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On the Performance of Cryptocurrency Funds*

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Abstract

We investigate the performance of funds that specialise in cryptocurrency markets and contribute to a growing literature that aims to understand the value of digital assets as investments. The main empirical results support the idea that cryptocurrency funds generate significantly alphas compared to passive benchmarks or conventional risk factors. 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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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 capitalization that stands roughly at $3 trillion at the time of writing - has led to increasingly large investments flows into a new category of specialised funds, namely cryptocurrency funds. As a result, while much of trading activity 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 became inherently linked to the 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 a heavily studied question 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. More 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 the mutual fund industry, cryptocurrency funds provide a peculiar context through which the value of active asset

[1] In addition to the most common such as Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC) and Ripple (XRP), at the time of writing there are more than 13,000 of digital assets. Each asset with rather different characteristics and features, and being traded on more than 300 exchanges worldwide (see `http://Coinmarketcap.com`).

[2] The anecdotal evidence is substantial. For instance, on June 2020 Fidelity run a survey on more than 800 institutional investors between the EU and the US. The results show that about a third of those investors owned digital assets. As a result, after two months, Fidelity itself launched its own Bitcoin fund for wealthy investors (see `https://www.bloomberg.com/news/articles/2020-08-26/fidelity-launches-inaugural-bitcoin-fund-for-wealthy-investors`)

[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.

management can be further understood. The reason is threefold: first, the fact that cryptocurrency markets have a highly fragmented, multi-platform structure, which is decentralised and granular, adds to the conjecture that there might be market segmentation, meaning the pricing factors for standard asset classes do not apply to cryptocurrencies (see Yermack, 2013; Liu and Tsyvinski, 2020; and Bianchi, 2020). This is possibly relevant from an investment management perspective and could affect active management decisions since an asset driven by forces and factors that are not common to others may offer considerable diversification benefits and ultimately attract more and more capital. The top-right panel of Figure 1 shows this case in point. The figure 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, and both an equal- and value-weighted market portfolio of cryptocurrencies as well as 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, a value that is typically associated with diversification benefits, at least within the context of a standard mean-variance portfolio allocation.[4]

Second, the competition in the crypto fund space is quite low compared to the traditional equity fund industry. The assets under management (AUM) are highly concentrated in few funds. The top-left panel of Figure 1 illustrates this case in point. The figure shows the Lorenz curve, a visual representation of the Gini index, for the size of cryptocurrency funds.[5] Around 90% of the funds own roughly 10% of the AUM in the industry, that is, 10% of the funds own 90% of total assets. Further, the top 1% of 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. The cryptocurrency fund space resembles an oligopoly where few funds dominate the industry in terms of size. In the empirical analysis, we document that managers of crypto funds are able to generate large and economically significant alphas, which might be explained by low

[4]More from a subjective perspective, cryptocurrencies are also perceived to have some diversification benefits by asset managers at large. For instance, on May 2, 2019, Fidelity released the results of a large-scale survey on institutional investments in digital assets and found that nearly half of traditional institutional investors surveyed found digital assets' low correlation to be a highly appealing characteristic. Similarly, nearly half of the respondents appreciated the innovative play of digital assets. Naturally, the innovation and low correlation of cryptocurrency returns go hand in hand, as these assets are in a minority that will not be as affected by traditional market trends. Ultimately, this could increase the interest of retail and less sophisticated investors in cryptocurrency funds. The report on the survey by Fidelity can be found here https://www.fidelity.com/bin-public/060_www_fidelity_com/documents/press-release/institutional-investments-in-digital-assets-050219.pdf.

[5]The Lorenz curve is often accompanied by a straight diagonal line with a slope of 1, which 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.

competition in the cryptocurrency market. Further, we demonstrate that conditional on a relatively low competitive environment, this performance is not dominated by a given strategy over others. Instead, we find that a fraction of fund managers have the skills to outperform others irrespective of the investment strategy adopted.[6]

Third, there is generally a rather lax regulatory oversight on funds that specialise in cryptocurrency investments. The bottom panels of Figure 1 show this case in point. Although around a half of funds in our sample are based in the US, only 8% of all funds are actually SEC registered and regulated. In addition, within the other half of the funds which are not based in the US, a relevant fraction of these is based in jurisdictions which do not regulate cryptocurrencies as securities and/or risky investments. These include some of the European countries and fiscal paradises.[7] The lack of specific regulatory oversight could ultimately affect the managers' decisions and risk taking behaviors. As a matter of fact, the regulatory framework in which fund managers operate in has been shown to play a key role for the value of active asset management (see, e.g., Novy-Marx and Rauh, 2011 and Andonov et al., 2017).

Among others, these three aspects jointly make institutional investing in cryptocurrencies quite peculiar. We argue that such setting could help to 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 particular relevant within the context of cryptocurrency markets. With so many outlying returns, when a fund is selected on the *ex-post* performance, disentangling *skill* versus *luck*, and therefore understanding the actual value of active asset management could be quite complicated.

Empirically, we look at the performance of 250 funds which specialise in cryptocurrency investments and have been actively managed between March 2015 to June 2021. To avoid survivorship bias, the sample includes not only those funds that are still active, but also the funds that have been

[6]Notice that 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 tend to coincide. The relatively short average length of the funds' life allows to some extent to conjecture that there is not much turnover within groups of funds. This is particularly relevant when investigating the performance at the aggregate type or strategy level as funds are aggregated on an equal-weight basis. If there is a particularly relevant change in a given fund management that should not change the aggregate performance in one direction or another. Also, by "skill" we follow the definition of Kosowski et al. (2006) and Fama and French (2010), that is, a given fund performance net of fees and exposure to sources of risk cannot simply reconciled by the random sampling variation of the returns.

[7]Most of the regulations in European countries are related to retail investments. Cryptocurrencies are broadly considered legal across the European Union, but cryptocurrency exchange regulations depend on individual member states. Cryptocurrency taxation also varies, but many member states charge capital gains tax on cryptocurrency-derived profits at rates of 0-50%.

created after the start of the sample and have been closed before the end of the sample. Although the sample size is limited, it is fairly representative of all market phases. Figure 2 shows this case in point. The left panel shows the compounded returns, assuming a 1$ initial investment in March 2015, of a value-weighted market portfolio of the top 100 cryptocurrencies sorted by the average market capitalization. Although the time series is relatively short, across the sample the market experienced a pronounced variation with a significant boom until December 2017, a major collapse from January 2018 to April 2018 – the so-called ICO bubble burst – a major market drop in the early stage of the COVID-19 pandemic and a subsequent impressive run up with Bitcoin, Ethereum and all other major cryptocurrencies reaching all-time high valuations by early 2021. Our sample also includes major regulatory and institutional changes such as the ban by the Chinese government on crypto exchanges and trading, the introduction of tradable Bitcoin futures contracts on the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE), and the bulk of the COVID-19 pandemic. The right panel of Figure 2 shows that, within the same period, 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 performance between 40% and 70% over the same period. In addition, the average crypto fund did not experience a large drop in value during the early stages of the Covid-19 pandemic unlike equity investments, which seems to suggest that indeed cryptocurrency funds might have provided some form of diversification for the average investor, at least over the medium term. As a whole, it is reasonable to assume that, although the sample is relatively short, it is fairly representative of the market development and likely ensure there is sufficient time series and cross-sectional variation in the data. The evidence on a significant gap in the performances of investments in traditional assets and cryptocurrencies also raises some interesting discussion of the risk-return trade-off within the context of cryptocurrency investments (see, e.g., Bianchi and Babiak, 2021).

In the empirical analysis we begin by looking at the aggregate, meaning average, performance of crypto funds in excess of alternative passive investment strategies such as a buy-and-hold investment in Bitcoin (BTC), an equal-weight portfolio invested in the top cryptos by market capitalization, 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). That is, 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 when aggregating funds there is some solid evidence of a superior fund performance compared to passive benchmarks. However, such performance is not homogeneous across different investment strategies, with `long-short` and `long-term` funds having higher alphas. A similar result is obtained when using a panel regression with fund type- or strategy-fixed effects and clustered standard errors. The evidence is slightly different when replacing the benchmark passive strategies with a set of anomaly-based 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 funds' betas, the results show that (1) there is a significant market exposure across funds and (2) Bitcoin plays the role of a "level" factor for the performance of crypto funds when it is used as an alternative to a value-weighted market portfolio.

