperformed both the average hedge fund and the aggregate equity market. For instance, the average crypto fund generated an astonishing 600% cumulative log-return, while equity funds exhibited a cumulative raw performance of 40% to 70% over the same period. In addition, the average crypto fund did not plummet in value during the early stages of the COVID-19 pandemic unlike equity investments. This evidence suggests that cryptocurrency funds may provide true diversification for the average investor. The significant gap in the performances of funds specializing in traditional assets or cryptocurrencies also motivates the analysis of the risk-return trade-off of cryptocurrency investments. Liu et al. (2019) and Bianchi and Babiak (2021) develop factor models for cryptocurrency returns to better understand the astonishing performance and key drivers of digital assets.

In the empirical analysis, we begin by looking at the aggregate performance of crypto funds in excess of alternative passive investment strategies. The passive benchmarks include a buy-and-hold investment in Bitcoin (BTC), an equal-weight portfolio of the top cryptos by market capitalisation, akin to the "dollar risk factor" adapted to cryptocurrencies from Lustig et al. (2011), a value-weight average of the tokens listed on Coinbase, and a buy-and-hold investment in Ethereum (ETH). Specifically, we estimate the alpha generated by equal-weight portfolios of all funds as well as funds clustered based on their type and investment strategy. The results show that aggregate funds outperform passive benchmarks. Such a performance is not homogeneous, however, since the aggregate funds for `long-short` and `long-term` investment strategies generate higher alphas. A panel regression with fund type- or strategy-fixed effects and clustered standard errors yields a similar result. The evidence is slightly different when replacing the benchmark passive strategies with a set of factor portfolios following Liu et al. (2019) and Bianchi and Babiak (2021). Alphas tend to be lower and less significant when using common risk factors instead of tradable passive benchmark portfolios. Turning to the fund betas, there is significant market exposure across funds. Interestingly, Bitcoin plays the role of a "level" factor when it is used as an alternative to a value-weight market portfolio.

We delve further into the analysis of fund performances and propose a panel semi-parametric bootstrap, following Kosowski et al. (2006) and Fama and French (2010). Our approach is robust to both time-series and cross-sectional correlations and allows for both the strategy-specific exposures to passive benchmarks (risk factors) and the within-strategy return correlations. We assume that the distribution from which the cross-section of returns is jointly drawn is unknown ex-ante and that fund returns are possibly highly correlated within investment strategies. The latter is empirically motivated by the large differences in the alphas and the benchmark (factor) betas of aggregate funds for different investment strategies. Across a wide array of statistical tests, our main results show that the benchmark- or risk-adjusted alphas of crypto funds cannot be due simply to random sampling variation of the returns. That is, the extreme outperformance of crypto funds is unlikely to be explained by the luck of fund managers. Interestingly, these results are not driven by the outperformance of a particular investment strategy. There is no systematic dominance of one strategy over the others, but rather the superior alphas are mainly spread across three strategies: `long-term`, `long-short`, and `multi-strategy`. However, the significance of the alphas becomes statistically weaker after considering the cross-sectional correlation in fund returns.

We conduct a variety of robustness checks. First, we analyse the fund performance across sub-samples. In particular, we split the sample from March 2015 to December 2017 and from January 2018 to June 2021. The cut-off date of December 2017 is chosen to separate the period pre- and post-ICO bubble. It is fair to conjecture that the burst of the ICO bubble could mark a significant change in the profitability of cryptocurrency investments and hence the performance of crypto funds. In addition, only a handful of funds were actually active before late 2017, which may call into a question the significance of our main empirical results when including the pre-ICO bubble period. The main results of the paper hold across sub-samples. Second, in order to investigate the impact of some of our bootstrap assumptions, we redo the main empirical analysis on individual fund performances by relaxing some of the main modeling assumptions. The main results of the paper remain unchanged if we account for short-term time-series dependencies of fund and benchmark returns or if we independently resample risk factors and residuals. An additional online appendix shows the results of tests for the persistence in the fund alphas, following Carhart (1997). We document significant persistence in the alphas for the top performing managers, a finding consistent with the main empirical analysis.

This paper contributes to the existing debate on the value of active investment management. On the one hand, Jensen (1968) and Carhart (1997) argue that, on average, active management creates little value to investors. A number of papers support this claim by documenting that (i) the average fund underperforms after fees (Ippolito, 1989; Gruber, 1996; Wermers, 2000; Davis, 2001), (ii) there is no persistence in the performance of the best funds (Brown et al., 1992; Malkiel, 1995; Elton et al., 1996; Phelps and Detzel, 1997), and (iii) some fund managers have skill, but few are skilled in excess of costs (Fama and French, 2010). On the other hand, there is an emerging literature now advocating for the existence of a significant and persistent value of active investment management. Kosowski et al. (2006) use a new bootstrap statistical technique to demonstrate persistence in superior alphas of fund managers.[6] Kacperczyk et al. (2014) document a cognitive ability of investors to either pick stocks or time the market at different times. Berk and Van Binsbergen (2015) express a manager's "value-added" in dollar terms and show that the average mutual fund generates around \$3.2 million per year. Kacperczyk et al. (2016) further provide a new attention allocation theory explaining the existence of managerial skills. Our contribution to this literature is to examine the value of active investment management in an emerging category of cryptocurrency funds, which has not been investigated before.

2 Data

2.1 Fund returns

We construct a novel data set on the monthly returns for cryptocurrency funds from three main sources. First, we collect data on fund performances and characteristics from Crypto Fund Research (CFR) and from Preqin. The former is a web-based data provider that collects in-depth crypto fund data, while the latter provides data and analytics for alternative investments at large. Second, we complement the data from these sources by hand-collecting information directly from fund managers. Notice that managers report fund returns on a voluntary basis since there is no legal obligation to disclose their performance to the public. The data is not usually revised after reporting for the first time, though a small subset of managers provide estimates before fully reporting. To avoid any revision bias, we consider only the initially reported actual returns.

We have introduced a variety of checks and filters to ensure the data is sufficiently representative of specialised active investment in the cryptocurrency landscape. First, we excluded from the sample those funds with less than \$2mln in assets under management. The threshold seems low in absolute value, but in relative terms it is not, considering that the median AUM for crypto hedge funds is slightly more than \$40mln, with a distribution that is concentrated around a few large funds (see the top-left panel in Figure 1). Second, we consider raw returns net of all fees, including incentive fees

[6] A number of early papers draw a similar conclusion by applying a "false discoveries" technique (Barras et al., 2010), Bayesian probability approaches (Busse and Irvine, 2006; Avramov and Wermers, 2006; Huij and Verbeek, 2007), or using filters to control for estimation errors (Mamaysky et al., 2007).

and management fees. The vast majority of the funds apply a typical 2% management fee + a 20% performance fee. Only a few funds apply a high-watermark threshold. Returns are all expressed in US dollars. By considering net-of-fee returns, our aim is to investigate whether fund managers can generate benchmark- or risk-adjusted returns above and beyond the expenses an investor nominally encounters. Third, to avoid survivorship bias, the sample includes not only those funds that are still actively quoted, but also those that have been closed before the end of the sample; the only requirement is that a fund should have at least 12 months of monthly return history.

After the filters above have been implemented, the data consists of a maximum of 204 different funds which have been actively managed for at least 12 months between March 2015 to June 2021. The bottom-right panel in Figure 1 shows the geographical distribution of the funds. Of note is that the majority of the funds are headquartered either in the US, Europe or the UK, while only a small fraction of institutional investors are located in Asia and countries often considered fiscal paradises. The remaining funds, although a residual part, are located in peripheral countries such as Russia, Brazil, and Australia.

Although the number of funds is relatively small, there is a substantial cross-sectional variation in the raw returns. Figure 3 reports a set of box charts which summarise the cross-sectional distribution of a variety of descriptive statistics such as the Sharpe ratio, returns skewness, autocorrelation, and the market beta. For the market beta, a value-weight portfolio of the top 100 cryptocurrencies by market capitalisation is used as a proxy of market risk. Contrary to conventional wisdom, not all of the funds generate positive average raw returns. Indeed, the left panel shows that a non-trivial fraction of the funds generate negative Sharpe ratios unconditionally. The distribution of Sharpe ratios is also highly positively skewed. While the median Sharpe ratio is equal to 1.1 annualised, the mean is equal to 1.3 in annual terms. The sample skewness also shows that the vast majority of fund returns are highly positively skewed. The right panel of Figure 3 shows two additional interesting insights. First, there is very low persistence in the fund returns, with an average AR(1) coefficient of 0.12. The 25th and 75th percentiles of the distribution of individual AR(1) coefficients are around 0.0 and 0.3, respectively, while the range of all values is from -0.5 to 0.7. Although a majority of funds tend to have a negligible autocorrelation in their returns, a small fraction show some sizable autocorrelation and some funds exhibit a reversal in their performances. Second, the exposure of funds to market risk is notably heterogeneous, with a median market beta of around 0.4.

2.1.1 Fund types. We focus on four categories of crypto funds: `hedge fund` (HF), `tokenized fund` (TF), `managed account` (MA), and `fund of funds` (FoF). We exclude private equity and venture capital funds given their valuations are much more sparse and data is highly scattered throughout the sample. A crypto `hedge fund` and `managed account` work in the same way as standard hedge and mutual funds, respectively, whereby high-net-worth individuals can access a high degree of customisation, expertise and greater tax efficiencies. By contrast, a `tokenized fund` is specific to the cryptocurrency space. Participating in a TF is similar to buying shares of a regular fund except that quotas are bought in the form of crypto-coins or tokens. The main advantage for investors is tradability, as shares in the `tokenized fund` can be freely traded on a secondary market. A `fund of funds` takes a multi-manager approach and invests in a set of different funds. There is no structural difference between a regular fund of funds and a crypto fund of funds. The left panel of Figure 4 shows a breakdown of the funds by their type. The HF category constitutes the vast majority of funds in our sample with around 60% of the managers. The TF group ranks second (10%), while even a smaller fraction of funds is labelled as MA (8%) or FoF (6%). There is a residual category of funds dubbed `other`, which consists of those funds for which we cannot provide a reliable classification.

Table 1 reports a set of descriptive statistics at the aggregate level (first column) by taking an equal-weight average of all funds in our sample and at a more granular fund type level (from column two to column six) by averaging out the returns of the funds pertaining to a given type. First, the annualised Sharpe ratio of the average fund (1.83) is higher than the cryptocurrency market portfolio (1.22), a buy-and-hold investment in Bitcoin (1.19) or Ethereum (0.99) as shown in Table 2. In addition, the returns on the average fund are positively skewed and have an AR(1) coefficient of 0.27. Next, the average returns per each fund type exhibit a range of high volatilities, which translate into annualised Sharpe ratios between 1.56 for the `other` category and 2.14 for the `managed account` group. In general, the returns of aggregate crypto funds are relatively persistent, with the highest AR(1) coefficients being equal to 0.29 for a `managed account` and 0.43 for a `tokenized fund`.

Panel B in Table 1 reports the descriptive statistics of proxies for global equity, bond, commodity, and real estate investments. We measure these investments via global ETFs from traditional asset classes: the Vanguard Total World Stock Index Fund ETF, the iShares Global Corporate Bond UCITS ETF, the S&P GSCI Commodity Index ETF, and the iShares Global REIT ETF. In addition, we include two traditional hedge fund indices such as the Barclay Hedge Fund and the Eurekahedge

Hedge Fund indices. Both indices represent equal-weight aggregation of individual returns from a large cross section of conventional hedge funds. Two observations are noteworthy. First, except for bonds, the index returns for other asset classes are negatively skewed, with the most negative skewness for the real estate ETF. Second, perhaps with the only exception of the Eurekahedge Index, which has an annualised Sharpe ratio of 1.17, none of the index returns from traditional asset classes is comparable with cryptocurrency funds in terms of Sharpe ratios. Panel C in Table 1 reports the correlations between the aggregate fund returns and the proxies of traditional investments. The unconditional correlations seem to extend to the institutional investment landscape the otherwise conventional wisdom that cryptocurrency returns may offer some diversification benefits to investors (see, e.g., Yermack, 2013; Liu and Tsyvinski, 2020; Bianchi et al., 2020). Historical correlations of monthly returns are quite mild across the board and range between 0.05 and 0.30 across different types of funds.

2.1.2 Investment strategies. The investment strategies of crypto funds can be classified in a similar way to traditional equity funds. Based on the information provided, we can group funds into five categories: `long-short`, `long-term`, `market neutral`, `multi-strategy`, and `opportunistic`. The strategy labels are allocated based on the information provided by the data sources, or are disclosed by the managers for those funds that have been hand-collected. `Long-short` funds primarily employ a short/medium term systematic quantitative investment process, which seeks to capitalise on the volatile behaviour of cryptocurrencies.[7] `Long-term` crypto funds tend to invest in early-stage token/coin projects, as well as to implement long-only strategies in the largest and more liquid cryptocurrencies. They tend to have the longest lock-up periods for investors. `Market neutral` crypto funds seek to have a neutral exposure to the market trend by overweighting or underweighting certain digital assets with respect to their market weight. Unlike `long-short` funds, `market neutral` strategies focus on making concentrated bets based on pricing discrepancies across cryptocurrencies, with the main goal of achieving a lower market beta to hedge out systematic risk. `Opportunistic` crypto funds target underpriced digital assets with the goal of exploiting special situations; these can take many forms such as announcements of joint ventures, forks, bugs in the protocols, and any other event that might affect a digital asset's short-term prospects. Finally, `multi-strategy` crypto funds

[7]The short side of the trades is often taken through derivatives contracts, such as futures traded on major exchanges including Binance, BitMEX, and Huobi Futures. To have a sense of the size of the derivatives market in the crypto space, the interested reader can look at `Coingecko.com`.

adopt a combination of the above strategies. For instance, within the limitation set in the prospectus, a `multi-strategy` crypto fund may be managed in part through a long-only strategy and in part as a long-short leveraged investment.

The right panel of Figure 4 shows that funds adopting `opportunistic` strategies are the minority, with only 2% of the funds in our sample. Although almost two-thirds of the funds implement either a `long-short` or a `long-term` strategy, Figure 4 shows that the composition of the sample of funds is somewhat heterogeneous in terms of investment styles. The last five columns of Table 1 report the performance of the average fund when grouped by investment strategy. There is significant heterogeneity in the raw performance of funds across different clusters; for instance, `multi-strategy` and `long-short` funds report a Sharpe ratio that is almost 50% higher than `market neutral` funds. The latter, however, have the lowest volatility, with a monthly standard deviation of the returns that is four times smaller than `long-term` funds. Similar to the average fund returns and returns aggregated per fund type, Panel B shows that, perhaps with the only marginal exception of the `market neutral` strategy, the average fund in each investment strategy tends to outperform investments in traditional asset classes. Interestingly, Panel C shows that `opportunistic` crypto funds tend to have a slightly higher correlation with traditional investments, which can be as high as 0.4.

2.2 Passive benchmark strategies and risk factors

We compare the fund returns against a set of alternative passive investment strategies (see, e.g., Berk and Van Binsbergen, 2015 and Dyakov et al., 2020), as well as a set of risk factors. The reason why we evaluate fund performances based on both passive benchmarks and risk-based portfolios is twofold. First, within the context of cryptocurrency markets, the use of passive investment benchmarks to extract the fund alphas is arguably more realistic than using factor portfolios. Passive investment strategies, such as a buy-and-hold investment in BTC, are the actual benchmarks used by the vast majority of the funds in our sample to calculate performance fees. In contrast, factor portfolios in the cryptocurrency space do not necessarily represent actual alternative investment opportunities, since they rarely incorporate transaction costs and trading restrictions. Such a discrepancy between the construction of factor portfolios and their actual implementation could result in systematic biases when estimating fund alphas (see, e.g., Huij and Verbeek, 2009). Second, despite its limitations, calculating risk-adjusting returns by conditioning on factor portfolios is still common practice in the mutual funds literature (see, e.g., Cremers et al., 2019). This justifies the use of both approaches.

2.2.1 Passive benchmark strategies. To construct the passive benchmarks and risk factors, we obtain data on daily prices and trading volumes from `Cryptocompare.com`, a web-based data provider that collects data from multiple exchanges. The data integrates transactions for over 300 exchanges globally. Recent work by Alexander and Dakos (2019) suggests that Cryptocompare data is among the most reliable for use in academic and practical settings.[8] We obtained data on a daily basis for the sample period from March 1st 2015 to June 31st 2021. The data is aggregated across exchanges based on a volume-weighting scheme, that is, prices and trading volumes, both expressed in USD, are averaged across exchanges based on the average daily trading volume on a given exchange. The aggregation thus gives the most liquid market prices more importance, while the price impact of illiquid exchanges – and therefore more sensitive to exogenous shocks – is negligible.

In order to mitigate the impact of erratic and fraudulent trading activity, we apply a variety of filters. First, trade outliers are excluded from the calculation of trading volume. For a trade to be considered an outlier, it must deviate significantly either from the median of the exchanges or from the previous aggregate price.[9] Second, exchanges are reviewed on a regular basis for each given cryptocurrency pair. Constituent exchanges are excluded if (1) posted prices are too volatile compared to the market average; (2) trading has been suspended by the exchange on a given day; (3) there are reports of false data provision; or (4) there is a malfunctioning of the public API of a given exchange.

The aggregate market price takes the last trade time into account to ensure that the exchanges, which are excluded on a given month, have an expiring price impact. Therefore, the last price on a given exchange expired with time and the aggregation move with the market without being affected significantly by the changes in the exchange composition. These steps mitigate the effect of fake volume and substantially reduce the exposure of the empirical analysis to concerns of misreporting of trading activity for some exchanges.

To reduce the impact of bias in selecting the benchmark returns, we choose four different strategies that are fairly representative of the spectrum of passive investments. We first consider a simple buy-and-hold investment either in BTC or in ETH, the two major digital assets currently traded. A third

[8]The reliability of CryptoCompare has been proven by a number of relevant strategic partnerships such as VanEck's indices division for pricing ETFs, Refinitiv (one of the world's largest providers of financial market data and infrastructure), and Yahoo Finance.

[9]These deviations can occur for a number of reasons, such as extremely low liquidity on a particular pair, erroneous data from an exchange, and the incorrect mapping of a pair in the API.

passive investment strategy is a simple equal-weight portfolio consisting of the top 100 cryptocurrencies in terms of market capitalisation. This is the equivalent of a *dollar risk* factor adapted from Lustig et al. (2011). The fourth passive benchmark replicates the so-called *Coinbase index*, which is a value-weight portfolio that give investors exposure to all cryptocurrencies listed on Coinbase and Coinbase Pro exchanges at each point in time.[10]

The first four columns of Table 2 report a set of descriptive statistics similar to Table 1. Compared to the average crypto fund, benchmark strategies earn a lower Sharpe ratio on an annual basis. This is primarily because they exhibit much higher volatility of returns than do crypto funds. This suggests that, on average, crypto funds produce returns per unit of risk, which are higher than the returns of cheaper passive investment strategies. Also, with the sole exception of BTC, all benchmark strategies show a positive skewness and exhibit weak persistence in realised returns.

2.2.2 Risk factors. Within cryptocurrency markets, a factor portfolio often does not represent a feasible investment strategy. The large investment frictions and costs retailers should face to take short positions make it prohibitive to implement profitable zero-cost long-short strategies based on individual characteristics such as momentum, liquidity, and volatility. Nevertheless, given their widespread use (see, e.g., Liu et al., 2019 and Bianchi and Babiak, 2021), it can still be useful to benchmark fund returns against factor portfolios (see, e.g., Barber et al., 2016; Berk and Van Binsbergen, 2016). Thus, we calculate risk-adjusted returns to compare our main results based on benchmark-adjusted returns to a more common approach taken in the literature. We construct a series of long-short portfolios to proxy risk factors based on the daily returns and volume data for a large cross-section of more than 300 cryptocurrencies. We follow Bianchi and Babiak (2021) and exclude stablecoins from the sample. The assets considered constitute approximately 90% of the total market capitalisation and trading activity as of June 2021.

We first consider the returns on a cross-sectional momentum strategy (`mom`) as outlined by Jegadeesh and Titman (2001), and on a simple reversal strategy that goes long on past losers and short on past winners (see De Bondt and Thaler, 1985). Both strategies are based on value-weighting schemes for the sub-portfolios. As far as the momentum strategy is concerned, the look-back period l is set to 6 months. For each cryptocurrency pair i at time t, if the cumulative log return over the

[10]Note that the fund returns are net of fees, whereas BTC, ETH and DOL are assumed to have no fee paid, and we assume a 70bps/month fee for ETF. A 0.7% fee for ETF is calculated by taking the average expense ratio of the top 8 blockchain ETF currently available on the market.

previous 180-days is positive; it signals a long position and vice versa. The skipping period for the returns calculation is one month after the portfolio is constructed. In addition, we consider two further sources of risk that are relevant in cryptocurrency markets: liquidity (`liq`) and volatility (`vol`) (see Bianchi and Dickerson, 2019). A typical way to proxy for liquidity risk would be to use high frequency information on bid-ask spreads. In the cryptocurrency space, however, such information is not easily available at the aggregate level. Bid-ask spreads on a single currency, at a given point in time, could substantially change across exchanges, generating fictitious arbitrage opportunities that are difficult to exploit in practice (see, e.g., Makarov and Schoar, 2020). For this reason, we follow Abdi and Ranaldo (2017) and Corwin and Schultz (2012) and proxy bid-ask spreads by using the aggregate open-high-low-close historical pricing data. For each day and for each of the cryptocurrency pairs, we calculate both the Abdi and Ranaldo (2017) and the Corwin and Schultz (2012) synthetic bid-ask spreads and take the average of the two measures. Next, we single sort each pair into quintiles based on the average bid-ask spread in a given month. A risk factor is then constructed by going long on an value-weight portfolio of illiquid pairs (fifth quintile) and going short into the liquid pairs (first quintile), again value-weight. This zero-cost long-short portfolio represents our liquidity factor portfolio.

Concerning the volatility portfolio, at each time t a rolling volatility estimate is computed using the average volatility estimator of Yang and Zhang (2000) within a given month. The volatility estimates are then lagged and the cross-section is then sorted from low to high volatility. The out-of-sample return is then computed by taking the value-weight mean of each decile. A short position is initiated in the sub-portfolio with the pairs that have the lowest volatility, whereas a long position is taken in the sub-portfolio with the pairs that have the highest volatility. This zero-cost long-short portfolio approximates the volatility risk factor through a tradable portfolio (see, e.g., Menkhoff et al., 2016). A similar logic applies to the construction of the short-term reversal (`rev`), in which assets are clustered into quintiles based on previous-day returns (see, e.g., Nagel, 2012). Finally, we consider the returns on the aggregate market (`mkt`) calculated as the returns on a value-weight portfolio of the top 100 cryptos by market capitalisation. The last five columns in Table 2 show summary statistics for the risk factors. With the sole exception of a pure reversal strategy, all factor portfolios deliver lower Sharpe ratios than the average fund. Similar to the fund returns, all risk-based portfolio returns have a positive skewness and very mild, if any, persistence, perhaps with the only exception being the reversal strategy.

3 Understanding the performance of crypto funds

3.1 Performance of aggregate funds

Table 1 shows that, at the aggregate level, crypto funds generate quite sizable returns and Sharpe ratios. We now first look at the benchmark- and risk-adjusted performance of aggregate funds. We define the alpha of a particular fund category as the expected value of the residual of a time-series regression without intercept, where the dependent variable is the returns of the aggregate fund and the independent variables are the returns of either passive benchmarks or risk factors. Formally, for each aggregate fund considered, we estimate a time-series regression $y_{kt} = \boldsymbol{\beta}_k' \boldsymbol{x}_t + \epsilon_{kt}$, where y_{kt} is the return of an equal-weight portfolio of crypto funds in a group k and $\boldsymbol{\beta}_k'$ is the exposure to passive benchmarks or risk factors $\boldsymbol{x}_t$. Note that despite the aggregation through equal weighting, the fund returns show significant outliers in the time series. To mitigate the effect of outlying observations on the regression estimates, we use a "bi-square" weighting scheme for the linear regression residuals. This method provides an effective alternative to deleting down-weight outliers altogether. Specifically, we first compute the residuals ϵ from the unweighted least squares estimate and then apply the following weight function $W(\epsilon) = \left(1 - \left(\frac{\epsilon}{6m}\right)^2\right)^2$, where m is the absolute deviation of the residuals. The weight is set to 0 if the absolute deviation of the residuals is larger than $6m$. This translates into a set of robust standard errors (and in turn t-statistics), which account for heteroskedasticity in the model residuals.

Once we estimate the betas with the robust estimator, we test for the significance of the time-varying alpha of the aggregate fund k defined as $\widehat{\alpha}_{kt} = y_{kt} - \widehat{\boldsymbol{\beta}}_k' \boldsymbol{x}_t$. We also report a direct test of the difference in the performance between the equal-weight portfolio of all crypto funds and the aggregate funds per each type or investment strategy. To test for the difference in their alphas, we use an approach á la Diebold and Mariano (2002). Specifically, we regress the difference in the benchmark- or risk-adjusted returns of a given fund type or investment strategy k, $\widehat{\alpha}_{kt}$, and the corresponding returns of the average crypto fund, $\widehat{\alpha}_{mt}$, onto a constant:

$$\widehat{\alpha}_{kt} - \widehat{\alpha}_{mt} = \gamma + \eta_t, \qquad \text{with} \qquad \widehat{\alpha}_{jt} = y_{jt} - \widehat{\boldsymbol{\beta}}_j' \boldsymbol{x}_t,\ j \in \{k, m\} \tag{1}$$

Testing for the difference in the performance boils down to a test for the significance in $\widehat{\gamma}$. In addition to the alphas of the aggregate funds estimated from time series regressions, we also obtain the alphas of funds per each type or investment strategy based on a panel regression. In this case, we work with the returns of individual funds instead of aggregate funds. Thus, we estimate a panel regression of individual fund returns with fund type or investment strategy fixed effects. In the estimation, we allow for type or strategy-specific exposures of fund returns to passive benchmarks or risk factors. Thus, the loadings vary across different groups of funds similarly to the betas obtained from a set of time-series regressions. Formally, we estimate a fixed effects model of the form $y_{ikt} = \alpha_k + \boldsymbol{\beta}_k' \boldsymbol{x}_t + \epsilon_{ikt}$, where y_{ikt} is the return at time t of a crypto fund i belonging to group k, α_k represents the alpha of funds for a given fund type or strategy k, and $\boldsymbol{\beta}_k'$ is the exposure of a given fund category k to the passive benchmark or risk factor $\boldsymbol{x}_t$.

3.1.1 Benchmark-adjusted alphas. Panel A of Table 3 reports the estimated alphas and t-statistics. When controlling for passive benchmarks, the average fund generates a significant alpha of 3.71% (t-stat: 3.91) on a monthly basis. A more granular classification by fund type shows that the performance is quite heterogeneous across different groups. For instance, an aggregate `tokenized fund` generates a monthly alpha of 8.15% (t-stat: 3.95), which is more than twice the alphas of a `fund of funds` (3.08%, t-stat: 2.90), a `hedge fund` (2.77%, t-stat: 3.30), and an `other` category (3.99%, t-stat: 2.70). Additionally, there is substantial heterogeneity across different investment strategies. The `long-short`, `long-term`, and `multi-strategy` funds record strongly significant alphas of 3.68% (t-stat: 3.54), 5.00% (t-stat: 3.32), and 2.64% (t-stat: 3.06) at monthly frequency, while an aggregate `market neutral` fund generates a borderline significant alpha.

Panel A of Table 3 further shows that the alphas of aggregate `tokenized` and `hedge funds` are larger and smaller, respectively, than the alpha of the average cryptocurrency fund in statistical terms. The performance of the remaining aggregate funds by their type is statistically comparable to the average fund. A similar degree of heterogeneity holds when clustering funds based on their investment strategy. An aggregate `market neutral` fund statistically underperforms the average cryptocurrency fund, with a difference of $\widehat{\gamma} = -2.54$ (t-stat: -2.92). The `multi-strategy` and `opportunistic` funds also underperform the average fund, although the difference in the performance is effectively zero in statistical terms. Overall, the results show that, at the aggregate level, cryptocurrency funds provide a positive value for investors by generating positive alphas.

Panel B of Table 3 reports the loadings of passive benchmarks from a set of time-series regressions. There is a substantial market level effect, which is captured by three passive benchmarks: BTC, ETH and ETF. When looking at the fund type classification, all aggregate funds are exposed to the market trend through a combination of significant loadings for the two largest cryptocurrencies (BTC and ETH) and other assets with the largest market size as proxied by ETF. Interestingly, an average `market neutral` fund is still correlated with BTC, which is unexpected given the nature of this strategy. The returns of aggregate funds for other investment strategies correlate significantly with the market movement. In sum, the results indicate that the heterogeneity in the benchmark-adjusted performances may be driven by the heterogeneous exposure of aggregate funds to passive investment strategies.

Panel C of Table 3 extends the time-series analysis of aggregate funds to a panel regression of individual funds with type or investment strategy fixed effects. It confirms that (1) there is substantial heterogeneity in the performances of aggregate funds across different types and investment strategies, and (2) the performances cannot be attributed solely to the exposure to the aggregate market trends as proxied by passive benchmarks.

3.1.2 Risk-adjusted alphas. Table 4 reports the results once we replace the passive benchmark portfolios with a set of risk factors. The independent variables in the regression specifications are the returns of the value-weight market index and factor portfolios sorted by liquidity, volatility, momentum and reversal (see Section 2). Panel A reports the risk-adjusted alphas from individual time-series regressions. When clustered by fund type, the risk-adjusted alphas are lower than the benchmark-adjusted performances. For instance, the alpha of the `tokenized fund` drops from 8.15% to 3.90%, whereas the performance of the remaining funds deteriorates by more than 1% on a monthly basis compared to the benchmark-adjusted results. Similarly, the estimated alphas for the funds clustered by investment strategy tend to decrease. For example, the risk-adjusted alpha for the `long-short` and `long-term` strategies become only weakly significant at the typical 5% thresholds (alphas of 2.05% and 2.75% with t-statistics of 2.24 and 2.39). Further, although the aggregate funds adopting other investment strategies generate a positive value to investors, their risk-adjusted alphas become statistically insignificant. Nevertheless, the average cryptocurrency fund still reports a positive and significant risk-adjusted alpha (1.85%, t-stat: 2.60).

The estimates of the risk factor loadings in Panel B of Table 4 suggest that the lower statistical significance of the performance is due to a large and significant exposure to a broader definition of market risk. Interestingly, the market beta is highly positive and significant across fund types and investment strategies. For the average crypto fund, $\widehat{\beta}_{MKT} = 0.51$ (robust t-stat: 19.99). For a `long-term` fund, which typically invests in large assets, the market beta is as high as 0.72 (robust t-stat: 21.67). Even a `market neutral` fund seems to be slightly exposed to market risk, although the market beta estimate takes a modest value of 0.08. Except for the exposure to a reversal factor, the significance of the other factor loadings tends to be modest and insignificant. For instance, when it comes to fund type classification, the exposure to reversal is significant for the `fund of funds`, the `hedge fund`, and the `other` category. For the strategy classification, all funds load significantly on the reversal factor. There is virtually no exposure to momentum, liquidity or volatility risks. The results suggest that the market trend represents the primary source of risk for active management in cryptocurrency funds.

Panel C of Table 4 extends the time-series results presented in Panel A to the panel estimation of aggregate fund alphas. We document that the magnitude of the alphas tends to be consistent with the values obtained from the time-series regressions, whereas the significance of the estimates may change. For instance, the alphas of `other` and `tokenized funds` change slightly from 2.17% and 2.48% for the former and from 3.90% to and 3.95% for the latter, however, both values become significant with t-statistics of 2.95 and 4.01, respectively. The economic magnitude of the risk-adjusted performance of `hedge funds` and `managed accounts` becomes weaker but remains significant. Turning to different investment strategies, `market neutral` and `opportunistic` funds do not produce significant risk-adjusted alphas, while those funds belonging `long-short`, `long-term`, and `multi-strategy` groups strongly outperform the market and factor-mimicking portfolios.

3.2 Performance of individual funds

Simply looking at the performance of aggregate funds based on fund type or investment strategy may give an incomplete or misleading picture of the value of active asset management. This is because the analysis at the aggregate level does not capture the cross-sectional heterogeneity in individual fund returns. The aggregation may average out the superior performance of some funds and, hence, would not reveal differences in the performance and skill of individual managers. Furthermore, the cross-section of individual fund alphas possibly represents a complex mixture of non-normal distributions due to the high volatility and non-normality of cryptocurrency returns. To address this issue, we build upon Kosowski et al. (2006) and Fama and French (2010) and propose a panel bootstrap procedure to evaluate the performance of individual cryptocurrency funds. We consider two key parameters to measure the fund performances, namely the estimated alpha $\widehat{\alpha}_i$ and the corresponding t-statistic $\widehat{t}_{\widehat{\alpha}_i}$. The $\widehat{\alpha}_i$ measures the economic size of the fund performance while controlling for passive benchmark strategies or sources of systematic risk. Being a function of the $\widehat{\alpha}$'s standard errors, the $\widehat{t}_{\widehat{\alpha}_i}$ offers two main advantages in the context of highly heteroskedastic and non-normal returns such as those of cryptocurrency funds. First, crypto funds tend to control small amounts of assets under management, have a short life span, and engage in a relatively high-risk asset class. Thus, the cross-sectional distribution of fund performances is likely to show spurious outliers. The t-statistics provides a correction to these outlying performances by normalising the alpha estimates by their standard errors. Second, with a relatively limited investment opportunity set compared to traditional equity funds, crypto funds operating within a given strategy framework could embark in overlapping investments, which in turn may generate highly correlated returns. By clustering standard errors at the strategy level, the resulting t-statistics explicitly take into account within-strategy return co-movement. For these reasons, we implement bootstrap $\widehat{\alpha}_i$ and $\widehat{t}_{\widehat{\alpha}_i}$ and comment on the bulk of the empirical results based on both the alpha estimates and t-statistics.