Delving further into the analysis of fund performances, we build upon Kosowski et al. (2006) and Fama and French (2010) and propose a panel semi-parametric bootstrap approach that is robust to both time-series and cross-sectional correlations while taking explicitly into account both the strategy-specific exposures to benchmark returns – or risk factors – and the within-strategy returns correlations. Specifically, we assume that the distribution from which the cross-section of returns is jointly drawn is unknown ex-ante and fund returns are possibly highly correlated, especially within investment strategies. The latter is empirically motivated by the large differences in both the alphas and the factor/benchmark betas. Across a wide array of statistical tests, our main results show that, after adjusting for passive benchmarks or risk factors, the funds performance distribution cannot be simply due to random sampling variation of the net-of-fee returns. In other words, we find that the extreme outperformance of crypto funds it 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. In this respect, we show that there is no systematic dominance of a strategy over the others, but rather the outlying performances 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.

In addition to the main empirical analysis, we implement a variety of robustness checks. First, we analyse the managers' performance across sub-samples. In particular, we split the sample from March 2015 to December 2017 and from January 2018 to August 2020. 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 might raise a question of the significance of our main empirical results when including the pre-ICO bubble period. The main results of the paper hold across sub-samples, in particular for the post-ICO bubble period, there is support for the main evidence that the positive benchmark and risk-adjusted fund performances are unlikely to be explained by the luck of fund managers. 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 empirical evidence holds throughout both if we account for time-series dependencies of fund and benchmark returns and if we independently resample risk factors and unexplained returns. Finally, an additional appendix reports the testing results for the persistence in the fund alphas by reconstructing a set of tests as in Carhart (1997). We document a significant persistence in the alphas for the top performing managers, a finding consistent with the main empirical analysis.

1.1 Related literature

This paper contributes to the existing debate on the value of active investment management. On the one hand, the conventional wisdom initially articulated by Jensen (1968) and Carhart (1997) states that, on average, active management creates little value to investors. A number of papers support this statement 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). The theoretical underpinning of these results is that active management can be considered as zero-sum game before costs: any gain for one manager is offset by a loss for another manager. After subtracting costs, active management becomes a game with a negative sum, and hence the average active manager should necessarily underperform.[8] On the other hand, there is an emerging literature now advocating for the existence of a significant and persistent value of active investment management. Kothari and Warner (2001) and Glode (2011) show that common choices of the benchmark models in prior

[8]See Sharpe (1991, 2013); Bogle (2005) and French (2008) among others. In addition, Pedersen (2018) provides evidence that the theoretical argument about active management being a zero-sum game does not hold in the real world.

research lead to underestimation of the value of active managers. Motivated by these shortcomings of the extant literature, a number of recent papers use alternative skill measures or novel estimation methods to show that many active managers actually provide a sizable value for investors. With respect to new proxies of skill, 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 by multiplying fund excess return over its benchmark by assets under management. They 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. Kosowski et al. (2006) use a new bootstrap statistical technique to demonstrate persistence in superior alphas of fund managers. A number of 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). Our contribution to this strand of the literature is to examine an alternative and emerging category of investment funds which has not been investigated before; that is, cryptocurrency funds. Due to the institutional differences of cryptocurrency markets and the statistical peculiarities of the funds' performances, we view this paper as an *out-of-sample* test of existing theories on active asset management.

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 henceforth) and from Preqin. The former is a website-based data provider that collects in-depth crypto fund data, whereas the latter provide 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 first before fully reporting. To avoid any revision bias, we consider only the reported actual returns.

A variety of checks and filters have been introduced to ensure the data are sufficiently representative of specialised active investment in the cryptocurrency landscape; first, we excluded from the sample those funds with less than \$2mln of assets under management. The threshold seems low in absolute value, but in relative terms it is not, considering the median AUM for crypto hedge funds is slightly more than \$40mln, with a distribution that is concentrated around few large funds (see top-left panel in Figure 1). Second, we consider raw returns net of all fees, including incentive fees and management fees. Returns are all expressed in US dollars.[9] 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 the funds that have been closed before the end of the sample; the only requirement is that a fund should have at least twelve 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; interestingly, the majority of the funds are headquartered either in the US, Europe or UK, while only a small fraction of institutional investors are actually located in Asia and 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. The latter is calculated by using a value-weighted portfolio of the top 100 cryptocurrencies by market capitalization as a proxy for market risk. Contrary to the 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. As a matter of fact, 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 the

[9]Notice for the vast majority of the funds a typical 2% management fee + 20% performance fee is applied. Only few funds apply a high-watermark threshold.

average AR(1) coefficient of 0.12 and the range of values from -0.5 to 0.7. That is, only a very small fraction of funds show some sizable autocorrelation in their returns, while some funds show even reversal in their performances. Second, there is a considerable heterogeneous exposure of funds to market risk, with the median market beta that is around 0.4. This implicitly means that the average fund is less than perfectly exposed to the aggregate market trend.

2.1.1 Fund types. We focus on four macro categories of crypto funds: `hedge funds` (HF), `tokenised funds` (TF), `managed accounts` (MA), and `fund of funds` (FoF). Crypto HF work in the same way of a typical alternative fund, whereby investors' accounts are managed by teams of expert investors, re-balanced on occasion, and constantly analysed. `Managed accounts` are very similar to boutique mutual funds, whereby high-net-worth individuals can access a high degree of customisation and greater tax efficiencies. Instead, `tokenised funds` are peculiar 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 `tokenised funds` can be freely traded on a secondary market. Finally, `fund of funds` take a multi-manager approach and invest 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 type; the HF category constitutes the vast majority of funds in our sample with around 60% of the managers. `Tokenised funds` rank second (10%), whereas only a small fraction of funds are labelled as MA (8%) or `fund of funds` (6%). There is also a residual category of funds dubbed `other` , which consists of those funds for which we cannot find a reliable classification.[10]

Table 1 reports a set of descriptive statistics at the aggregate level – by taking an equal-weight average of all funds in our sample – and at a more granular fund type level (from column 2 to column 6), by averaging out the returns of the funds pertaining a given type.[11] First, looking at the aggregate statistics, the annualised Sharpe ratio of the aggregate average fund (1.83) is higher than the cryptocurrency market portfolio (1.22) and a buy-and-hold investment in Bitcoin (1.19) or Ethereum (0.99) as shown later in Table 2. In addition, the returns on the average fund are positively skewed

[10]One comment is in order: a significant fraction of funds that invest in cryptocurrencies are Private Equity (PE) and Venture Capital (VC) funds. The rationale for excluding both PE and VCs funds is twofold: first, valuations are much more sparse and data are scattered throughout the sample, which effectively limit the possibility for any sensible empirical analysis on an already relatively short sample period. Second, the investment decision process in VC and PE funds is more focused on passive `long-term` investments in ICOs, whereas our aim is to focus on more active forms of delegated investment management, as is often done in the literature (see, e.g., Cremers et al., 2019).

[11]Notice that, by looking at the equal-weight aggregation of the funds we are interested in understanding the average fund performance, both at the aggregate level, and by type and strategy.

and have very low persistent, with 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` type) and 2.14 (for `managed accounts`). In general, the returns of cryptocurrency funds are not persistent, with the highest AR(1) coefficients being equal to 0.29 and 0.43 for `managed accounts` and `tokenised funds` while being almost negligible for the other type of funds.

Panel B in Table 1 reports 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, respectively. 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 index returns from traditional asset classes are comparable with cryptocurrency funds in terms of Sharpe ratios. Panel C in Table 1 reports the correlations between the aggregate cryptocurrency fund returns and the above described 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 within a standard mean-variance framework (see, e.g., Yermack, 2013, Liu and Tsyvinski, 2020 and Bianchi et al., 2020). Historical correlations of monthly returns are pretty mild across the board and, on average, 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 somewhat 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`.[12] `Long-short` funds primarily employ a short/medium term systematic quantitative investment process, which seeks to capitalise on the volatile behaviour of cryptocurrencies.[13]

[12] Notice that the label of the strategy is given by the data providers for those funds which are available and is disclosed by the managers for the funds which have been hand-collected by the authors.