For each fund i, the historical alpha estimates $\widehat{\alpha}_i$, the corresponding t-statistics $\widehat{t}_{\widehat{\alpha}_i}$, and the residuals $\widehat{\epsilon}_{ikt}$ obtained from a panel regression of the form $y_{ikt} = \alpha_i + \boldsymbol{\beta}_k^{'}\boldsymbol{x}_t + \epsilon_{ikt}$, where y_{ikt} is the return at time t for a fund i for the investment strategy k, α_i are the individual fund fixed effects, and $\boldsymbol{\beta}_k^{'}$ is the vector of exposures to passive benchmarks or risk factors $\boldsymbol{x}_t$ for the funds following the investment strategy k. Now let T_{0i} and T_{1i} represent the dates of the first and the last available returns for the fund i, respectively. We draw a sample with replacement from both the fund residuals and the benchmark investment returns: $\left\{\widehat{\epsilon}^b_{ikt},\ \boldsymbol{x}^b_t;\ t = s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}\right\}$, where $b = 1, \ldots, B$ is the bootstrap index and $s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}$ are drawn randomly from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for each fund i defined as:

$$y^b_{ikt} = \widehat{\boldsymbol{\beta}}_k \boldsymbol{x}^b_t + \widehat{\epsilon}^b_{ikt}, \qquad b = 1, \ldots, B. \tag{2}$$

By construction, the sequence of returns y^b_{ikt} has a true alpha that is zero. However, when we regress the zero-alpha returns on the bootstrap factors $\boldsymbol{x}^b_t$ for a given bootstrap sample b, a positive and significant alpha may still arise from pure sampling variation. For each bootstrap iteration b, we estimate the bootstrap alphas $\widehat{\alpha}^b_i$ and t-statistics $\widehat{t}^b_{\widehat{\alpha}_i}$ via a panel regression for the constructed panel of synthetic fund returns. We further compute the bootstrap t-statistics with and without clustered standard errors, where clustering is made at the strategy level. After repeating all bootstrap iterations $b = 1, \ldots, B$, we build the distribution of cross-sectional draws of alphas and t-statistics resulting purely from sample variation. If there are fewer superior alphas and t-statistics among the bootstrap values than the actual empirical estimates, then sampling variation cannot be the sole source of the outperformance of the best funds. We execute $B = 10,000$ iterations in all of our bootstrap tests. Appendix A provides a more detailed description of the main bootstrap procedure. Our bootstrap methodology is closely related to Kosowski et al. (2006) and Fama and French (2010). These papers employ similar bootstrap procedures to draw inferences about skilled managers in a cross-section of US equity mutual funds. The key difference is that we propose a panel regression bootstrap instead of a time-series analysis of individual fund alphas. This offers two major advantages over estimating separate time-series regressions as in Kosowski et al. (2006) and Fama and French (2010). First, the fund fixed effects absorb the variation in fund returns due to the cross-sectional differences in manager skills, as long as skills remain constant over time (see, e.g., Pástor et al., 2015). The assumption of time-invariant skills seems innocuous and is consistent with the theoretical model of Berk and Green (2004). In their model, skills are time-varying only from a subjective perspective, whereas objectively the skills remain constant in the data generating process.[11] Second, combining the cross-sectional and time-series dimensions of the data increases the power of the test on the alphas and enhances the reliability of the t-statistics. Thus, pooling information from different funds allows us to obtain more precise estimates of the performance despite a short lifespan of the funds.

One comment is in order. The baseline bootstrap specification assumes that the fund residuals and the benchmark investment returns or the returns on the risk factors are uncorrelated, or mildly correlated, over time. In addition, we assume that the exposure to a given benchmark portfolio or risk factor is strategy-specific. We relax both assumptions in a series of robustness checks by considering a block-bootstrap approach, an independent resampling approach, and a panel regression with constant betas across all funds.

3.2.1 Cross-section of individual fund performances. Figure 5 compares the distributions of actual alphas and t-statistics with the distributions of bootstrap values. For ease of exposition, we

[11] Although in Berk and Green's model investors cannot observe the skills of the fund manager i, which corresponds to α_i, such skills are time-varying only from a subjective perspective, whereas the true, objective α_i remains constant in the data-generating process. As a result, all of the time-series variation in α_i is due to unpredictable, zero mean, random noise which reflects news and surprises in fund activity. By taking a historical perspective - that is, the perspective of an econometrician rather than of an investor who needs to make investment decisions in real time - the assumption that the skills are time invariant seems somewhat innocuous.

report the cross-sectional distributions of $\widehat{\alpha}$ and $\widehat{t_{\alpha}}$ as color-coded box charts. A blue color corresponds to the actual values and a red color denotes the bootstrap estimates. Panel A reports the alphas and t-statistics based on the passive benchmarks, while Panel B illustrates the statistics based on the risk factors. Each panel shows the alphas (a left plot), the standard t-statistics (a middle plot), and the t-statistics with clustered standard errors at the strategy level (a right plot).

The benchmark-adjusted results point to three key observations. First, the figures confirm our intuition about the possible heterogeneity in individual fund performances, as indicated by a significant cross-sectional variation in the alphas estimates. For instance, although the majority of crypto funds produce actual alphas within a modest range of 0% to 5%, the performances of the worst and best managers can reach -17% and +38% on a monthly basis, respectively. Thus, while the results reported in Section 3 mainly reflect the aggregate performance figures, they do not illustrate huge alphas of a small number of outlying funds. Furthermore, the comparison between actual and bootstrap alphas demonstrates that the probability mass of the actual estimates is shifted upward. This suggests that the actual performance of a handful of the best crypto funds is stronger than those that could be explained only by sampling variation.

Second, the cross-sectional distribution of the standard t-statistics demonstrates that a non-trivial fraction of funds cross the conventional 5% confidence threshold. Similar to the alpha estimates, the probability mass of the actual t-statistics experiences a pronounced upward shift compared to the distribution generated by the bootstrap procedure. This evidence leads us to conclude that a fraction of fund managers are able to generate economically large alphas that are also statistically significant and cannot be fully explained by sampling variation. Third, when considering the within-strategy correlation in fund returns, the standard errors become wider, substantially reducing the value of the t-statistics. This suggests that the sizable uncertainty around the alphas weakens their statistical significance. Yet the distribution of the actual and bootstrap robust t-statistics is far from overlapping. The right tail of the actual t-statistics with standard errors clustered at the strategy level is still much thicker than its bootstrap counterpart.

Panel B for the risk-adjusted results demonstrates that the alphas and t-statistics show similar patterns when passive benchmarks are replaced by traditional risk factors. The economic magnitude of the estimates is similar to that obtained using the benchmark strategies. For instance, the bulk of alphas is concentrated within the interval of 0% to 5% on a monthly basis, and there is a sizable number of outlying funds with performances well above 10 on a monthly basis. All panels show that sampling variation cannot explain the estimates of the right tail.

Table 5 provides a more granular representation of the differences between the actual and bootstrap estimates. We report the actual and simulated values of alphas and t-statistics as well as the percentage of actual estimates greater than the simulated value at selected percentiles (see, e.g., Fama and French, 2010). We first compute the actual alphas and t-statistics at selected percentiles of their distributions. We then obtain the corresponding simulated values by taking the averages across the 10,000 simulation runs of the $\widehat{\alpha}$ and $\widehat{t_{\widehat{\alpha}}}$ estimates at selected percentiles. We further quantify the discrepancy between the empirical and bootstrap distributions of alphas and t-statistics by calculating the percent of actual estimates above the simulated value at a particular percentile. The benchmark-adjusted results show that the 1$^{\text{st}}$ percentile of the actual $\widehat{\alpha}$ is -9.58% and the simulated value is -11.9%. Further, 99.02% of actual observed alphas are greater than the simulated estimate at the 1$^{\text{st}}$ percentile.

Overall, Berk and Green (2004)'s prediction that most fund managers have sufficient skill to cover their costs compared to benchmark passive strategies or risk portfolios seems to be supported by the empirical results. The left tail percentiles of $\widehat{t_{\widehat{\alpha}}}$ from the actual returns are far above the corresponding average value from the bootstrap simulations. For example, the 10$^{\text{th}}$ percentile of the actual t-statistics of -0.21 and -0.67 for the benchmark- and risk-adjusted results are much less extreme than the average estimates from the bootstrap simulations equal to -1.00. In fact, for the benchmark- and risk-adjusted performances, the actual t-statistics are above the average bootstrap simulation values for all percentiles considered. This holds regardless of whether $\widehat{t_{\widehat{\alpha}}}$ is calculated with standard errors clustered by investment strategy.

The results presented in Figure 5 and Table 5 are in stark contrast with some earlier results on the value of active investment management. We show that, at least within the fast-growing industry of cryptocurrency markets, there is some evidence that fund managers have enough skill to produce superior benchmark- and risk-adjusted returns to cover their costs. One word of caution. Although there is evidence of a strong economic performance which is not simply due to random sampling variation, the statistical significance of such a performance is weak when the correlation structure of fund returns is taken into account. We could interpret this result as being the nature of investment in cryptocurrency markets. Managers are exposed to a highly volatile and risky market, and their performances are quite correlated given the overlapping asset menus. We show that ignoring this correlation comes at the cost of artificially inflating the significance of the benchmark- and risk-adjusted returns (see, e.g., McNemar, 1947).

We next try to understand whether the superior performances are driven by a specific fund style or the best funds are spread across different groups. Figure 6 reports the cross-sectional distributions of the actual alphas and t-statistics separately for each investment strategy. Three interesting facts emerge. First, the majority of outlying performances are concentrated in the `long-short` and `long-term` fund groups, with some residual tail performances belonging to the `multi-strategy` category. Thus, the majority of funds in the right tail of the distribution reported in Figure 5 possibly belong to these classes. Second, there is no systematic dominance of a given strategy over others. When we exclude the tails, the strategy-specific cross-sectional distributions of alphas tend to be largely overlapping. This suggests that, while the vast majority of superior performances are concentrated in two main classes, the remaining funds across different investment strategies tend to perform similarly. The only partial exception is the `opportunistic` strategy, which neither shows any outlying performances nor has an average alpha or t-statistic of a magnitude comparable to others. Third, the results are similar for both benchmark- and risk-adjusted cases. We document the concentration of outperforming funds in the two classes and no systematic dominance of a given investment strategy over others.

3.3 Sub-sample analysis

Figure 2 shows that cryptocurrency markets were marked by a significant run-up in prices until late 2017 and a large drop in valuations from January 2018. This is the so-called ICO bubble, which may be the reaction to the media hype surrounding the astonishing surge in Bitcoin valuation. It contributed to the conventional wisdom that cryptocurrency markets are merely a playground for speculators in search of yields. It is fair to conjecture that the burst of the ICO bubble could mark a significant change in the profitability of cryptocurrency investments and hence the performance of crypto funds. In addition, only a handful of funds were active before late 2017, which might raise questions about the significance of our main empirical results when including the pre-ICO bubble period. To address this, we split our main sample of observations into two sub-samples: the pre-ICO bubble from March 2015 to December 2017 and the post-ICO bubble period from January 2018 to June 2021. Splitting the sample around the peak of the ICO bubble, when hundreds of new crypto-assets were introduced into the market primarily for speculative purposes, allows us to further investigate the value of active investment management within the context of a drastically changing investment opportunity set.

We first look at the descriptive statistics of aggregate funds across sub-samples. Table 6 reports the results. The mean and volatility of returns tend to be much lower for the second part of the total sample. The only exception is an average `opportunistic` fund, which exhibits a dramatic increase in the first two moments from 1.59% and 0.85% on a monthly basis in the first sub-sample to 4.17% and 10.11% in the second sub-period. In relative terms, average returns decrease more than realized volatilities across most types and investment strategies. Thus, the Sharpe ratios also tend to be substantially lower for the second sub-sample. This evidence is consistent with the idea that investment opportunities were more favourable before the ICO bubble. Despite lower average returns, an average `market neutral` fund shows relatively constant Sharpe ratios of 1.28 and 1.50 in the pre- and post-ICO bubble periods. This suggests that while these funds may not be neutral to market trends in terms of raw returns, they are stable once the performance is adjusted for risk. The persistence of fund returns remains relatively low across both sub-samples, which supports the main bootstrap procedure. Nevertheless, the robustness analysis further presents the block bootstrap specification to capture the possible persistence in fund returns. We demonstrate that the results are robust to different bootstrap methods, refuting a concern about the impact of serial correlation.

Turning to the analysis of individual funds, Figure 7 reports the alphas and t-statistics for the post-ICO bubble period. The reason we focus on the post-2018 period is twofold. First, fund performances are much stronger in the pre-ICO bubble period. Removing the data before 2018 tests whether our results become weaker. Second, only a handful of funds were effectively available for investors in the pre-ICO bubble period. A few interesting aspects emerge. The individual fund alphas become slightly smaller in the second sub-period than those obtained from the total sample (see Figure 5). This evidence confirms the inflating effect of the pre-ICO bubble period on the performance of funds. We observe a similar effect of the pre-ICO bubble period on the magnitude of both types of t-statistics. This suggests that while the alphas might be slightly lower, so are the volatilities of the returns. In addition, the distributions of actual alphas and t-statistics are shifted upward compared to those of simulated estimates. This result shows that the skill of outperforming funds is not driven by the spike in valuations in the pre-ICO bubble period. Both benchmark- and risk-adjusted results share the same patterns and lead to the same conclusions.

We now construct the distributions of the actual and simulated estimates at selected percentiles based on the post-ICO bubble data. Table 7 reports the results for both the benchmark- and the risk-adjusted values. Several observations are noteworthy. Starting from the 10^{th} percentile, the actual alphas are larger than the simulated values at the corresponding percentiles. This provides evidence of an economic performance that cannot be simply reconciled by the sampling variation of the returns. Hence, we extend the key conclusion from the main empirical analysis to the sub-sample after the ICO bubble. We find similar patterns between the actual and simulated values of the standardised performances $\widehat{t_{\widehat{\alpha}}}$. Specifically, the empirical t-statistics are consistently above the average values across simulations regardless of our approach to dealing with standard errors. Interestingly, the observed patterns in actual and simulated statistics hold for both benchmark- and risk-adjusted returns. Thus, evidence of skill sufficient to cover costs does not depend on the nature of conditioning information as reflected by our choice of passive benchmarks or risk factors.

3.4 Robustness

In this section, we provide a set of additional results and robustness checks to show the sensitivity of the main empirical analysis to a variety of different modeling choices. For ease of exposition, we focus on the benchmark-adjusted results unless specified otherwise. The risk-adjusted results are available upon request.

3.4.1 Block bootstrap and independent resampling. We begin by relaxing two technical assumptions of our panel bootstrap approach that are related to the autocorrelation of the residuals and the correlation between fund returns and passive benchmarks. Our main bootstrap procedure assumes that the residuals are only weakly autocorrelated. Table 1 and Figure 3 show that the persistence of individual and aggregate fund returns is weaker than traditional equity mutual funds.[12] We further explore the sensitivity of our results to the possibility of some conditional dependence in fund returns. Specifically, we compare the results of the main bootstrap procedure to its modification, where we re-sample returns in blocks of a fixed size. Due to the short length of data, we set the size of the bootstrap blocks equal to three months. If the length of the historical data for a specific fund is not a divisor of 3, one of the blocks will contain one or two observations only. More details on the procedure can be found in Appendix A.1. Panel A of Figure 8 presents the fund alphas and their

[12] In an online Appendix we further reports the autocorrelation function up to 20 lags of aggregate fund returns. There is weak evidence of autocorrelation in the returns of aggregate funds.

t-statistics for the block-bootstrap approach. There is a pronounced discrepancy between the actual statistics and the average simulated values. Thus, allowing for a short-term autocorrelation in our bootstrap procedure, the results are largely in line with the main empirical analysis. This is confirmed by the more granular representation of the discrepancy between the actual and the bootstrap alphas. Table 8 reports the results.

Overall, the main empirical results that most fund managers have sufficient skill to cover their costs compared to benchmark passive strategies or risk portfolios are supported by the block-bootstrap approach. The left tail percentiles of $\widehat{t_{\widehat{\alpha}}}$ from the actual returns are far above the corresponding average value from the bootstrap simulations. For example, the 10^{th} percentile of the actual t-statistics of -0.21 and -0.67 for the benchmark- and risk-adjusted results are much less extreme than the average estimates from the bootstrap simulations equal to -1.00 and -0.97, respectively. In fact, for both benchmark- and risk-adjusted performances, the actual t-statistics are above the average bootstrap simulation values for all percentiles considered. Such an observation holds regardless of whether $\widehat{t_{\widehat{\alpha}}}$ is calculated with standard errors clustered by investment strategy.

Panel B of Figure 8 reports the estimates for $\widehat{\alpha}$ (a left panel) and $\widehat{t_{\widehat{\alpha}}}$ with and without clustered standard errors (a middle and right panel). These are obtained through an alternative bootstrap approach in which the benchmark returns and the residuals are sampled independently. This approach breaks any possible time correlation between explanatory returns and model residuals. As outlined in Kosowski et al. (2006), such a correlation could arise if the performance model specified does not fully capture the set of possible explanatory factors. The results are virtually the same as in the main empirical analysis, that is, we provide evidence that fund managers are able to cover their costs and exhibit skill. An online Appendix reports a granular representation of the discrepancy between the actual and bootstrap alphas and t-statistics, similar to Table 5. The distributions of the empirical and bootstrap $\widehat{t_{\widehat{\alpha}}}$ estimates confirm the main results that most fund managers have sufficient skill to cover their costs compared to benchmark passive strategies or risk portfolios.

3.4.2 Constant betas and time-series regressions. We now restrict the exposure of fund returns to passive benchmarks to be the same across fund strategies, i.e., $\boldsymbol{\beta}_j^{'} = \boldsymbol{\beta}^{'}$ for $j = 1, \ldots, J$. Figure 9 shows the results. The left panel reports the alphas, while the right panel reports the t-statistics with clustered standard errors. Except for a few nuances, the results of the main empirical analysis hold. Specifically, there is a wide discrepancy between the cross-sectional distributions of the actual estimates and the corresponding simulated values. Following Kosowski et al. (2006), this provides evidence that fund managers display sufficient skills to produce benchmark-adjusted returns that cover costs. An online Appendix replicates the analysis in Table 5. We show that the cross-sectional distribution of actual estimates dominates the distribution of the bootstrap values in nearly all quantiles considered, confirming the main empirical results.

Finally, we estimate alphas for each fund separately based on a simple time-series regression. In this case, $\boldsymbol{\beta}_i^{\prime}$ becomes fund-specific and we do not assume correlation within strategies or fund types. This approach is obviously sub-optimal relative to the panel estimation given the relatively short length of data for some funds. However, it is consistent with the more traditional procedure of obtaining the fund alphas from time-series regressions. Figure 9 shows the alphas and t-statistics based on Newey and West (1986) robust standard errors. Two interesting facts emerge. First, the estimated alphas are significantly larger than those obtained from a panel regression (see Figure 5). This suggests that the short length of the data may generate a small-sample bias in the estimates. Second, the cross-sectional distribution of the t-statistics shows a strong evidence in favor of fund skill. The distribution of actual alphas and t-statistics has a pronounced upward shift relative to the bootstrap statistics. Further, we observe a much larger mass of funds above a standard 5% significance threshold compared to Figure 5. The average t-statistic from individual time-series regressions is much higher than the panel regression estimates without clustered standard errors at the strategy level. This suggests that our panel approach is more conservative when it comes to estimating fund alphas. This result reinforces the reliability of our main empirical results.

4 Conclusion

This paper provides a comprehensive analysis of the value of active asset management in the new and unregulated industry of cryptocurrency markets. The empirical analysis is based on a novel dataset of more than 200 actively managed funds over the period from March 2015 to June 2021. We investigate the performance of funds both at the aggregate level through regression analysis and at the individual level through a panel regression and a bootstrap approach, which take into account specific features of cryptocurrency funds such as outlying returns and within-strategy correlations.

We consider a set of benchmark strategies and risk factors to disentangle the fund managers' performances. Our results show that fund managers can generate benchmark- and risk-adjusted returns, which cover their cost and could create positive value for investors, a finding consistent with the prediction of Berk and Green (2004). While existing research has long debated the value of active management in traditional asset classes, no study has tested the existence of such value in the new and fast-growing industry of cryptocurrency funds. In this respect, we see this paper as an "out-of-sample" test of existing theories, which typically focus on the equity market.

References

Abdi, F. and Ranaldo, A. (2017). A simple estimation of bid-ask spreads from daily close, high, and low prices. *The Review of Financial Studies*, 30(12):4437–4480.

Alexander, C. and Dakos, M. (2019). A critical investigation of cryptocurrency data and analysis. *Working Paper*.

Amihud, Y. and Goyenko, R. (2013). Mutual fund's r 2 as predictor of performance. *The Review of Financial Studies*, 26(3):667–694.

Andonov, A., Bauer, R. M., and Cremers, K. (2017). Pension fund asset allocation and liability discount rates. *The Review of Financial Studies*, 30(8):2555–2595.

Avramov, D. and Wermers, R. (2006). Investing in mutual funds when returns are predictable. *Journal of Financial Economics*, 81(2):339–377.

Barber, B. M., Huang, X., and Odean, T. (2016). Which factors matter to investors? evidence from mutual fund flows. *The Review of Financial Studies*, 29(10):2600–2642.

Barras, L., Scaillet, O., and Wermers, R. (2010). False discoveries in mutual fund performance: Measuring luck in estimated alphas. *The journal of finance*, 65(1):179–216.

Berk, J. B. and Green, R. C. (2004). Mutual fund flows and performance in rational markets. *Journal of political economy*, 112(6):1269–1295.

Berk, J. B. and Van Binsbergen, J. H. (2015). Measuring skill in the mutual fund industry. *Journal of Financial Economics*, 118(1):1–20.

Berk, J. B. and Van Binsbergen, J. H. (2016). Assessing asset pricing models using revealed preference. *Journal of Financial Economics*, 119(1):1–23.

Bianchi, D. and Babiak, M. (2021). A factor model for cryptocurrency returns. *Available at SSRN 3935934*.

Bianchi, D. and Dickerson, A. (2019). Trading volume in cryptocurrency markets. *Working Paper*.

Bianchi, D., Guidolin, M., and Pedio, M. (2020). Dissecting time-varying risk exposures in cryptocurrency markets. *BAFFI CAREFIN Centre Research Paper*, (2020-143).

Bogle, J. C. (2005). The relentless rules of humble arithmetic. *Financial Analysts Journal*, 61(6):22–35.

Brown, S. J., Goetzmann, W., Ibbotson, R. G., and Ross, S. A. (1992). Survivorship bias in performance studies. *The Review of Financial Studies*, 5(4):553–580.

Busse, J. A. and Irvine, P. J. (2006). Bayesian alphas and mutual fund persistence. *The Journal of Finance*, 61(5):2251–2288.

Carhart, M. M. (1997). On persistence in mutual fund performance. *The Journal of finance*, 52(1):57–82.

Corwin, S. A. and Schultz, P. (2012). A simple way to estimate bid-ask spreads from daily high and low prices. *The Journal of Finance*, 67(2):719–760.

Cremers, K. M., Fulkerson, J. A., and Riley, T. B. (2019). Challenging the conventional wisdom on active management: A review of the past 20 years of academic literature on actively managed mutual funds. *Financial Analysts Journal*, 75(4):8–35.

Davis, J. L. (2001). Mutual fund performance and manager style. *Financial Analysts Journal*, 57(1):19–27.

De Bondt, W. F. and Thaler, R. (1985). Does the stock market overreact? *The Journal of finance*, 40(3):793–805.

Diebold, F. X. and Mariano, R. S. (2002). Comparing predictive accuracy. *Journal of Business and economic statistics*, 20(1):134–144.

Dyakov, T., Jiang, H., and Verbeek, M. (2020). Trade less and exit overcrowded markets: Lessons from international mutual funds. *Review of Finance*, 24(3):677–731.

Elton, E. J., Gruber, M. J., and Blake, C. R. (1996). Survivor bias and mutual fund performance. *The Review of Financial Studies*, 9(4):1097–1120.

Fama, E. F. and French, K. R. (2010). Luck versus skill in the cross-section of mutual fund returns. *The Journal of Finance*, 65(5):1915–1947.

French, K. R. (2008). Presidential address: The cost of active investing. *The Journal of Finance*, 63(4):1537–1573.

Gruber, M. J. (1996). Another puzzle: The growth in actively managed mutual funds. *The journal of finance*, 51(3):783–810.

Hoberg, G., Kumar, N., and Prabhala, N. (2017). Mutual fund competition, managerial skill, and alpha persistence. *The Review of Financial Studies*, 31(5):1896–1929.

Huij, J. and Verbeek, M. (2007). Cross-sectional learning and short-run persistence in mutual fund performance. *Journal of Banking & Finance*, 31(3):973–997.

Huij, J. and Verbeek, M. (2009). On the use of multifactor models to evaluate mutual fund performance. *Financial Management*, 38(1):75–102.

Ippolito, R. A. (1989). Efficiency with costly information: A study of mutual fund performance, 1965–1984. *The Quarterly Journal of Economics*, 104(1):1–23.

Jegadeesh, N. and Titman, S. (2001). Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of Finance*, 56(2):699–720.

Jensen, M. C. (1968). The performance of mutual funds in the period 1945–1964. *The Journal of finance*, 23(2):389–416.

Kacperczyk, M., Nieuwerburgh, S. V., and Veldkamp, L. (2014). Time-varying fund manager skill. *The Journal of Finance*, 69(4):1455–1484.

Kacperczyk, M. and Seru, A. (2007). Fund manager use of public information: New evidence on managerial skills. *The Journal of Finance*, 62(2):485–528.

Kacperczyk, M., Sialm, C., and Zheng, L. (2005). On the industry concentration of actively managed equity mutual funds. *The Journal of Finance*, 60(4):1983–2011.

Kacperczyk, M., Van Nieuwerburgh, S., and Veldkamp, L. (2016). A rational theory of mutual funds' attention allocation. *Econometrica*, 84(2):571–626.

Kosowski, R., Timmermann, A., Wermers, R., and White, H. (2006). Can mutual fund "stars" really pick stocks? new evidence from a bootstrap analysis. *The Journal of finance*, 61(6):2551–2595.

Liu, Y. and Tsyvinski, A. (2020). Risks and Returns of Cryptocurrency. *The Review of Financial Studies*.

Liu, Y., Tsyvinski, A., and Wu, X. (2019). Common risk factors in cryptocurrency. Technical report, National Bureau of Economic Research.

Lustig, H., Roussanov, N., and Verdelhan, A. (2011). Common risk factors in currency markets. *The Review of Financial Studies*, 24(11):3731–3777.

Makarov, I. and Schoar, A. (2020). Trading and arbitrage in cryptocurrency markets. *Journal of Financial Economics*, 135(2):293–319.

Malkiel, B. G. (1995). Returns from investing in equity mutual funds 1971 to 1991. *The Journal of finance*, 50(2):549–572.

Mamaysky, H., Spiegel, M., and Zhang, H. (2007). Improved forecasting of mutual fund alphas and betas. *Review of Finance*, 11(3):359–400.

McNemar, Q. (1947). Note on the sampling error of the difference between correlated proportions or percentages. *Psychometrika*, 12(2):153–157.

Menkhoff, L., Sarno, L., Schmeling, M., and Schrimpf, A. (2016). Information flows in foreign exchange markets: Dissecting customer currency trades. *The Journal of Finance*, 71(2):601–634.

Moneta, F. (2015). Measuring bond mutual fund performance with portfolio characteristics. *Journal of Empirical Finance*, 33:223–242.

Nagel, S. (2012). Evaporating liquidity. *The Review of Financial Studies*, 25(7):2005–2039.

Newey, W. K. and West, K. D. (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelationconsistent covariance matrix.

Novy-Marx, R. and Rauh, J. (2011). Public pension promises: how big are they and what are they worth? *The Journal of Finance*, 66(4):1211–1249.

Pástor, L., Stambaugh, R. F., and Taylor, L. A. (2015). Scale and skill in active management. *Journal of Financial Economics*, 116(1):23–45.

Phelps, S. and Detzel, L. (1997). The nonpersistence of mutual fund performance. *Quarterly Journal of Business and Economics*, pages 55–69.

Wermers, R. (2000). Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses. *The Journal of Finance*, 55(4):1655–1695.

Yang, D. and Zhang, Q. (2000). Drift-independent volatility estimation based on high, low, open, and close prices. *The Journal of Business*, 73(3):477–492.

Yermack, D. (2013). Is bitcoin a real currency? An economic appraisal. *National Bureau of Economic Research*.

Table 1: **A first look at cryptocurrency funds**

This table reports a set of descriptive statistics for the returns of aggregate crypto funds, global ETFs, S&P500, and two hedge fund indices. Panel A reports descriptive statistics of equal-weight portfolio returns aggregated across all funds (first column), each type of funds: `fund of funds`, `hedge fund`, `managed account`, `tokenized fund`, and `other` (from column two to column six), and each investment strategy: `long-short` , `long-term`, `market neutral`, `multi-strategy`, and `opportunistic` (the last five columns). It shows the sample mean and standard deviation (%, monthly), the annualized Sharpe ratio, the skewness and autocorrelation of returns of fund portfolios. Panel B reports descriptive statistics of the returns of global ETFs from traditional asset classes (equity, corporate bond, commodity, and real estate markets), S&P500, and two hedge fund indices. Panel C reports the correlations of aggregate fund returns with the returns of global ETFs, stock market, and hedge fund indices. The sample period is from March 2015 to June 2021.

Panel A: Descriptive statistics for cryptocurrency funds

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opportunistic
Mean (%)	8.53	5.89	7.85	11.20	9.61	12.82	7.37	11.28	2.21	7.13	3.60
Std (%)	16.12	11.57	15.38	18.10	21.41	23.37	14.36	24.66	5.93	12.97	8.96
SR (annualized)	1.83	1.76	1.77	2.14	1.56	1.90	1.78	1.58	1.29	1.90	1.39
Skewness	1.36	0.96	1.13	1.10	1.80	1.98	1.77	1.59	4.03	0.61	1.73
AR(1)	0.27	0.14	0.19	0.29	0.21	0.43	0.46	0.21	0.16	0.11	0.30

Panel B: Descriptive statistics for traditional asset classes

	Equity	Bond	Commodity	Real Estate	S&P500	HF Index 1	HF Index 2
Mean (%)	0.66	0.25	-0.34	0.04	0.94	0.51	0.51
Std (%)	4.26	2.59	7.15	4.98	4.21	1.98	1.51
SR (annualized)	0.54	0.34	-0.17	0.03	0.77	0.90	1.17
Skewness	-0.81	0.38	-1.70	-2.42	-0.61	-1.32	-0.88
AR(1)	0.00	-0.07	0.22	0.01	-0.06	0.13	0.17

Panel C: Correlations between cryptocurrency funds and traditional asset classes

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opportunistic
Global Equity	0.24	0.25	0.24	0.2	0.24	0.15	0.21	0.24	0.11	0.27	0.26
Global Bond	0.08	0.05	0.11	0.11	0.06	-0.04	-0.05	0.08	-0.01	0.17	-0.04
Global Commodity	0.12	0.16	0.14	0.12	0.08	0.13	0.13	0.13	0.10	0.13	0.28
Global Real Estate	0.22	0.27	0.23	0.18	0.20	0.10	0.17	0.22	0.09	0.28	0.26
S&P500	0.21	0.25	0.22	0.16	0.20	0.08	0.15	0.21	0.09	0.27	0.26
HF Index 1	0.27	0.27	0.28	0.24	0.26	0.19	0.25	0.26	0.15	0.32	0.36
HF Index 2	0.30	0.29	0.30	0.28	0.30	0.20	0.29	0.28	0.18	0.35	0.40

Table 2: **Descriptive statistics for benchmark strategies and factor portfolios**

This table reports a set of descriptive statistics for the returns of the passive benchmarks and risk factors. A full description of each risk factor is provided in the main text. We report the sample mean and standard deviation (%, monthly), the annualized Sharpe ratio, the skewness, and autocorrelation of returns. The sample period is from March 2015 to June 2021.

	Passive benchmarks				Risk factors				
	BTC	DOL	ETF	ETH	LIQ	MKT	MOM	REV	VOL
Mean (%)	7.08	5.64	8.28	10.14	14.19	9.77	9.97	64.46	15.12
Std (%)	20.69	33.82	23.26	35.64	52.30	27.81	87.97	104.33	53.04
SR (annualized)	1.19	0.58	1.23	0.99	0.94	1.22	0.39	2.14	0.99
Skewness	-0.18	1.23	0.96	0.64	3.51	0.96	2.76	1.54	3.46
AR(1)	0.15	0.19	0.32	0.21	0.08	0.15	0.19	0.61	0.06

Table 3: **The benchmark-adjusted performance of aggregate funds**

This table reports the benchmark-adjusted performance of aggregate funds across all crypto funds, each fund type and strategy. Specifically, we run a set of time-series regressions in which the dependent variable is the equal-weight portfolio returns aggregated across all funds (first column), each type of funds: `fund of funds`, `hedge fund`, `managed account`, `tokenized fund`, and `other` (from column two to column six), and each investment strategy: `long-short`, `long-term`, `market neutral`, `multi-strategy`, and `opportunistic` (the last five columns). The independent variables are the passive benchmarks outlined in the main text and summarized in Table 2. When computing equal-weight portfolio returns in each period, we calculate the sample equal-weight average of active funds in the corresponding time period. Panel A reports the alpha estimates and robust t-statistics (in parentheses) from the corresponding OLS regression. In order to test for the difference in the alphas, we use an approach á la Diebold and Mariano (2002). Panel A also reports the estimate $\hat{\gamma}$ as for Eq.(1) and robust t-statistics (in parenthesis) for the difference in alphas. Panel B reports the estimates and robust t-statistics (in parenthesis) of passive benchmark loadings (betas) and the adjusted R^2 of the regressions. Panel C reports the estimates and t-statistics (in parenthesis) of fund type (investment strategy) fixed effects from the panel regression of fund returns. For the panel approach, we introduce dummies per fund type (investment strategy) and report their estimates. The sample covers the period from March 2015 to June 2021.