[13] 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 notice that, as of August 31st 2020, the average traded volume of futures contracts at Binance, BitMEX, and Huobi combined was $12bln (Source Coingecko.com `https://www.coingecko.com/en/exchanges/derivatives`). This

`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 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 a 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 tend 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 performance based on both passive benchmarks and risk-based portfolios is twofold:

is more than three times the total AUM of crypto funds at the same date.

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. As a matter of fact, 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 hardly 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 and the references therein). This justifies the use of both approaches to evaluate the performance of cryptocurrency funds.

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 website-based data provider that collects data from multiple exchanges. Precisely, 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 both academic and practical settings.[14] We obtained data on a daily basis for the sample period from March 1st 2015 to June 31st 2021. The data are 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. As such, the aggregation gives the most liquid market prices more importance, and 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 a variety of filters has been implemented: 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.[15] Second, exchanges are reviewed on a regular basis for each given cryptocurrency pair. Constituent exchanges are excluded if (1) posted prices are too volatile

[14]Notice the reliability of CryptoCompare has been proved by a number of relevant strategic partnerships such as VanEck's indices division (to price ETFs), Refinitiv, one of the world's largest providers of financial markets data and infrastructure, and Yahoo Finance (the popular platform uses CryptoCompare's data on over 100 cryptocurrency quote pages).

[15]Such 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.

compared to 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. In order to ensure that the exchanges that are excluded on a given month have an expiring price impact, the aggregate market price takes the last trade time into account, 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 reduces the exposure of the empirical analysis to concerns of misreporting of trading activity for some exchanges.

To reduce the impact of the bias in selecting the benchmark returns, we chose four different strategies that are fairly representative of the spectrum of passive investments. Specifically, we first consider a simple buy-and-hold investment either in BTC or in ETH, which are widely recognised as the two major digital asset currently traded. A third passive investment strategy is a simple equal-weight portfolio comprising the top 100 cryptocurrencies in terms of market capitalisation. This is the equivalent of a *dollar risk* factor adapted from Lustig et al. (2011).[16] The fourth and last passive benchmark replicates the so-called *Coinbase index*, which is a value-weighted portfolio that give investors exposure to all cryptocurrencies listed on Coinbase and Coinbase Pro exchanges at each point in time.[17]

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 due a much higher volatility of the returns compared to 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 only exception of BTC, all benchmark strategies show a positive skewness and exhibit weak persistence in realised returns.

2.2.2 Risk factors. The vast majority of the literature on mutual funds is built upon the use of observable risk factors to disentangle the alpha from simple exposures to sources of systematic risk. Within the context of cryptocurrency markets, a factor portfolio often does not represent a feasible

[16] Equal-weight portfolios have been proved to be a rather difficult benchmark to beat once fees and expenses are considered (see, e.g., DeMiguel et al., 2009).

[17] Note that the fund returns are net of fees, whereas BTC, ETH and DOL are assumed that there is no fee paid, and we assume a 70bps/month fee for ETF. A 0.7% fee for the ETF is calculated taking the average expense ratio of the top 8 blockchain ETF currently available on the market (see link `https://etfdb.com/themes/blockchain-etfs/#complete-list__expenses&sort_name=assets_under_management&sort_order=desc&page=1`here).

investment strategies. In particular, the large investment frictions and costs retailers should face to take short positions make quite prohibitive to implement profitable zero-cost long-short strategies based on anomalies 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). In other words, by calculating risk-adjusted returns instead of benchmark-adjusted returns, we can nevertheless compare our main results 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 more than 95% of the total market capitalization and the 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 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.[18] In addition, we consider two additional sources of risk that are relevant in cryptocurrency markets: liquidity (`liq`) and volatility (`vol`) (see Bianchi and Dickerson, 2019). A relatively convenient way to proxy for liquidity risk would be to use high frequency information on bid-ask spreads. In the cryptocurrency space, 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. In particular, 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 an value-weight portfolio of illiquid pairs (fifth quintile) and going short into the liquid pairs (first quintile), again value-weighted. This zero-cost long-short portfolio represents our liquidity factor portfolio.

[18] As far as the momentum strategy is concerned, the look-back period l is set to 6 months and maximum leverage equal to 125%. For each cryptocurrency pair i at time t, if the cumulative log return over the 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.

As far as the volatility portfolio is concerned, 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-weighted 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-weighted portfolio of the top 100 cryptos by market capitalization.

The last five columns in Table 2 show summary statistics for the risk factors. With the only exception of a pure reversal strategy, all factor portfolios deliver lower Sharpe ratios than average funds. 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 of the reversal strategy.

3 Understanding the performance of crypto funds

3.1 Performance of the average fund

Table 1 shows that, on average, crypto funds generate quite sizable returns and Sharpe ratios. We now look at the benchmark- and risk-adjusted performances of aggregate funds. The alpha $\hat{\alpha}$ of a group of funds is calculated as the intercept of a time-series regression where the dependent variable is an equal-weight portfolio of crypto funds and the independent variables are either the benchmark returns or the mimicking portfolios outlined in Section 2.[19] We also report a direct test of the difference in the performance between the average fund for the whole cross section – first column –

[19] More precisely, we estimate a time-series regression of the form

$$y_t = \alpha + \hat{\boldsymbol{\beta}}' \boldsymbol{x}_t + \epsilon_t,$$

where y_t is an equal-weight portfolio of crypto funds, α is the estimated performance, and $\hat{\boldsymbol{\beta}}'$ is the exposure to the benchmark returns (or risk factors) $\boldsymbol{x}'_t$. Notice that despite the aggregation through equal weighing, the fund returns show significant outliers in the time series. To mitigate the effect of outlying observations in the regression estimates, we use a "bi-square" weighting scheme for the linear regression residuals. This method provides an effective alternative to deleting specific points. Extreme outliers are deleted, but mild outliers are down-weighted rather than deleted altogether. More precisely, we first compute the residuals ϵ from the unweighted OLS fit and then apply the following and the performance of the average funds per type or investment strategy. To test for the difference in the alphas, we use an approach á la Diebold and Mariano (2002). In particular, we regress the difference in the benchmark-adjusted returns for a given fund type/strategy j, $\alpha_{t,j}$, and the aggregate crypto fund market, $\alpha_{t,m}$, onto a constant:

$$\alpha_{t,j} - \alpha_{t,m} = \gamma + \eta_t, \tag{1}$$

where $\alpha_{t,k} = y_{t,k} - \hat{\boldsymbol{\beta}}_k' \boldsymbol{x}_t$. Testing for the difference in the performance boils down to a test for the significance in $\hat{\gamma}$. In addition to the individual time series regressions, we also estimate the alphas per type or strategy based on a panel regression with type/strategy fixed effects. More specifically, we estimate a fixed-effect model of the form:

$$y_{t,k} = \alpha_k + \boldsymbol{\beta}' \boldsymbol{x}_t + \eta_{t,k}, \tag{2}$$

where α_k represents the estimate of the type/strategy specific performance net of the benchmark or risk factors $\boldsymbol{x}_t$.

3.1.1 Benchmark-adjusted alphas. Panel A of Table 3 reports the estimated alphas and the t-statistics based on heteroskedastic-robust standard errors. When controlling for passive benchmark strategies, the average fund generate a significant 3.40% (robust t-stat: 3.57) risk-adjusted performance on a monthly basis. A more granular classification by fund type and investment strategy, however, shows the fund performance is quite heterogeneous. For instance, `tokenized funds` generate a benchmark-adjusted alpha of 6.76% (robust t-stat: 3.86), which is more than double the performance of `fund of funds` (3.20%, robust t-stat: 3.39). There is a substantial heterogeneity also across different investment strategies. For instance, `long-short` and `multi-strategy` funds report strongly significant alphas of 3.59% (robust t-stat: 3.74) and 3.21% (robust t-stat: 3.31), while `market neutral` funds do not generate a statistically significant alpha. These results show that, despite the stellar nominal performance of the managers, the possibly high volatility of the returns make the

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.

benchmark-adjusted performance for some category of funds not significantly different from zero.