Panel A: Benchmark-adjusted alphas

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
Alpha	3.71	3.08	2.77	6.00	3.99	8.15	3.68	5.00	1.15	2.64	2.49
	(3.91)	(2.90)	(3.30)	(3.91)	(2.70)	(3.95)	(3.54)	(3.32)	(1.95)	(3.06)	(2.32)
Difference		-0.63	-0.94	0.99	0.28	3.14	-0.03	1.29	-2.54	-1.07	-2.52
		(-0.51)	(-2.11)	(0.88)	(0.28)	(2.17)	(-0.04)	(1.85)	(-2.92)	(-1.27)	(-1.62)

Panel B: Passive benchmark betas

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
β_{BTC}	0.20	0.22	0.33	0.39	0.30	0.10	0.22	0.49	0.09	0.48	0.15
	(3.20)	(3.42)	(5.61)	(4.77)	(4.29)	(0.90)	(3.76)	(6.11)	(4.24)	(8.27)	(2.53)
β_{DOL}	0.08	0.04	0.08	0.02	0.25	0.00	0.07	0.13	0.02	0.01	0.02
	(1.79)	(0.90)	(1.80)	(0.26)	(5.10)	(0.05)	(1.71)	(2.16)	(1.02)	(0.30)	(0.38)
β_{ETF}	0.20	0.10	0.12	0.17	0.27	0.15	0.10	0.09	0.03	0.07	-0.01
	(3.45)	(1.63)	(2.21)	(2.18)	(4.13)	(1.45)	(1.75)	(1.14)	(1.31)	(1.24)	(-0.23)
β_{ETH}	0.15	0.02	0.12	0.10	-0.01	0.26	0.09	0.14	0.01	0.05	0.01
	(4.01)	(0.62)	(3.43)	(1.67)	(-0.30)	(3.50)	(2.58)	(2.84)	(0.79)	(1.30)	(0.24)
Adj. R^2	0.77	0.51	0.78	0.76	0.81	0.64	0.69	0.77	0.59	0.74	0.30

Panel C: Panel fixed-effect estimates

	Fund type					Fund strategy				
	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
Alpha	2.67	3.29	4.67	4.33	5.88	4.37	4.33	1.56	3.50	3.15
	(2.20)	(8.49)	(4.53)	(5.63)	(6.59)	(8.01)	(8.90)	(1.86)	(5.73)	(1.72)

Table 4: **The risk-adjusted performance of aggregate funds**

This table reports the risk-adjusted performance of aggregate funds across all crypto funds, each fund type and strategy. Specifically, we run a set of time-series regressions in which the dependent variable is the equal-weight portfolio returns aggregated across all funds (first column), each type of funds: `fund of funds`, `hedge fund`, `managed account`, `tokenized fund`, and `other` (from column two to column six), and each investment strategy: `long-short` , `long-term`, `market neutral`, `multi-strategy`, and `opportunistic` (the last five columns). The independent variables are the risk factors outlined in the main text and summarized in Table 2. When computing equal-weight fund monthly return in each period, we calculate the sample equal-weight average of active funds in the corresponding time period. Panel A reports the alpha estimates and robust t-statistics (in parentheses) from the corresponding OLS regression. In order to test for the difference in the alphas, we use an approach á la Diebold and Mariano (2002). Panel A also reports the estimate $\hat{\gamma}$ as for Eq.(1) and robust t-statistics (in parenthesis) for the difference in alphas. Panel B reports the estimates and robust t-statistics (in parenthesis) of passive benchmark loadings (betas) and the adjusted R^2 of the regressions. Panel C reports the estimates and t-statistics (in parenthesis) of fund type (investment strategy) fixed effects from the panel regression of fund returns. For the panel approach, we introduce dummies per fund type (investment strategy) and report their estimates. The sample covers the period from March 2015 to June 2021.

Panel A: Risk-adjusted alphas

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
Alpha	1.85	1.46	1.49	4.14	2.17	3.90	2.06	2.75	0.82	0.59	1.11
	(2.60)	(1.42)	(2.28)	(3.01)	(1.78)	(1.57)	(2.24)	(2.39)	(1.44)	(0.68)	(1.16)
Difference		-0.39	-0.37	1.62	0.32	1.37	0.21	0.90	-0.86	-1.26	-1.41
		(-0.33)	(-1.02)	(1.59)	(0.38)	(0.71)	(0.27)	(1.53)	(-1.11)	(-1.37)	(-1.11)

Panel B: Risk factor betas

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
β_{LIQ}	0.00	-0.06	-0.03	0.02	0.07	0.17	0.02	-0.02	-0.02	0.04	-0.05
	(-0.17)	(-1.99)	(-1.03)	(0.31)	(2.32)	(2.49)	(0.59)	(-0.52)	(-1.13)	(1.17)	(-1.37)
β_{MKT}	0.51	0.31	0.52	0.43	0.57	0.40	0.42	0.72	0.08	0.43	0.09
	(19.99)	(10.88)	(21.22)	(11.22)	(20.04)	(8.2)	(15.19)	(21.67)	(6.11)	(14.49)	(3.15)
β_{MOM}	0.00	-0.01	0.00	0.03	0.02	0.01	0.00	0.00	0.00	0.00	0.00
	(0.12)	(-0.55)	(-0.57)	(1.62)	(2.34)	(0.45)	(-0.18)	(-0.33)	(0.46)	(0.25)	(-0.39)
β_{REV}	0.02	0.02	0.02	0.02	0.02	0.03	0.01	0.02	0.01	0.02	0.03
	(3.18)	(2.83)	(2.95)	(1.76)	(3.24)	(1.72)	(1.95)	(2.50)	(2.49)	(3.01)	(3.00)
β_{VOL}	0.02	0.06	0.04	0.01	-0.07	0.00	0.00	0.02	0.02	0.01	0.03
	(0.77)	(1.84)	(1.27)	(0.20)	(-2.12)	(0.07)	(0.08)	(0.60)	(1.31)	(0.32)	(0.67)
Adj. R^2	0.84	0.62	0.85	0.74	0.85	0.66	0.75	0.86	0.39	0.73	0.32

Panel C: Panel fixed-effect estimates

	Fund type					Fund strategy				
	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opport
Alpha	1.16	1.35	2.36	2.48	3.95	2.12	1.87	0.74	2.06	1.41
	(0.87)	(3.13)	(2.06)	(2.95)	(4.01)	(3.51)	(3.52)	(0.78)	(3.06)	(0.67)

Table 5: **The cross-sectional distribution of benchmark- and risk-adjusted alphas**

This table reports the actual (Act) and simulated (Sim) values of alphas and t-statistics as well as the percentage of actual estimates greater than the simulated value at selected percentiles (% >Sim) as a measure of distribution discrepancy (see Fama and French, 2010). Specifically, the table compares (i) the actual values of the benchmark- and risk-adjusted alphas $\hat{\alpha}$ and the corresponding t-statistics $\hat{t}_{\hat{\alpha}}$ at selected percentiles of the cumulative distribution function for the cross-section of funds and (ii) the averages across the 10,000 simulation runs of the $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ estimates at the same percentiles. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The sample period is from March 2015 to June 2021.

	Panel A: Passive benchmarks									**Panel B:** Risk factors								
	Alpha			t-statistics (stand)			t-statistics (clust)			Alpha			t-statistics (stand)			t-statistics (clust)		
Pct	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim
1	-11.94	-9.58	99.02	-2.83	-1.90	100.00	-0.51	-0.34	100.00	-11.86	-11.98	99.02	-2.86	-2.50	99.51	-0.52	-0.45	99.51
10	-4.00	-1.02	98.04	-1.00	-0.21	98.04	-0.18	-0.04	98.04	-3.93	-2.88	95.10	-1.00	-0.67	96.08	-0.18	-0.12	96.08
20	-2.28	0.24	95.59	-0.57	0.06	96.57	-0.10	0.01	96.57	-2.22	-1.62	84.80	-0.56	-0.40	85.78	-0.10	-0.07	86.27
30	-1.31	1.15	92.65	-0.33	0.28	93.14	-0.06	0.05	93.14	-1.27	-0.46	76.96	-0.32	-0.13	77.94	-0.06	-0.02	78.43
40	-0.61	2.10	88.24	-0.15	0.50	88.24	-0.03	0.09	88.24	-0.59	0.34	72.06	-0.15	0.09	70.10	-0.03	0.02	70.59
50	-0.03	2.68	82.84	-0.01	0.74	82.84	0.00	0.13	82.84	-0.04	1.05	65.69	-0.01	0.25	65.69	0.00	0.04	65.69
60	0.53	3.64	77.45	0.13	0.94	76.96	0.02	0.17	76.96	0.50	1.69	58.33	0.13	0.46	55.88	0.02	0.08	55.88
70	1.20	4.83	69.61	0.30	1.22	68.63	0.05	0.22	68.63	1.15	2.77	48.04	0.30	0.72	49.02	0.05	0.13	49.02
80	2.19	6.35	59.80	0.55	1.56	57.35	0.10	0.28	57.35	2.08	4.58	33.82	0.53	1.11	35.29	0.10	0.20	34.80
85	2.90	7.71	48.04	0.73	1.91	50.00	0.13	0.34	50.00	2.76	5.60	29.90	0.70	1.42	30.39	0.13	0.26	30.39
86	3.07	7.94	44.61	0.77	1.96	49.51	0.14	0.35	50.00	2.94	5.74	28.92	0.75	1.50	29.41	0.13	0.28	29.41
87	3.26	8.44	43.14	0.82	2.08	45.59	0.15	0.38	45.59	3.13	6.03	28.92	0.79	1.63	27.94	0.14	0.29	27.94
88	3.46	8.69	42.16	0.87	2.25	43.63	0.16	0.41	44.12	3.34	6.19	28.92	0.84	1.65	26.47	0.15	0.31	26.47
89	3.70	8.89	38.73	0.92	2.33	41.67	0.17	0.42	41.67	3.57	6.41	27.45	0.90	1.80	25.00	0.16	0.32	25.00
90	3.96	9.70	35.78	0.98	2.41	38.24	0.18	0.44	38.73	3.82	7.77	25.98	0.97	1.83	25.00	0.17	0.33	25.00
91	4.25	10.08	33.33	1.06	2.46	34.80	0.19	0.44	34.80	4.11	8.00	23.04	1.04	2.12	24.51	0.19	0.38	24.51
92	4.60	10.68	30.88	1.14	2.57	31.86	0.20	0.46	31.86	4.45	8.33	21.57	1.12	2.19	19.12	0.20	0.40	20.10
93	5.00	11.05	29.41	1.23	2.82	29.90	0.22	0.51	29.90	4.86	8.97	18.14	1.21	2.28	17.16	0.22	0.41	17.16
94	5.49	11.44	26.47	1.34	3.18	25.00	0.24	0.57	25.00	5.34	9.29	16.18	1.33	2.44	15.69	0.24	0.44	15.69
95	6.11	12.84	21.08	1.49	3.28	21.57	0.27	0.59	21.57	5.94	10.96	13.24	1.47	2.54	14.22	0.27	0.46	14.71
96	6.91	13.73	17.16	1.67	3.48	19.12	0.30	0.63	19.12	6.73	12.30	10.78	1.66	3.11	11.76	0.30	0.57	12.25
97	8.03	15.74	13.73	1.93	3.94	14.22	0.34	0.71	14.71	7.83	14.07	9.80	1.92	3.59	9.80	0.35	0.65	9.80
98	9.76	20.44	9.31	2.34	4.78	10.78	0.42	0.86	11.76	9.57	18.64	5.39	2.32	4.36	6.37	0.42	0.79	6.37
99	13.36	24.90	4.41	3.18	6.55	5.88	0.56	1.18	6.37	13.18	22.78	3.43	3.16	6.54	3.92	0.58	1.19	3.92
100	22.10	36.68	1.96	5.00	8.98	1.96	0.88	1.62	1.96	22.01	39.01	0.98	5.05	8.44	1.47	0.91	1.53	1.47

Table 6: **Descriptive statistics of crypto funds across sub-samples**

This table reports a set of descriptive statistics for the returns net of both management and performance fees. Fund returns are split before (Panel A) and after (Panel B) the peak of the market prices in December 2017 when the monthly price of BTC reached its highest point. We report a set of descriptive statistics of the equal-weight portfolio returns aggregated across all funds (first column), each type of funds: `fund of funds`, `hedge fund`, `managed account`, `tokenized fund`, and `other` (from column two to column six), and each investment strategy: `long-short` , `long-term`, `market neutral`, `multi-strategy`, and `opportunistic` (the last five columns). We report the sample mean and standard deviation (%, monthly), the annualized Sharpe ratio, the skewness and autocorrelation of returns. The sample period is from March 2015 to June 2021.

Panel A: Sample until Dec 2017

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opportunistic
Mean (%)	13.13	8.57	12.23	28.49	13.78	39.83	10.17	17.92	2.95	10.01	1.59
Std (%)	18.82	13.57	17.45	21.74	25.06	33.01	17.27	29.03	7.99	14.12	0.85
SR (annualized)	2.42	2.19	2.43	4.54	1.90	4.18	2.04	2.14	1.28	2.46	6.45
Skewness	1.40	0.93	1.26	0.38	2.03	0.61	1.77	1.70	3.80	0.72	0.54
AR(1)	0.26	-0.02	0.16	-0.32	0.25	-0.02	0.52	0.23	0.10	0.03	0.25

Panel B: Sample from Jan 2018

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opportunistic
Mean (%)	4.80	3.72	4.31	6.26	6.24	5.10	5.09	5.90	1.68	4.79	4.17
Std (%)	12.60	9.27	12.61	13.58	17.52	11.80	11.19	19.18	3.87	11.61	10.11
SR (annualized)	1.32	1.39	1.18	1.60	1.23	1.50	1.58	1.07	1.50	1.43	1.43
Skewness	0.37	0.27	0.31	0.87	0.65	0.61	0.81	0.36	0.33	0.23	1.40
AR(1)	0.21	0.36	0.16	0.30	0.14	0.32	0.25	0.13	0.49	0.23	0.30

Table 7: **The cross-sectional distribution of benchmark- and risk-adjusted alphas: post ICO-bubble period**

This table reports the actual (Act) and simulated (Sim) values of alphas and t-statistics as well as the percentage of actual estimates greater than the simulated value at selected percentiles (% >Sim) as a measure of distribution discrepancy (see Fama and French, 2010). Specifically, the table compares (i) the actual values of the benchmark- and risk-adjusted alphas $\hat{\alpha}$ and the corresponding t-statistics $\hat{t}_{\hat{\alpha}}$ at selected percentiles of the cumulative distribution function for the cross-section of funds and (ii) the averages across the 10,000 simulation runs of the $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ estimates at the same percentiles. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The sample period corresponds to the post-ICO bubble stage from January 2018 to June 2021.