The performance of the average fund is statistically comparable across most fund types, with the only exception of `managed accounts` and `tokenized funds` ($\hat{\gamma} = 1.76$ and $\hat{\gamma} = 2.28$, respectively). `Managed accounts` and `tokenized funds` both generate a benchmark-adjusted performance that is higher than the average fund, although the difference in the performance is only borderline different once heteroskedasticity and autocorrelation in the performance is fully taken into account. A similar degree of heterogeneity holds when clustering funds based on their investment strategy. `Market neutral` funds show a benchmark-adjusted performance which is statistically lower than the average cryptocurrency funds, with a difference of $\hat{\gamma} = -2.28$ (robust t-stat: -2.92). The `opportunistic` funds tend to perform, in benchmark-adjusted terms, below the fund average, although the difference in the performance is not different from zero in statistical terms.

Panel B of Table 3 suggests that the heterogeneity in the benchmark-adjusted performance is primarily due to the heterogeneous exposure of the fund returns to the performance of passive investment strategies. As far as the more granular fund classification is concerned, two interesting facts emerge: first, there is a substantial market level effect, which comes from BTC, ETH, and ETF passive benchmark. Recall that the latter is a value-weighted portfolio of some of the largest assets by market capitalization. When looking at different fund types, the evidence suggests that all funds are somewhat exposed to the market trend, either through a direct exposure on the largest assets, such as BTC and ETH, or a combination of BTC, ETH, and other assets with relevant market size. Second, by looking at the strategy-based clustering, we can see that `market neutral` strategies tend to be uncorrelated with any of the proxies for the aggregate market trend as proxied by BTC, ETH or the ETF portfolio. This is expected given the nature of the strategy. On the other hand, for all other strategies, the raw net-of-fee returns correlate significantly with the aggregate market trend. The results of Panel A and B together show that, despite the significant exposure to the aggregate market trend, the performance of crypto funds is somewhat positive and significant.

Panel C of Table 3 extends this result to a panel regression by restricting the funds to be equally exposed to the passive benchmarks. Thus, we estimate the benchmark-adjusted alphas of the average funds clustered by type or investment strategy via a panel regression with type or strategy fixed effects. Panel C confirms that (1) there is a substantial heterogeneity in the performances of aggregate funds across different types and investment strategies, and (2) the performance cannot be attributed solely to the exposure to the aggregate market trends as proxied by passive benchmarks.

3.1.2 Risk-adjusted alphas. We replace the passive benchmark portfolios with a set of risk factors outlined in Section 2. Table 4 reports the results. The independent variables in the regression specifications are the factors portfolios sorted on liquidity, volatility, and both a momentum and a reversal portfolio in addition to the returns on the value-weighted market index.

Panel A reports the risk-adjusted alphas from the individual time-series regressions. When clustered by type, the risk-adjusted alphas are slightly lower than the benchmark-adjusted performances. For instance, the alpha of the `fund of funds` and `hedge funds` decreases by 1% on a monthly basis compared to the benchmark-adjusted estimates. Similarly, the estimated alphas for the funds clustered by investment strategy tend to decrease. For example, the risk-adjusted alpha for the `long-short` strategy is now borderline significant at the typical 10% thresholds (1.93%, robust t-stat: 1.88). Further, although `long-term` and `multi-strategy` investments keep a relatively strong statistical significance, the risk-adjusted alpha from the `opportunistic` strategy becomes insignificant. Nevertheless, the average crypto fund – first column in Panel A – still reports a positive and significant risk-adjusted alpha (2.59%, robust t-stat: 3.49).

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, $\hat{\beta}_{MKT} = 0.54$ (robust t-stat: 16.74). Regardless of the type classification, $\hat{\beta}_{MKT}$ is always positive and significant. For `long-term` funds, which typically invest in large assets, the market beta is as high as 0.81 (robust t-stat: 12.90). Even `market neutral` funds seem to be slightly exposed to market risk, although the market beta estimate takes a much more modest value of 0.13. Except few nuances, the significance of all other factor loadings is relatively modest. For instance, when it comes to the funds type classification, the exposure to reversal is significant only for crypto `hedge funds`. As far as the strategy classification is concerned, `market neutral` and `opportunistic` load significantly on the reversal factor. There is virtually no exposure to either momentum and/or volatility risk. This result suggests that the market trend represents the primary source of risk for active management in cryptocurrency funds.

Panel C of Table 4 extends the results presented in Panel A to the panel estimation of aggregate fund alphas. Interestingly, we document that `tokenised funds` generate a substantially smaller and insignificant alpha, whereas the risk-adjusted performance of `fund of funds` and the `other` funds becomes statistically significant. Turning to the investment strategies, `market neutral` and `opportunistic` funds do not produce significant risk-adjusted alphas, whereas those funds following `long-short`, `long-term` and `multi-strategy` provide a strong outperformance above and beyond the market and factor-mimicking portfolios.

3.2 Performance of the individual funds

By simply looking at the performance of aggregate funds by their type or investment strategy, one may have an incomplete or even misleading picture of the value of active asset management. This is due to the cross-sectional heterogeneity in the fund returns and the limitations of aggregation when it comes to controlling for the differences in managers' risk-taking behaviors and skills (see, e.g., Kosowski et al., 2006). Further, the returns on individual cryptocurrency funds exhibit large volatility and significant departures from the Normal distribution.[20] That is, the cross-section of individual alphas might represent a complex mixture of non-normal distributions and aggregation based on returns averaging likely dilute important sources of cross-sectional heterogeneity.

To address these issues, 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 $\hat{\alpha}$ and the corresponding t-statistic $\hat{t}_{\hat{\alpha}}$. The $\hat{\alpha}$ measures the economic size of the fund performance while controlling for passive benchmark strategies or sources of systematic risk. Being a function of the $\hat{\alpha}$'s standard errors, the $\hat{t}_{\hat{\alpha}}$ 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

[20]For instance, the returns of individual funds exhibit large departures from normality, such as large positive skewness and massive kurtosis.

within-strategy return comovement. For these reasons, we implement bootstrapped $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ and comment the bulk of the empirical results based on both the t-statistic and the alpha estimates.

Similarly to the aggregate results, we estimate the alphas of individual funds by comparing the historical net-of-fees fund returns with a set of alternative investment opportunities as represented by low-cost passive benchmarks (see, e.g., Berk and Van Binsbergen, 2015 and Dyakov et al., 2020) or factor-mimicking portfolio strategies. The alphas are estimated from a panel regression of the form

$$y_{it} = \alpha_i + \sum_{j=1}^{J} \boldsymbol{\beta}_j^{'} \boldsymbol{x}_t + \epsilon_{it}, \qquad i = 1, \ldots, N \qquad t = 1, \ldots, T \tag{3}$$

where y_{it} is the net-of-fees return on fund i at time t, α_i is the fund-specific Jensen's alpha, and $\boldsymbol{\beta}_j^{'}$ is the vector of exposures to benchmark/factor returns $\boldsymbol{x}_t$ for the funds in the jth strategy.

A panel regression as in Eq.(3) offers several advantages compared to estimating separate time-series regressions as in Kosowski et al. (2006) and Fama and French (2010). First, the fund fixed effects α_i absorb the variation in fund performance due to the cross-sectional differences in fund skill, as long as that skill remains constant over time (see, e.g., Pástor et al., 2015). This is consistent with theoretical models such as Berk and Green (2004) whereby skills are time-varying only from a subjective perspective, whereas the true, objective α_i remains constant in the data generating process.[21] Second, by combining both the cross-sectional and the time-series dimension of the data, one can increase the power of the test on the alphas and, therefore, on the reliability of the $\hat{t}_{\hat{\alpha}}$ estimates, by employing information on the behavior of the whole set of funds jointly. Thus, by pooling information from different funds, we can obtain more precise estimates of the fund performances despite their short life span.