	Panel A: Passive benchmarks									**Panel B:** Risk factors								
	Alpha			t-statistics (stand)			t-statistics (clust)			Alpha			t-statistics (stand)			t-statistics (clust)		
Pct	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim
1	-10.46	-15.35	98.52	-2.75	-3.03	98.52	-0.54	-0.58	98.52	-10.43	-17.50	98.52	-2.77	-3.48	98.52	-0.51	-0.67	98.03
10	-3.84	-0.89	98.03	-1.05	-0.26	98.03	-0.19	-0.05	98.03	-3.67	-3.18	93.60	-1.02	-0.79	95.57	-0.19	-0.15	95.57
20	-2.22	0.41	96.06	-0.62	0.12	97.04	-0.11	0.02	97.04	-2.11	-1.68	83.74	-0.59	-0.49	83.74	-0.11	-0.09	83.74
30	-1.26	1.33	93.10	-0.36	0.33	94.09	-0.07	0.06	94.09	-1.20	-0.71	75.37	-0.34	-0.22	73.40	-0.06	-0.04	73.40
40	-0.60	1.89	86.70	-0.17	0.51	88.18	-0.03	0.10	88.18	-0.55	0.13	67.98	-0.15	0.04	67.00	-0.03	0.01	67.00
50	-0.06	2.64	84.24	-0.02	0.75	84.24	0.00	0.14	84.24	-0.05	0.72	61.58	-0.01	0.18	61.58	0.00	0.04	61.58
60	0.45	3.20	79.31	0.13	0.97	79.80	0.02	0.19	79.31	0.46	1.45	53.69	0.13	0.40	55.17	0.03	0.08	54.19
70	1.07	4.49	72.41	0.30	1.30	70.44	0.06	0.25	70.44	1.09	2.31	44.33	0.31	0.66	41.87	0.06	0.13	41.87
80	2.01	6.02	58.62	0.57	1.64	57.64	0.11	0.31	56.16	1.99	3.72	32.02	0.57	0.94	33.50	0.11	0.18	33.50
85	2.67	7.01	49.26	0.75	1.95	49.75	0.15	0.37	49.26	2.62	5.03	27.09	0.74	1.24	28.57	0.14	0.24	27.59
86	2.83	7.79	47.29	0.79	1.99	48.77	0.15	0.38	47.78	2.78	5.15	25.12	0.77	1.35	26.60	0.15	0.26	26.11
87	3.00	8.18	41.87	0.84	2.14	46.31	0.16	0.41	46.31	2.94	5.37	24.14	0.82	1.41	24.63	0.16	0.27	24.63
88	3.19	8.49	39.90	0.89	2.17	44.83	0.17	0.41	44.83	3.11	5.83	22.66	0.86	1.50	23.65	0.17	0.29	22.66
89	3.41	8.72	38.42	0.94	2.30	40.89	0.18	0.44	40.89	3.30	6.06	22.17	0.92	1.62	20.20	0.18	0.31	20.20
90	3.65	9.50	35.96	1.01	2.43	39.41	0.19	0.47	39.41	3.52	6.42	21.67	0.98	1.79	19.21	0.19	0.35	18.23
91	3.92	9.67	34.48	1.09	2.68	35.96	0.21	0.51	36.45	3.78	6.96	19.70	1.05	2.04	17.73	0.20	0.39	17.73
92	4.22	9.98	32.51	1.16	2.75	33.50	0.22	0.53	33.50	4.10	7.54	18.23	1.13	2.12	17.24	0.22	0.42	17.24
93	4.55	10.53	28.57	1.25	2.94	32.51	0.24	0.56	32.02	4.44	8.26	17.24	1.22	2.47	15.76	0.24	0.48	15.27
94	4.95	11.25	24.63	1.36	3.23	28.57	0.26	0.62	28.57	4.91	8.69	15.27	1.33	2.52	14.29	0.26	0.48	13.79
95	5.48	12.43	21.67	1.48	3.74	25.62	0.29	0.71	24.63	5.42	10.12	12.81	1.46	2.75	12.32	0.29	0.53	11.82
96	6.20	13.34	18.72	1.65	3.91	19.70	0.32	0.75	18.72	6.01	11.94	11.33	1.65	3.28	10.84	0.32	0.63	10.34
97	7.20	16.25	14.78	1.90	4.32	15.27	0.36	0.83	16.26	6.90	13.61	9.36	1.87	3.78	9.85	0.37	0.73	9.85
98	8.65	18.13	11.33	2.28	4.48	11.33	0.43	0.86	11.33	8.28	15.57	6.90	2.25	4.47	7.39	0.43	0.86	7.39
99	11.80	21.96	5.42	3.10	6.05	5.91	0.57	1.15	6.90	11.02	19.53	4.93	2.96	5.41	4.93	0.60	1.04	3.94
100	19.89	36.37	1.48	5.33	6.58	1.48	0.87	1.26	1.97	17.98	39.60	1.48	4.68	5.72	1.97	0.96	1.10	1.97

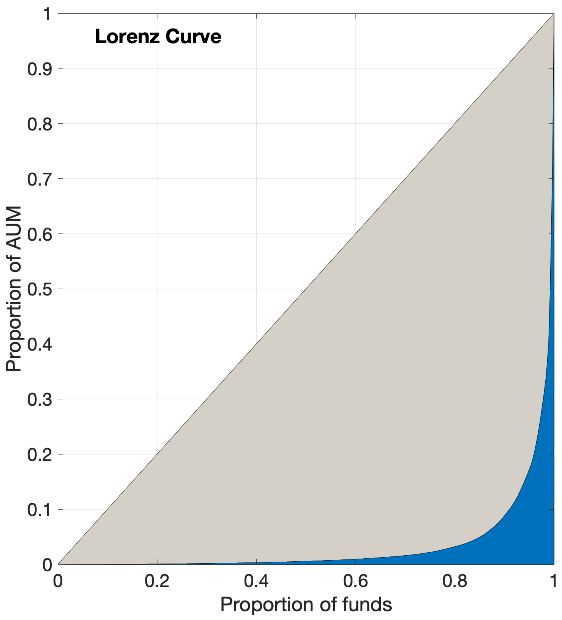
Table 8: **The cross-sectional distribution of benchmark- and risk-adjusted alphas: block bootstrap**

This table reports the actual (Act) and simulated (Sim) values of alphas and t-statistics as well as the percentage of actual estimates greater than the simulated value at selected percentiles (% >Sim) as a measure of distribution discrepancy (see Fama and French, 2010). Specifically, the table compares (i) the actual values of the benchmark- and risk-adjusted alphas $\hat{\alpha}$ and the corresponding t-statistics $\hat{t}_{\hat{\alpha}}$ at selected percentiles of the cumulative distribution function for the cross-section of funds and (ii) the averages across the 10,000 simulation runs of the $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ estimates at the same percentiles. The simulated values are based on a block bootstrap procedure with a block size of three observations. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The sample period is from March 2015 to June 2021.

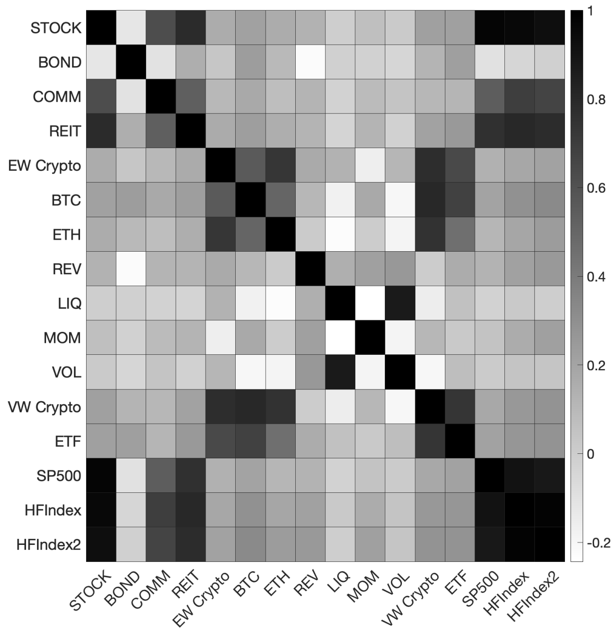
	Panel A: Passive benchmarks									**Panel B:** Risk factors								
	Alpha			t-statistics (stand)			t-statistics (clust)			Alpha			t-statistics (stand)			t-statistics (clust)		
Pct	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim
1	-11.85	-9.58	99.02	-2.84	-1.90	100.00	-0.53	-0.34	100.00	-11.23	-11.98	99.02	-2.76	-2.50	99.02	-0.53	-0.45	99.51
10	-4.04	-1.02	98.04	-1.00	-0.21	97.55	-0.18	-0.04	97.55	-3.87	-2.88	95.10	-0.97	-0.67	96.08	-0.18	-0.12	96.08
20	-2.26	0.24	95.59	-0.57	0.06	96.08	-0.10	0.01	96.08	-2.15	-1.62	84.80	-0.55	-0.40	85.78	-0.10	-0.07	85.78
30	-1.27	1.15	92.65	-0.32	0.28	93.14	-0.06	0.05	92.65	-1.21	-0.46	76.47	-0.31	-0.13	77.45	-0.06	-0.02	77.45
40	-0.58	2.10	87.75	-0.15	0.50	88.24	-0.03	0.09	88.24	-0.55	0.34	70.10	-0.14	0.09	70.10	-0.03	0.02	70.10
50	-0.03	2.68	82.84	-0.01	0.74	82.84	0.00	0.13	82.84	0.02	1.05	64.22	0.00	0.25	64.22	0.00	0.04	64.22
60	0.51	3.64	77.45	0.13	0.94	76.96	0.02	0.17	76.96	0.60	1.69	56.86	0.15	0.46	55.39	0.03	0.08	55.39
70	1.20	4.83	69.61	0.30	1.22	68.63	0.06	0.22	68.14	1.26	2.77	45.10	0.32	0.72	46.57	0.06	0.13	48.04
80	2.17	6.35	59.80	0.55	1.56	57.35	0.10	0.28	56.86	2.18	4.58	33.82	0.55	1.11	34.31	0.10	0.20	33.82
85	2.85	7.71	48.53	0.71	1.91	50.00	0.13	0.34	50.00	2.84	5.60	28.92	0.72	1.42	29.90	0.13	0.26	29.90
86	3.00	7.94	46.08	0.75	1.96	50.00	0.14	0.35	49.02	3.00	5.74	28.92	0.76	1.50	28.92	0.14	0.28	28.43
87	3.17	8.44	43.63	0.80	2.08	46.57	0.15	0.38	45.59	3.17	6.03	28.92	0.80	1.63	27.45	0.15	0.29	27.45
88	3.38	8.69	42.16	0.85	2.25	44.61	0.16	0.41	44.12	3.39	6.19	28.92	0.85	1.65	26.47	0.16	0.31	26.47
89	3.64	8.89	40.20	0.91	2.33	41.67	0.17	0.42	41.67	3.63	6.41	26.47	0.90	1.80	25.00	0.17	0.32	25.00
90	3.89	9.70	36.27	0.97	2.41	38.73	0.18	0.44	38.24	3.89	7.77	25.49	0.97	1.83	25.00	0.18	0.34	25.00
91	4.17	10.08	33.33	1.03	2.46	35.78	0.19	0.44	33.82	4.15	8.00	23.04	1.03	2.12	24.51	0.19	0.38	24.02
92	4.51	10.68	31.86	1.12	2.57	31.86	0.21	0.46	31.86	4.48	8.33	21.08	1.11	2.19	20.10	0.20	0.40	19.12
93	4.90	11.05	29.90	1.21	2.82	29.90	0.22	0.51	28.92	4.84	8.97	18.63	1.21	2.28	17.16	0.22	0.41	17.16
94	5.32	11.44	27.45	1.32	3.18	26.96	0.24	0.57	23.53	5.29	9.29	16.18	1.32	2.44	15.69	0.24	0.44	15.69
95	5.87	12.84	23.04	1.46	3.28	22.55	0.27	0.59	21.57	5.82	10.96	13.73	1.44	2.54	14.71	0.27	0.46	14.71
96	6.67	13.73	17.65	1.62	3.48	19.12	0.30	0.63	19.12	6.56	12.30	10.78	1.63	3.11	12.75	0.30	0.57	12.25
97	7.71	15.74	15.20	1.87	3.94	16.67	0.35	0.71	14.71	7.61	14.07	10.29	1.89	3.59	9.80	0.35	0.65	9.80
98	9.28	20.44	10.78	2.20	4.78	12.25	0.41	0.86	11.76	9.23	18.64	5.88	2.29	4.36	6.86	0.42	0.79	6.37
99	12.86	24.90	4.90	3.12	6.55	6.37	0.56	1.18	6.37	13.12	22.78	3.43	3.16	6.54	3.92	0.56	1.19	3.92
100	21.41	36.68	1.96	5.07	8.98	1.96	0.90	1.62	1.96	22.93	39.01	0.98	5.28	8.44	1.47	0.89	1.54	1.47

Figure 1: **Some facts about cryptocurrency funds**

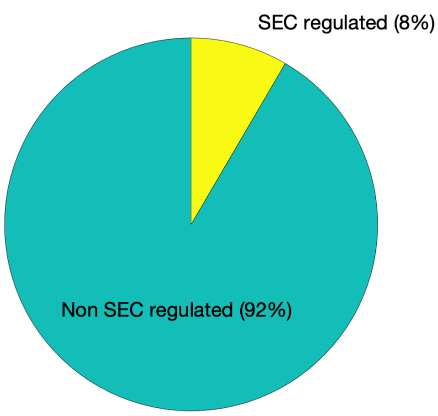
The figure reports a set of aggregate characteristics for the sample of funds used in the main empirical analysis. The top-left panel shows the concentration of assets under management (AUM) via a visual representation of the Gini coefficient, i.e., Lorenz curve. The top-right panel shows the unconditional correlation between the average crypto fund, buy-and-hold positions in BTC and ETH, long-short cryptocurrency-based strategies, global ETFs from traditional asset classes, S&P500, and two hedge fund indices. The bottom panels reports the regulatory framework, namely SEC registration (a left panel) and the geographical dispersion (a right panel) of the funds in our sample. The sample period is from March 2015 to June 2021.



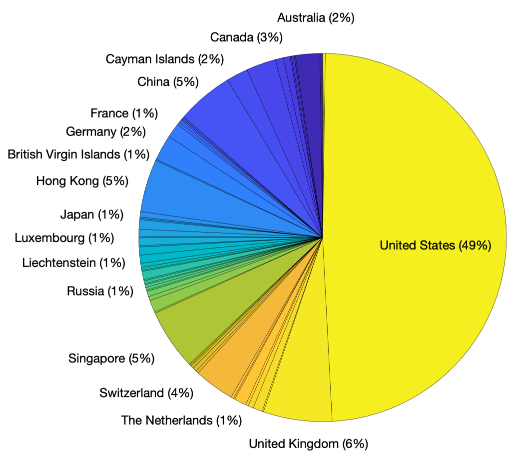
(a) AUM concentration



(b) Correlation of cryptos with other assets



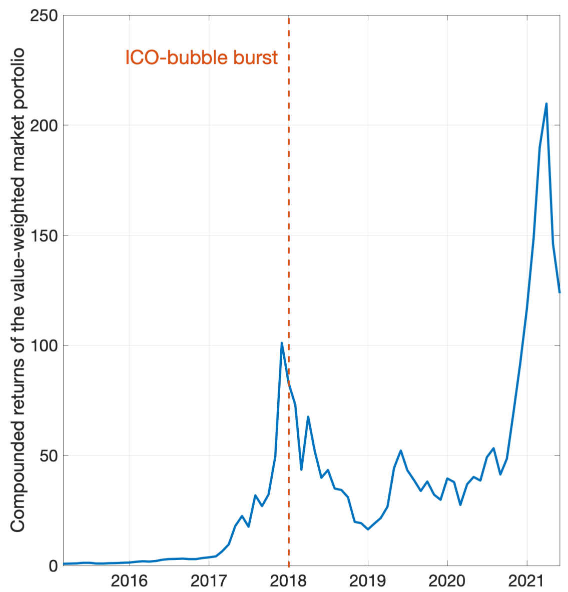
(c) SEC regulated funds



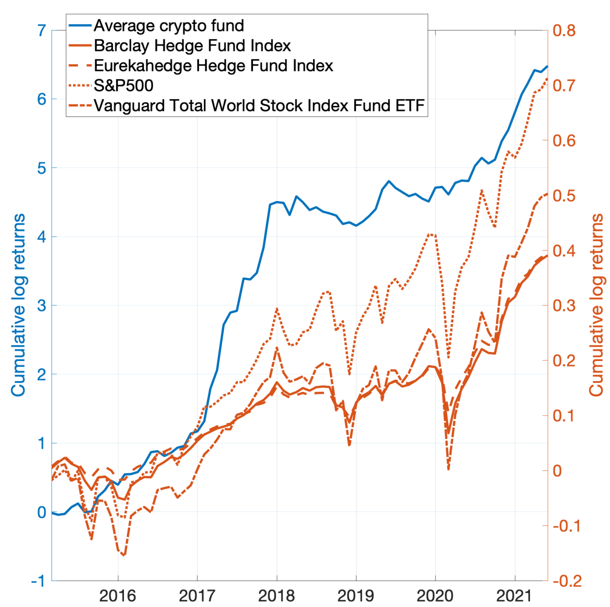
(d) Geographical distribution

Figure 2: **A snapshot of the cryptocurrency market**

The left panel shows the compounded returns, assuming $1 initial investment, from a value-weight market portfolio of the top 100 cryptocurrencies sorted by average market capitalisation. The right panel shows the cumulative log returns of the average cryptocurrency fund, S&P500 Index, the Vanguard Total World Stock Index Fund ETF and two hedge fund indices from Barclay and Eurekahedge. The sample period is from March 2015 to June 2021.



(a) Compounded returns of the crypto market portfolio



(b) Cumulative log-returns

Figure 3: **The cross-sectional distribution of descriptive statistics of fund returns**

This figure plots the cross-sectional distribution of the Sharpe ratio (annualised), the skewness, the first-order autoregressive coefficient (AR(1)) and the market beta for each of the fund in our sample. The market beta is calculated by using a value-weight index of the top 100 cryptocurrencies by market capitalisation. The sample period is from March 2015 to June 2021.