We now turn to the description of our bootstrap procedure. For each fund i, the historical alpha estimates $\hat{\alpha}_i$, the corresponding t-statistics $\hat{t}_{\hat{\alpha}_i}$, and the residuals $\hat{\epsilon}_{it}$ obtained from Eq.(3) are saved. 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 $\left\{\hat{\epsilon}_{it}^{b},\ \boldsymbol{x}_t^{b};\ t = s_{T_{0i}}^{b}, \ldots, s_{T_{1i}}^{b}\right\}$, where $b = 1, \ldots, B$ is the bootstrap index and $s_{T_{0i}}^{b}, \ldots, s_{T_{1i}}^{b}$ are

[21] Although in Berk and Green's model investors cannot observe the skills of the fund manager i, which corresponds to α_i in Eq.(3), 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.

drawn randomly from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for this fund i as

$$y_{it}^b = \sum_{j=1}^{J} \hat{\boldsymbol{\beta}}_j \boldsymbol{x}_t^b + \hat{\epsilon}_{it}^b, \qquad b = 1, \ldots, B. \tag{4}$$

By construction, the sequence of returns y_{it}^b has a true alpha that is zero. However, when we regress the alpha-adjusted returns on the bootstrap factors $\boldsymbol{x}_t^b$ for a given bootstrap sample b, a positive alpha (and t-statistic) may still arise from pure sampling variation, that is, by luck. We report the results for $\hat{t}_{\hat{\alpha}_i}$ calculated both with and without clustered standard errors where clustering is made at the strategy level.

We estimate the bootstrapped alphas and t-statistics via the panel regression for the constructed panel of synthetic fund returns for each bootstrap iteration b. Repeating for all bootstrap iterations $b = 1, \ldots, B$ we then build the distribution of cross-sectional draws of alphas $\hat{\alpha}_i^b$ and t-statistics $\hat{t}_{\hat{\alpha}_i}^b$ resulting purely from sample variation. If we find that there are far fewer positive values of alphas and t-statistics among the bootstrapped estimates compared to the actual, historical, cross-sectional distribution, then we conclude that sampling variation, or luck, cannot be the sole source of performance but that eventually genuine skills may actually exist. In all of our bootstrap tests we execute $B = 10,000$ iterations. A more detailed description of the main bootstrap procedure is provided in Appendix A.1.

As far as the bootstrap methodology is concerned, the two closest papers to ours are Kosowski et al. (2006) and Fama and French (2010). They both use bootstrap simulations to draw inferences about performance in the cross-section of fund returns. The key difference of our approach is that we rely on a panel regression bootstrap approach with strategy-dependent betas to extract the fund performance. The implications for inference on the fund performance are far from trivial. First, when drawing observations as a cluster, i.e., resampling of funds with replacement and combining all returns for any fund drawn, the bootstrap standard errors are the same as the individual clustered standard errors (see Cheng et al., 2005; Petersen, 2009). As a result, our approach explicitly takes into account autocorrelation and heteroskedasticity in the alpha standard errors estimated jointly, which is ultimately reflected in the t-statistics $\hat{t}_{\hat{\alpha}}$. Second, by combining the information in the time series and the cross section, we increase the degrees of freedom and the power of the test, which is again reflected in our key variable of interest, $\hat{t}_{\hat{\alpha}}$. Third, the bootstrap fund fixed effects $\hat{\alpha}_i^b$ explicitly accounts for the unobservable cross-sectional variation in fund performance that comes purely from luck and not skill (see Pástor et al., 2015). Fourth, we can explicitly consider the performance correlation by both considering strategy-specific correlations with the benchmark portfolios and by clustering the fund-specific standard errors at the strategy level. Section 3.4 compares our main estimate with the same bootstrap approach adopted by Kosowski et al. (2006) and Fama and French (2010). The results show that when simple time-series regressions are considered he distribution of standardised returns is significantly inflated upwards compared to our main panel bootstrap estimates.

3.2.1 The cross-section of individual fund performances. Figure 5 compares the distributions of actual alphas and t-statistics with the distributions of bootstrapped values. For the ease of exposition, we report the cross-sectional distributions of $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ 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, whereas 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).

Panel A for the the benchmark-adjusted results hints 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 $\hat{\alpha}$ estimates. For instance, although the majority of crypto funds produce the actual alphas within a modest range from 0% to 5%, the performances of the worst and best managers can reach -17% and +38% on a monthly basis, respectively. Thus, while the average performance 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 the 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 the one that could have been explained only by sampling variation.

Second, the cross-sectional distribution of the standard t-statistics demonstrates that a non-trivial fraction of funds actually 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 to the conclusion that the fraction of fund managers are able to generate economically large alphas, which 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 implicitly suggests that the large uncertainty around the alpha estimates makes the statistical significance of $\hat{\alpha}$ rather weak. Yet, the right tail of the actual $\hat{t}_{\hat{\alpha}}$ estimates 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 corresponding t-statistics show similar patterns when passive benchmarks are replaced by traditional risk factors. In particular, the economic magnitude of $\hat{\alpha}$ is rather similar to that obtained using the benchmark strategies. The major bulk of alphas are concentrated within the interval from 0% to 5% on a monthly basis, and there is a sizable amount of outlying funds with performances well above 10 on a monthly basis. As shown in all panels, 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 Fama and French, 2010). Specifically, in our examination of the empirical and bootstrap distributions, we first compute the actual values of the alphas and the corresponding t-statistics at selected percentiles of the cumulative distribution function for the cross-section of funds. We then obtain the corresponding simulated values by taking the averages across the 10,000 simulation runs of the $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ estimates at selected percentiles. Finally, we 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. Panels A and B report the benchmark- and risk-adjusted measures. For example, the benchmark-adjusted results show that the 1$^{\text{st}}$ percentile of the actual $\hat{\alpha}$ is -9.58% and the average estimate from the simulations is -11.9%. Furthermore, 99.02% of actual observed alphas are greater than the average simulated value at the 1$^{\text{st}}$ percentile.

Overall, the 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 seem to be supported by the empirical results. The left tail percentiles of $\hat{t}_{\hat{\alpha}}$ 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-statistic estimates of -0.21 and -0.67 for the benchmark- and risk-adjusted performance, are much less extreme than the average estimates from the bootstrap simulation equal to -1.00. In fact, for the benchmark- and risk-adjusted performances, the actual t-statistic are above the average bootstrap simulation values for all percentiles considered. Such observation holds regardless of the fact that $\hat{t}_{\hat{\alpha}}$ is estimated with or without standard errors clustered by strategy. Thus, the distributions of the empirical and bootstrap $\hat{t}_{\hat{\alpha}}$ estimates suggests that there is some skill sufficient to cover costs.

The results presented in Figure 5 and Table 5 are in stark contrast with some earlier evidence on the value of active investment management in the traditional mutual fund industries, such as Kosowski et al. (2006) and Fama and French (2010). We find that, at least within the fast-growing industry of cryptocurrency markets, there is some evidence of fund managers having enough skills to produce benchmark- and risk-adjusted net returns that cover their costs. This is largely consistent with the prediction in Berk and Green (2004). One word of caution is needed though. Although there is evidence of a strong economic performance, which is not simply due to random sampling variation, the statistical significance of such performance is weak when the correlation structure of fund returns is considered to calculate the standardised performances. One could interpret this result through the lens of the very nature of the investment process in cryptocurrency markets. Indeed, 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 such correlation comes at the cost of artificially inflating the significance of the standardized benchmark- and risk-adjusted returns (see, e.g., McNemar, 1947).

Although we can control for within-strategy correlations in fund returns when computing $\hat{t}_{\hat{\alpha}}$, we now try to understand whether the superior performances is driven by a specific fund style or the best funds are spread more evenly across different groups. Figure 6 reports a disaggregated version of the cross-sectional distribution of the actual alphas and t-statistics per each investment strategy. Panels A and B report the benchmark- and risk-adjusted results. Three interesting facts emerge: first, the majority of outlying performances are concentrated in two groups, namely the `long-short` and `long-term` strategies, with some residual tail performances also in the `multi-strategy` class. This suggests that the majority of funds, which belong to the right tail of the distribution reported in Figure 5, possibly come from these two classes of funds. Second, and perhaps more interestingly, there is no systematic dominance of a given strategy over others. Indeed, when we exclude the tails, the strategy-specific cross-sectional distributions of the fund performances tend to be largely overlapping. This suggests that, while the vast majority of outlying performances is concentrated around two main classes, all 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-statistics of the magnitude comparable to others. Third, the results are similar for both benchmark- and risk-adjusted net performances. We document the concentration of outlying fund alphas in two classes and no systematic dominance of a given investment strategy regardless the benchmarks used.

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 was often an instinctive reflection of 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 actually active before late 2017, which might raise a question of the significance of our main empirical results when including the pre-ICO bubble period. To address this issue, 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, whereby hundreds of new crypto-assets and cryptocurrencies 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 descriptive statistics for the raw returns across sub-samples. Table 6 reports the mean, standard deviation, Sharpe ratio, skewness, and AR(1) coefficient for the equal-weight aggregation of all the funds (first column) and for a more granular classification of funds according to the fund type (from the second to the fourth column) and the investment style (last six columns). Few observations are noteworthy. First, there is robust evidence that the average net-of-fees returns of funds are much higher for the first part of the total sample, in fact, almost three times higher, which is consistent with the idea that investment opportunities were much more favourable during the ICO-bubble. Second, a decreasing performance during the second part of the total sample is evident for all types of funds and all investment strategies, with the only exception of `opportunistic` funds. Interestingly, despite lower returns, `market neutral` funds show relatively constant Sharpe ratios across sub-samples with 1.28 in the pre-ICO bubble period and 1.50 from January 2018 to the end of the sample. This suggests that while these funds may not be neutral with respect to market trends in terms of actual returns, they are stable once the performance is adjusted for risk. Third, Sharpe ratios are substantially lower during the second sub-sample with the only exception of `market neutral` funds; that is, average returns decrease more than proportionally to realised volatility across different types and strategies. Further, the persistence of fund returns remain relatively low across both sub-samples, which is somewhat reassuring when it comes to the main bootstrap specification.

Turning to the individual fund performances, Figure 7 reports both $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ estimates for the post-ICO bubble period.[22] Few interesting aspects emerge: first, the alphas become lower in the second sub-sample compared to those obtained for the whole sample (see Figure 5), but the drop in estimates is not very large. This confirms the inflating effect of the pre-ICO bubble period on the fund performances, however, it does not overrule the quantitative and qualitative findings from the main analysis based on the longer sample. Second, we observe a similar effect of the pre-ICO bubble period on the t-statistics estimates obtained either with or without strategy-clustered standard errors. This suggests that while the alpha values might be slightly lower, so is the volatility of the returns. Third, both benchmark- and risk-adjusted results share the same patterns. Specifically, the weaker performance does not depend on a different exposure to the aggregate market trend or other sources of risks in the pre- and post-ICO bubble periods.

We now present a more granular representation of the actual and simulated distributions of the alphas and corresponding t-statistics. Specifically, we report the actual and simulated estimates at selected percentiles and then compute the percentage of actual estimates greater than the simulated value to quantify the discrepancy between the empirical and simulated distributions for the post-ICO bubble sample. Table 7 reports the results for both the benchmark- and the risk-adjusted estimations. Several observations are noteworthy. First, except for the left tail of the distribution below the 10^{th} percentile, the actual $\hat{\alpha}$ estimates are larger than the average simulated values at the same percentiles. This provides the evidence of an economic performance, which cannot be simply reconciled by the sampling variation of the returns, a finding from cryptocurrency markets supporting the prediction of Berk and Green (2004). Hence, we extend the key conclusion from the main empirical analysis

[22] The reason why we focus on the post-2018 period is twofold: first, raw performances are much weaker than in the pre-ICO bubble period, as shown in Table 6. This might suggest that, by taking out the spike in valuations before 2018, our results might actually be weaker. Second, in the pre-ICO bubble period, only a handful of highly profitable funds were effectively available for investors, which raises some questions about the informativeness of our panel bootstrap approach.

to the sub sample after the ICO bubble. Second, we find similar patterns between the actual and simulated values of the standardized performances $\hat{t}_{\hat{\alpha}}$. Specifically, regardless of our approach to dealing with the standard errors, the empirical $\hat{t}_{\hat{\alpha}}$ are consistently above the average values across simulations. Third, the observed patterns in actual and simulated statistics hold for both benchmark- and risk-adjusted returns. Hence, evidence of skill sufficient to cover costs does not depend on the nature of conditioning information, that is, our choice of an adjustment either for passive benchmarks or standard risk factors.

3.4 Robustness

We now 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.

3.4.1 Constant betas and time-series regressions. Our main bootstrap approach is based on a panel regression with fund fixed effects and strategy-dependent loadings on passive benchmarks, where we are able to compute standard errors with or without clustering at the strategy level (see Eq.(3)). Such an approach allows us to (1) increase the amount of information to estimate the model parameters as fund returns are pooled together, (2) acknowledge unobserved fund-specific heterogeneity, (3) control for correlations between individual fund performances within a given investment strategy when standardizing the fund performances, and (4) assume that betas on benchmark strategies or risk factors may differ across investment mandates. We now delve further into all of these modeling choices and test the robustness of our results when we relax some of these underlying assumptions. For the ease of exposition, we focus on the benchmark-adjusted results unless specified otherwise.[23]

We begin by restricting the exposure of the 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 8 shows the results. The left panel reports the alphas, whereas the right panel reports the t-statistics with clustered standard errors. Except for few nuances, the results of the main empirical analysis hold. Specifically, there is a widespread discrepancy between the cross-sectional distributions of the actual and standardized fund alphas and the corresponding average simulated values. Following Kosowski et al. (2006) and Fama and French (2010), this provides evidence that managers display sufficient skills to produce expected benchmark-adjusted net returns that cover costs.

[23] The risk-adjusted results are available upon request.

Next, we estimate alphas for each fund separately based on a simple time-series regression. In this case, $\boldsymbol{\beta}_i^{'}$ becomes fund-specific and we do not assume correlation within strategies and/or fund types. This approach is obviously sub-optimal relative to the panel estimation given a relatively short length of the data for some funds, but it is consistent with a more traditional procedure of obtaining the fund alphas from time-series regressions. Figure 8 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 time series available for some of the funds may generate a small-sample bias in time-series estimates. Second, the cross-sectional distribution of the t-statistics shows some evidence of skill. Indeed, 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. Interestingly, the average t-statistic from individual time-series regressions is even 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 performances. This result reinforces the reliability of our main empirical results.

3.4.2 Block bootstrap and independent resampling. We now relax two technical assumptions of our panel bootstrap approach that are related to the assumptions about 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 fund returns is low compared to traditional equity mutual funds.[24] For the sake of completeness, 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. More details on the procedure can be found in Appendix A.2. Due to the short length of data, we set the size of the bootstrap blocks equal to three months.[25] Panel A of Figure 9 presents the fund alphas and their t-statistics for the block-bootstrap approach. Again, there is a pronounced

[24]The persistence of fund returns is also explored in more detail in Appendix B where we look at the autocorrelation function up to 20 lags for different types of funds and investment strategies. Except for few nuances, namely `market neutral` funds, there is weak evidence of autocorrelation in the returns. In fact, the fund returns are only mildly autocorrelated.

[25]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.

discrepancy between the actual statistics and the average simulated values. Overall, allowing for for a short-term autocorrelation in our bootstrap procedure, the results are largely in line with the main empirical analysis.

Furthermore, we present the results of an additional bootstrap exercise following Kosowski et al. (2006). Specifically, we implement an alternative bootstrap approach whereby 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 possibly arise if the performance model specified does not fully capture the set of possible explanatory factors. Panel B of Figure 9 reports both the estimates for the $\hat{\alpha}$ and the standardised performance $\hat{t}_{\hat{\alpha}}$ with and without clustered standard errors (a middle and right panel). 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.