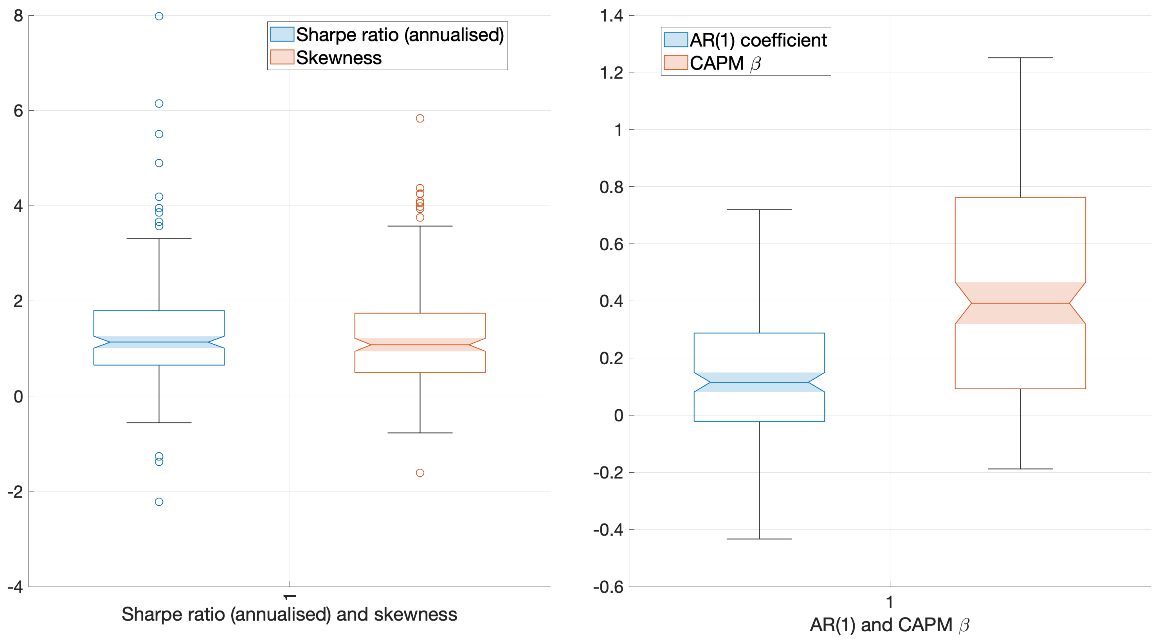
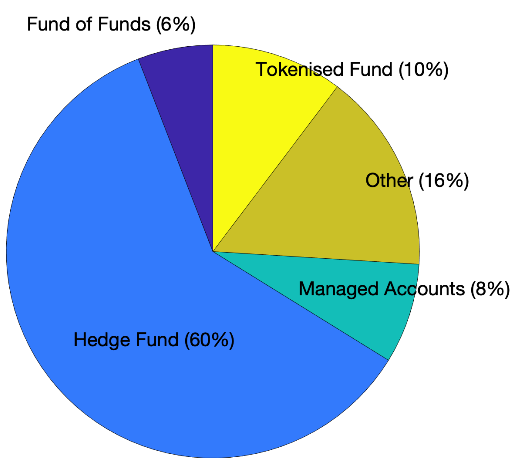
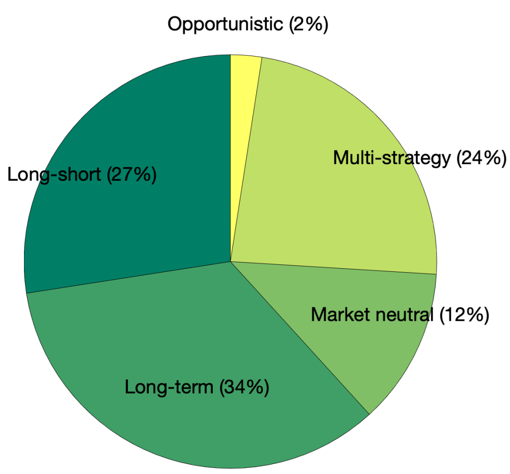


Figure 4: **Classification of funds by type and investment strategy**

This figure plots the distributions of funds per fund type (a left panel) and investment strategy (a right panel). Funds are clustered by type and labeled as `fund of funds`, `hedge fund`, `managed account`, `tokenized fund`, and `other`. Classification by investment strategy is defined as `long-short` , `long-term`, `market neutral`, `multi-strategy`, and `opportunistic`. The sample period is from March 2015 to June 2021.



(a) Fund classification by type

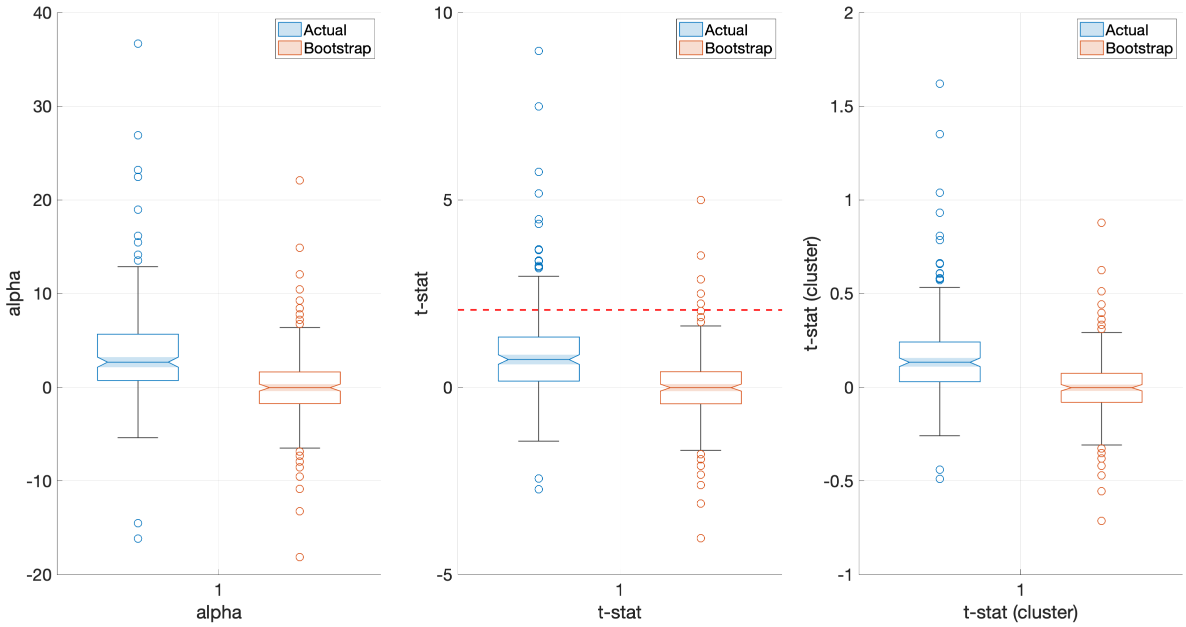


(b) Fund classification by investment strategy

Figure 5: **The cross-section of individual fund alphas**

This figure plots the box charts of the benchmark-adjusted (Panel A) and risk-adjusted (Panel B) alphas and corresponding t-statistics. The latter are calculated without (middle panels) and with (right panels) clustering the standard errors by investment strategy. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The panels report actual (blue box charts) and bootstrap (red box charts) cross-sectional distributions. The red dashed line in the middle panel represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to June 2021.

Panel A: Benchmark-adjusted alphas



Panel B: Risk-adjusted alphas

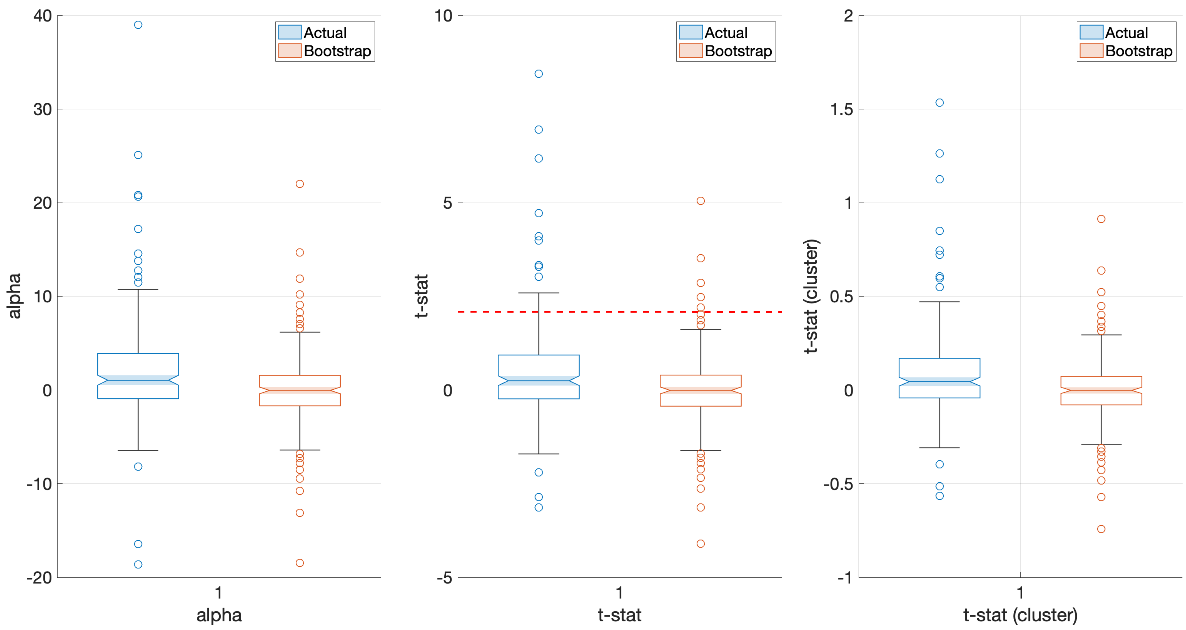
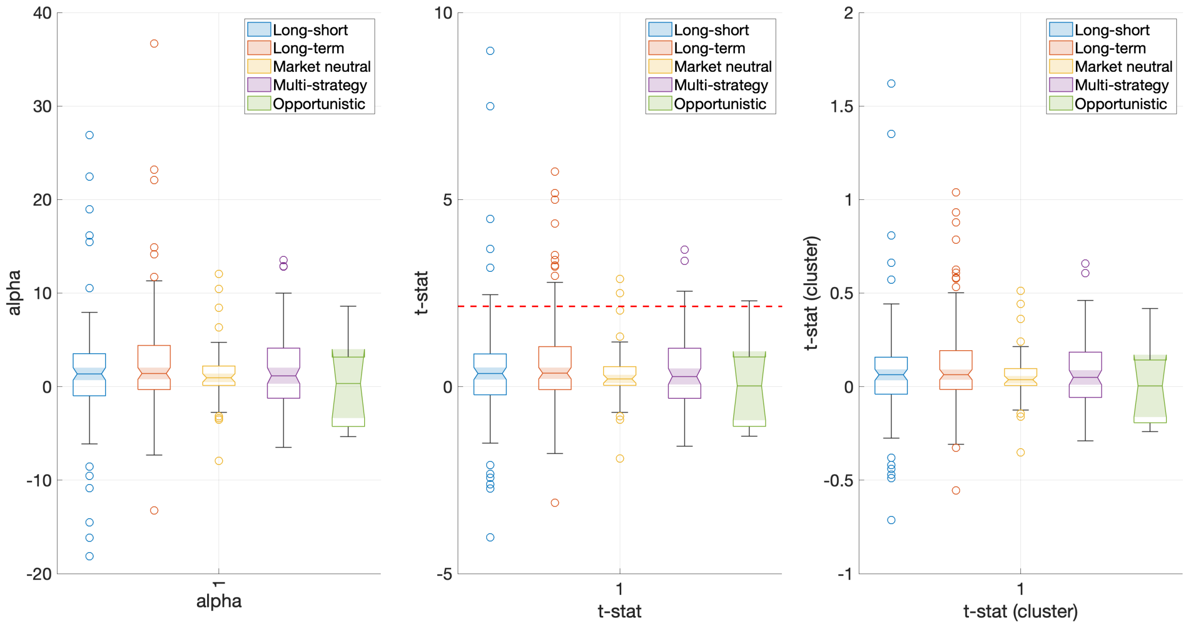


Figure 6: **The cross-section of alphas for different investment strategies**

This figure plots the box charts of the benchmark-adjusted (Panel A) and the risk-adjusted (Panel B) alphas and corresponding t-statistics for different investment strategies. Classification by investment strategy is defined as `long-short`, `long-term`, `market neutral`, `multi-strategy`, and `opportunistic`. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The red dashed line in the middle panel represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to June 2021.

Panel A: Benchmark-adjusted alphas



Panel B: Risk-adjusted alphas

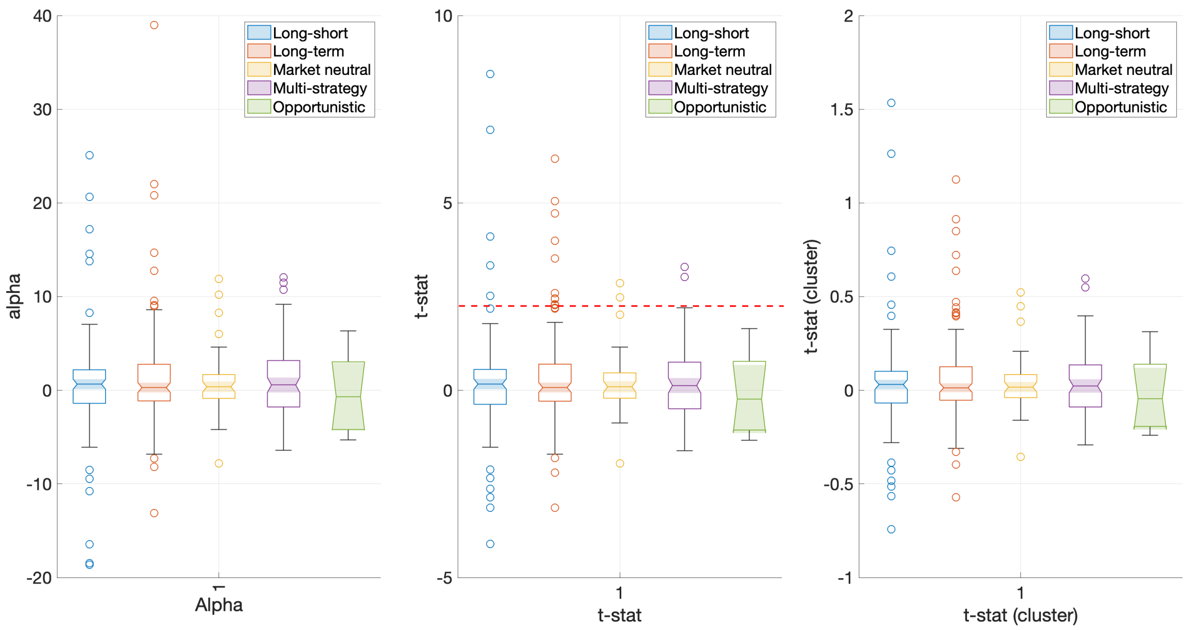
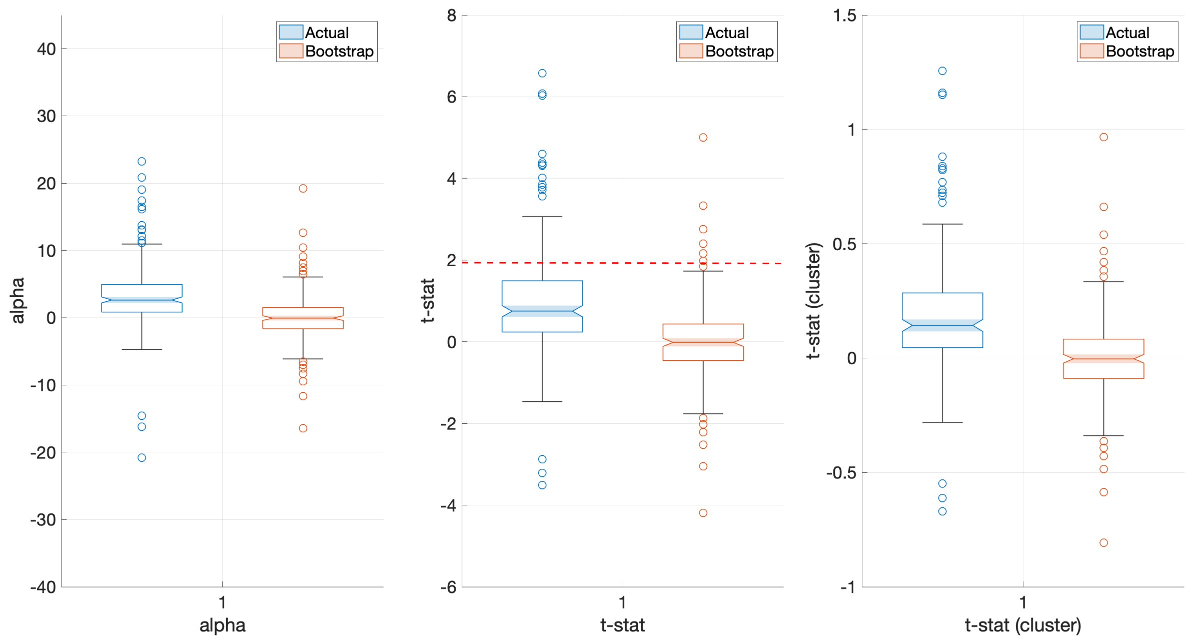


Figure 7: **The cross-section of alphas for the post ICO-bubble period**

This figure plots the box charts of the benchmark-adjusted (Panel A) and risk-adjusted (Panel B) alphas and corresponding t-statistics. The latter are calculated without (middle panels) and with (right panels) clustering the standard errors by investment strategy. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The panels report actual (blue box charts) and bootstrap (red box charts) cross-sectional distributions. The red dashed line in the middle panel represents a threshold of 1.96 for the t-statistic. The sample period is from January 2018 to June 2021.