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 the lens of 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 possibly could create a positive value for investors, a finding consistent with the prediction of Berk and Green (2004). While existing research has long been debating the value of active management in traditional asset classes, no study has tested the existence of such a 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.

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

This table reports a set of descriptive statistics for the returns of funds, global ETFs, S&P500, and two hedge fund indices. The top panel reports descriptive statistics of equal-weight portfolio returns aggregated across all funds (first column), each type of funds: `fund of funds`, `hedge fund`, `managed accounts`, `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. The middle panel 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. The bottom panel 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 aggregated 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 accounts`, `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 fund monthly return in each period, we calculate the sample equal-weight average of active funds in the corresponding time period. The top panel 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). The top panel also reports the estimate $\hat{\gamma}$ as for Eq.(1) and robust t-statistics (in parenthesis) for the difference in alphas. The middle panel reports the estimates and robust t-statistics (in parenthesis) of passive benchmark loadings (betas) and the adjusted R^2 of the regressions. The bottom panel reports the estimates and robust 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	3.40	3.20	3.02	6.24	3.07	6.76	3.59	3.55	0.96	3.21	2.47
	(3.57)	(3.39)	(3.18)	(4.35)	(2.40)	(3.86)	(3.74)	(2.55)	(1.88)	(3.31)	(2.43)
Difference		-0.20	-0.38	1.76	-0.33	2.28	0.19	0.15	-2.28	-0.20	-2.01
		(-0.21)	(-1.36)	(1.72)	(-0.49)	(1.81)	(0.25)	(0.26)	(-2.92)	(-0.31)	(-1.50)

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	0.18	0.25	0.17	0.24	-0.10	0.08	0.28	-0.01	0.37	0.14
	(2.22)	(2.26)	(3.49)	(1.13)	(1.90)	(-0.52)	(0.66)	(2.18)	(-0.20)	(5.38)	(2.80)
β_{DOL}	0.08	0.02	0.10	0.00	0.08	0.01	0.11	0.12	0.03	0.03	0.03
	(1.18)	(0.36)	(1.60)	(0.06)	(0.81)	(0.11)	(1.92)	(1.10)	(0.73)	(0.68)	(0.78)
β_{ETF}	0.20	0.04	0.17	0.14	0.24	0.31	0.16	0.29	0.12	0.09	-0.06
	(2.74)	(0.56)	(2.31)	(2.01)	(2.28)	(1.95)	(2.21)	(2.63)	(1.50)	(1.15)	(-1.00)
β_{ETH}	0.15	0.10	0.11	0.24	0.23	0.37	0.12	0.26	0.01	0.04	0.04
	(2.15)	(1.39)	(2.12)	(1.93)	(1.97)	(2.29)	(1.34)	(2.39)	(0.60)	(0.84)	(0.81)
Adj. R^2	0.77	0.36	0.77	0.66	0.70	0.60	0.61	0.76	0.34	0.66	0.18

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	2.35	3.05	4.49	5.14	6.16	4.36	4.32	1.56	3.49	3.15
	(5.14)	(8.74)	(0.15)	(6.11)	(0.80)	(6.01)	(7.77)	(3.80)	(6.76)	(2.24)

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

This table reports the factor-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 accounts`**, **`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. The top panel 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). The top panel also reports the estimate $\hat{\gamma}$ as for Eq.(1) and robust t-statistics (in parenthesis) for the difference in alphas. The middle panel reports the estimates and robust t-statistics (in parenthesis) of passive benchmark loadings (betas) and the adjusted R^2 of the regressions. The bottom panel reports the estimates and robust 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	2.59	2.15	2.04	4.52	2.41	6.25	1.93	2.72	0.29	2.28	0.74
	(3.49)	(1.66)	(2.79)	(3.27)	(1.91)	(3.10)	(1.88)	(2.34)	(0.72)	(2.45)	(0.75)
Difference		-0.44	-0.55	1.20	-0.18	2.94	-0.66	0.12	-2.11	-0.31	-2.58
		(-0.31)	(-1.50)	(1.25)	(-0.21)	(1.93)	(-0.82)	(0.23)	(-2.78)	(-0.32)	(-2.01)

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}	-0.03	-0.02	-0.04	0.01	-0.03	0.04	0.02	-0.08	-0.02	0.00	-0.09
	(-0.84)	(-0.57)	(-1.15)	(0.13)	(-0.62)	(0.49)	(0.43)	(-1.58)	(-0.88)	(0.06)	(-2.08)
β_{MKT}	0.54	0.26	0.52	0.45	0.67	0.60	0.43	0.81	0.13	0.38	0.10
	(16.74)	(6.05)	(19.35)	(8.44)	(10.35)	(6.80)	(10.83)	(12.90)	(2.57)	(10.47)	(2.93)
β_{MOM}	0.00	0.00	-0.01	0.02	0.01	0.02	0.01	-0.01	-0.01	0.01	-0.02
	(0.01)	(-0.15)	(-0.68)	(1.47)	(1.22)	(1.20)	(0.83)	(-0.84)	(-0.97)	(1.06)	(-1.28)
β_{REV}	0.01	0.02	0.01	0.02	0.01	-0.02	0.01	0.02	0.01	0.02	0.04
	(1.47)	(1.88)	(2.03)	(1.01)	(0.96)	(-0.88)	(1.05)	(1.26)	(2.33)	(1.82)	(2.53)
β_{VOL}	0.03	0.03	0.04	0.00	0.02	0.03	0.02	0.06	0.02	0.00	0.04
	(0.93)	(0.72)	(1.23)	(0.04)	(0.40)	(0.30)	(0.37)	(1.32)	(1.03)	(0.00)	(1.15)
Adj. R^2	0.86	0.38	0.86	0.66	0.77	0.61	0.67	0.84	0.38	0.68	0.34

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	1.12	1.07	2.23	3.36	3.91	2.11	1.87	0.73	2.06	1.40
	(2.43)	(5.41)	(3.49)	(2.51)	(0.15)	(2.67)	(2.96)	(1.70)	(3.89)	(1.27)

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, e.g., 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 (top panel) and after (bottom panel) 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 accounts`, `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

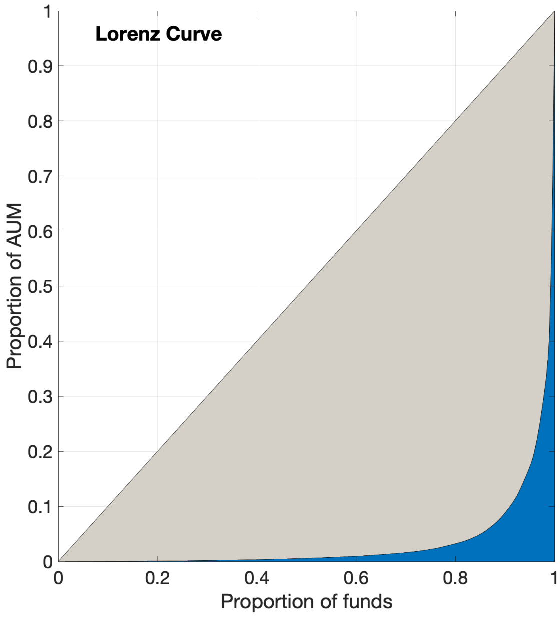
Table 7: **The cross-sectional distribution of benchmark- and risk-adjusted alphas: sample from January 2018**

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, e.g., Pástor et al., 2015). The sample period corresponds to the post-ICO bubble stage from January 2018 to June 2021.