Panel A: Benchmark-adjusted alphas



Panel B: Risk-adjusted alphas

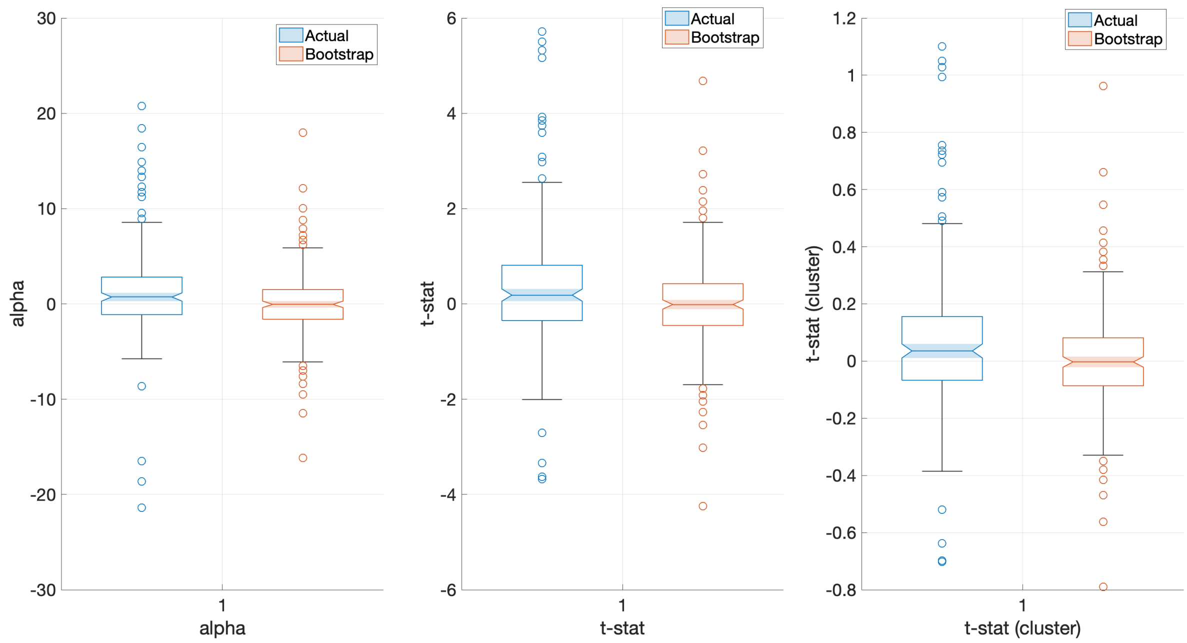
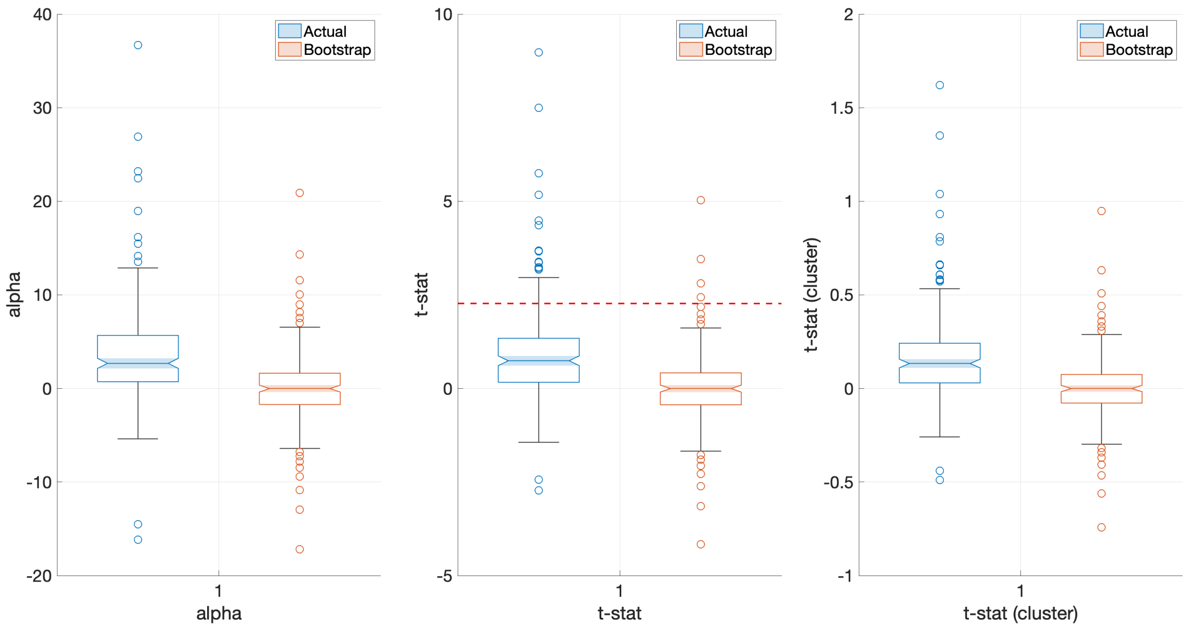


Figure 8: **Alternative bootstrap procedures**

This figure plots the box charts of the benchmark-adjusted alphas (left panels) and the corresponding t-statistics. The latter are calculated without (middle panels) and with (right panels) clustering the standard errors by investment strategy. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). The figure reports the actual (blue box charts) and bootstrap (red box charts) cross-sectional distributions. Panels A and B report the results for the two bootstrap extensions: a block bootstrap procedure and a bootstrap independently resampling benchmark returns and residuals. The red dashed line in the middle panel represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to June 2021.

Panel A: Block bootstrap



Panel B: Independent resampling of benchmark returns and residuals

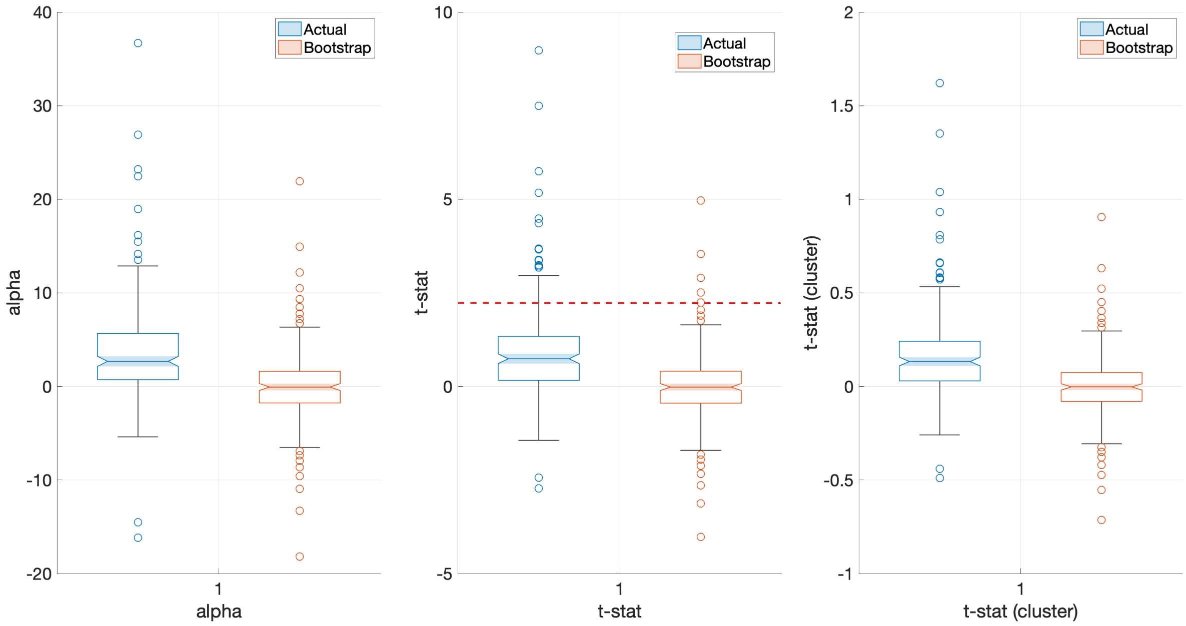
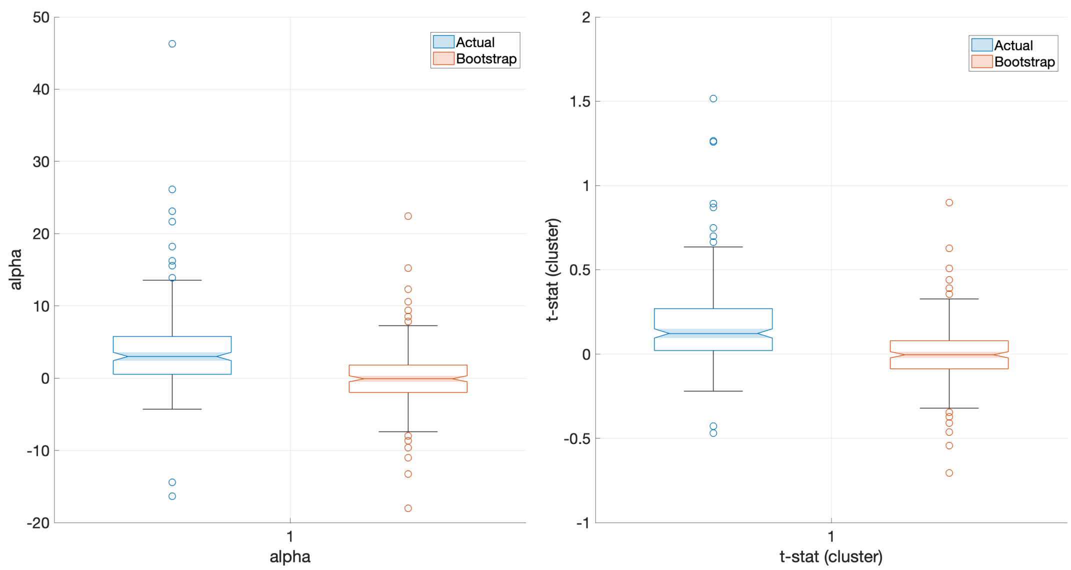


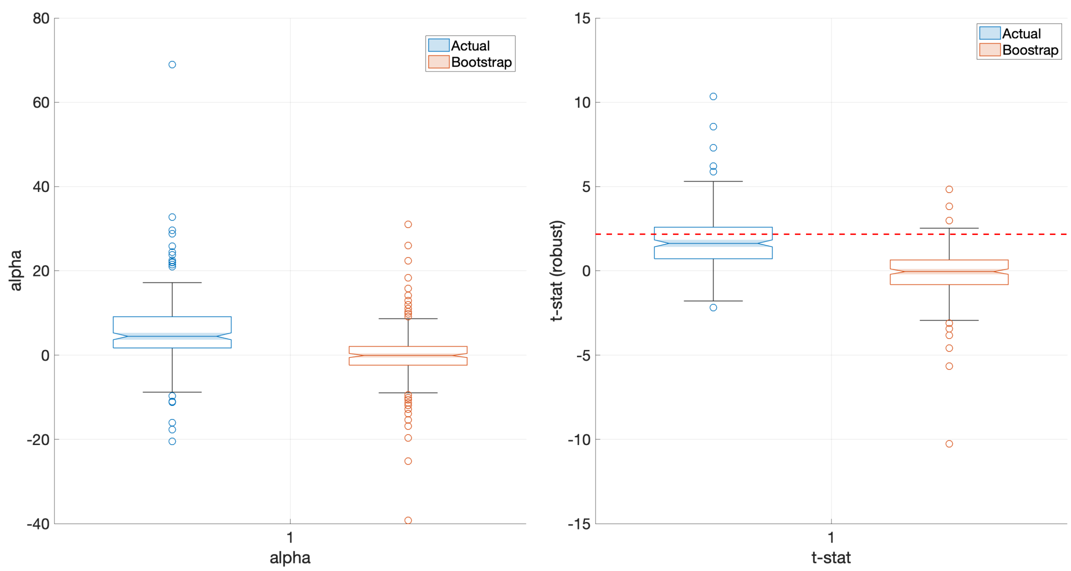
Figure 9: **Constant betas and time-series regressions**

Panel A plots the box charts for the benchmark-adjusted alphas (a left panel) and the t-statistics obtained with clustering the standard errors by investment strategy (a right panel). Unlike the main empirical analysis, the betas of the benchmark portfolios are restricted to be constant in the whole cross section of funds. The individual alphas are calculated as the individual fund fixed effects from a panel regression (see Pástor et al., 2015). Panel B shows the results from time-series regressions performed for each individual fund separately as in Kosowski et al. (2006) and Fama and French (2010). The t-statistics are based on the Newey and West (1986) robust standard errors. The panels report actual (blue box charts) and bootstrap (red box charts) cross-sectional distributions. The red dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to June 2021.

Panel A: Panel regression with constant betas



Panel B: Individual time series regressions



Appendix

A Bootstrap methods

This appendix provides the details of the baseline procedure with the residual resampling that extends the methodology outlined in Kosowski et al. (2006) and Fama and French (2010). For each fund in our sample, we draw a random sample (with replacement) from the fund residuals conditional on the returns of passive benchmarks (risk factors), creating a pseudo time-series of resampled residuals. Next, an artificial panel of monthly net-of-fees returns is constructed imposing the restriction that a true alpha for each fund is equal to zero. For each pseudo panel, we estimate the benchmark-adjusted (factor-adjusted) fund alphas as the individual fund fixed effects from the panel regression (see, e.g., Pástor et al., 2015). Thus, we obtain a set of individual fund alphas and their t-statistics based on random samples of months under the null of true fund alphas being zero. We repeat the above steps 10,000 times and save bootstrap alphas and t-statistics for all simulation runs. We then report the distribution of these cross-sectional alphas and t-statistics.

Procedure

Estimate a benchmark (factor) model using the panel regression as outlined in the main text.

for *all bootstrap iterations* $b = 1, ..., B$

for *all funds* $i = 1, ..., N$

- Draw a sample of months $\{s^b_{T_{0,i}}, ..., s^b_{T_{1,i}}\}$ where $T_{0,i}$ and $T_{1,i}$ are, respectively, the dates of the first and last months when returns of fund i are available
- Construct a time-series of resampled residuals $\{\widehat{\epsilon}^b_{ikt} : t = s^b_{T_{0,i}}, ..., s^b_{T_{1,i}}\}$
- Generate a time-series of "synthetic" zero-alpha returns as

$$y^b_{ikt} = \widehat{\boldsymbol{\beta}}'_k \boldsymbol{x}^b_t + \widehat{\epsilon}^b_{ikt},$$

in which $\boldsymbol{x}^b_t$ are the returns of passive benchmarks (risk factors)

end

Estimate the individual fund fixed effects from a panel regression with the benchmark (factor) returns on the right-hand side:

$$y^b_{ikt} = \alpha^b_i + \beta'_k \boldsymbol{x}^b_t + \varepsilon^b_{ikt}$$

end

Output: The bootstrap individual fixed effects $\{\widehat{\alpha}^b_i : b = 1, ..., B\}$ and the corresponding t-statistics $\{\widehat{t}^b_{\widehat{\alpha}_i} : b = 1, ..., B\}$.

A.1 Bootstrap extensions

A.1.1 Block bootstrap. The baseline bootstrap assumes the residuals obtained from the panel regression are independently and identically distributed. This is because we resample the residuals in each period independently. The first extension relaxes this assumption by drawing months in blocks. Due to a short sample period, we resample the residuals in blocks of three months. Once the pseudo panel of fund returns is generated by blocks, we apply the remaining steps from the baseline procedure as in Section A.

A.1.2 Independent resampling of residuals and explanatory returns. The second bootstrap extension allows for independent draws of the benchmark (risk factor) returns and residuals. The procedure is constructed as follows:

Procedure

Estimate a benchmark (factor) model using the panel regression.

for *all bootstrap iterations* $b = 1, ..., B$

for *all funds* $i = 1, ..., N$

- Draw a sample of months for the residuals $\{s^b_{T_{0,i}}, ..., s^b_{T_{1,i}}\}$, and a sample of month for the benchmark returns $\{\tau^b_{T_{0,i}}, ..., \tau^b_{T_{1,i}}\}$, where $T_{0,i}$ and $T_{1,i}$ are the dates of the first and last months when returns of fund i are available
- Construct a time-series of resampled residuals $\{\widehat{\epsilon}^b_{ikt_\epsilon} : t_\epsilon = s^b_{T_{0,i}}, ..., s^b_{T_{1,i}}\}$
- Construct a time-series of resampled benchmark returns $\{\boldsymbol{x}^b_{i,t_x} : t_x = \tau^b_{T_{0,i}}, ..., \tau^b_{T_{1,i}}\}$
- Generate a time-series of "synthetic" zero-alpha returns as

$$y^b_{ikt} = \widehat{\boldsymbol{\beta}}'_k \boldsymbol{x}^b_{t_x} + \widehat{\epsilon}^b_{ikt_\epsilon},$$

in which $\boldsymbol{x}^b_{t_x}$ are resampled returns of passive benchmarks (risk factors)

end

Estimate the individual fund fixed effects from a panel regression with the benchmark (factor) returns on the right-hand side:

$$y^b_{ikt} = \alpha^b_i + \beta'_k \boldsymbol{x}^b_{t_x} + \epsilon^b_{ikt_\epsilon}$$

end

Output: The bootstrap individual fixed effects $\{\widehat{\alpha}^b_i : b = 1, ..., B\}$ and the corresponding t-statistics $\{\widehat{t}^b_{\widehat{\alpha}_i} : b = 1, ..., B\}$.