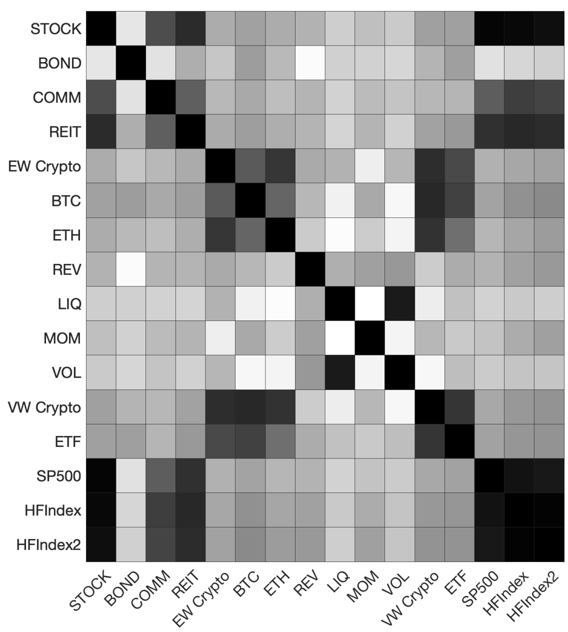
	Panel A: Passive benchmarks									**Panel B:** Risk factors								
	Alpha			t-statistics (stand)			t-statistics (clust)			Alpha			t-statistics (stand)			t-statistics (clust)		
Pct	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim	Sim	Act	% >Sim
1	-10.46	-15.35	98.52	-2.75	-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

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

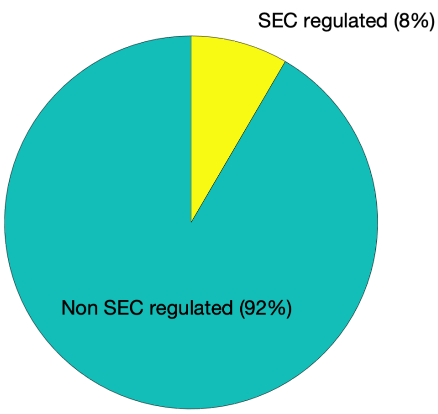
The figure reports a set of aggregate characteristics for the sample of funds used in the main empirical analysis. The top-left panel shows the concentration of the assets under management (AUM) via a visual representation of the Gini coefficient, i.e., Lorenz curve. The top-right panel shows the unconditional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



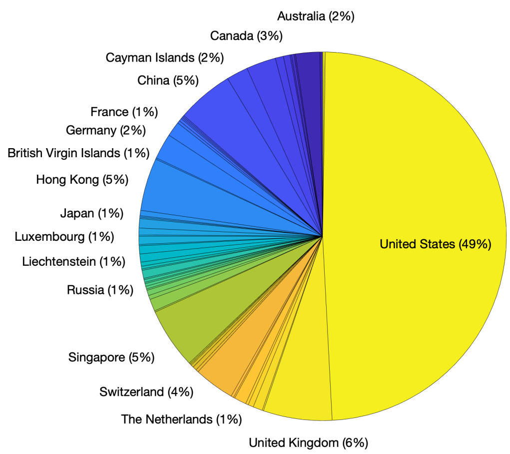
(a) AUM concentration



(b) Correlation of cryptos with other assets



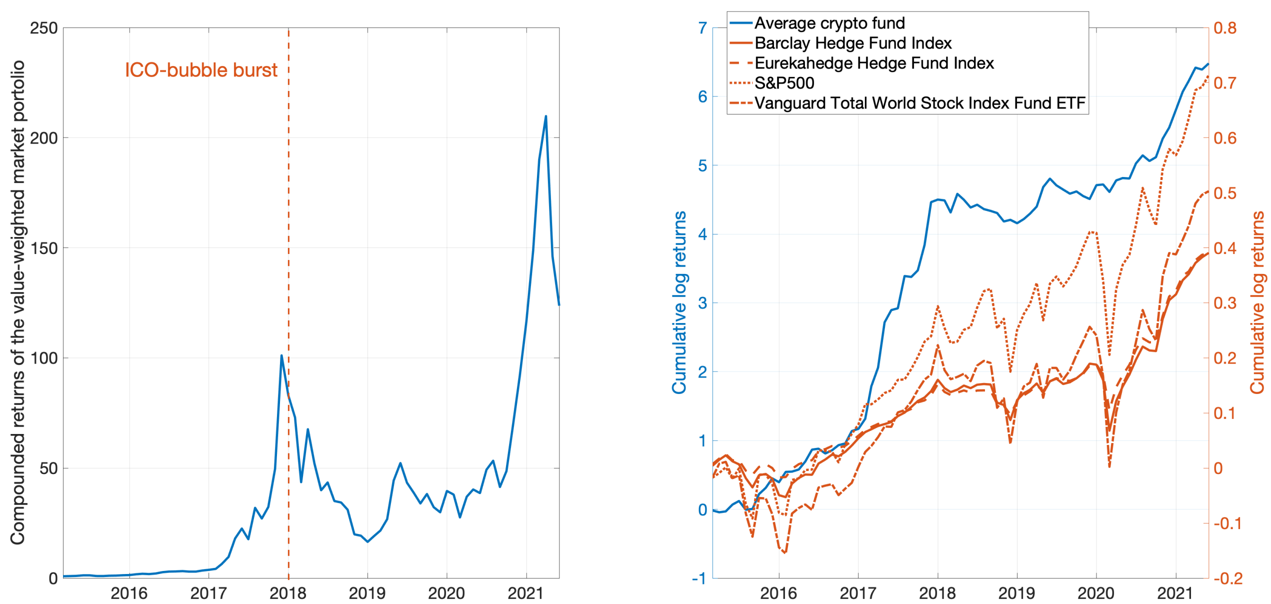
(c) SEC regulated funds



(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-weighted market portfolio of the top 100 cryptocurrencies sorted by average market capitalization. The right panel shows the cumulative log returns of the average cryptocurrency fund and the S&P500 Index, the Vanguard Total World Stock Index Fund ETF and two alternative 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-weighted index of the top 100 cryptocurrencies by market capitalization. The sample period is from March 2015 to June 2021.

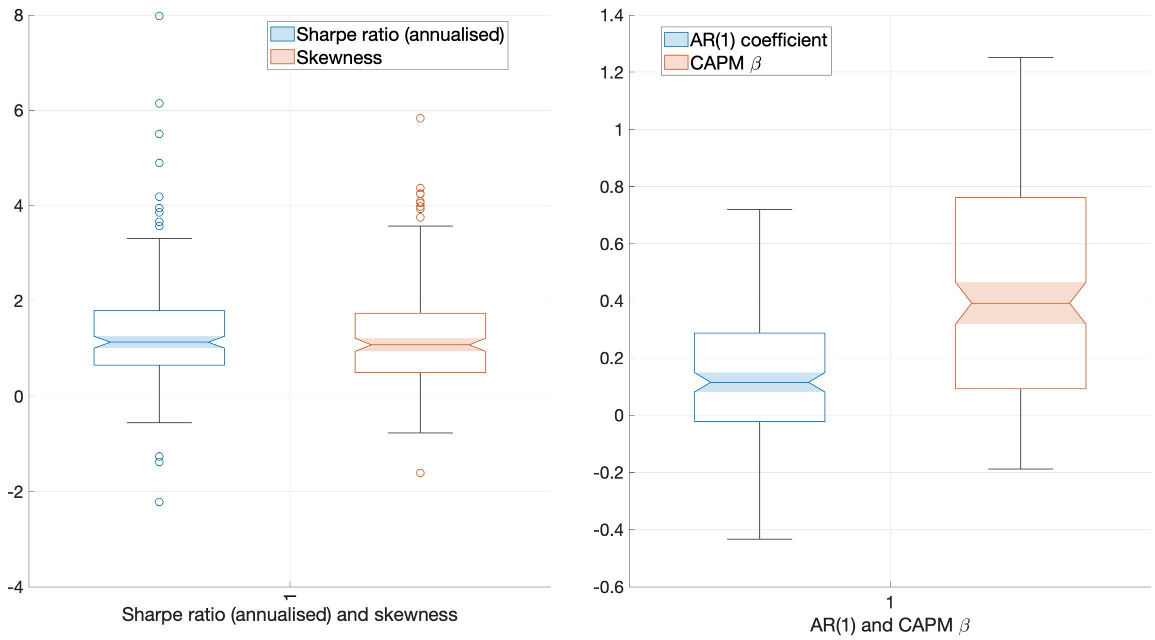
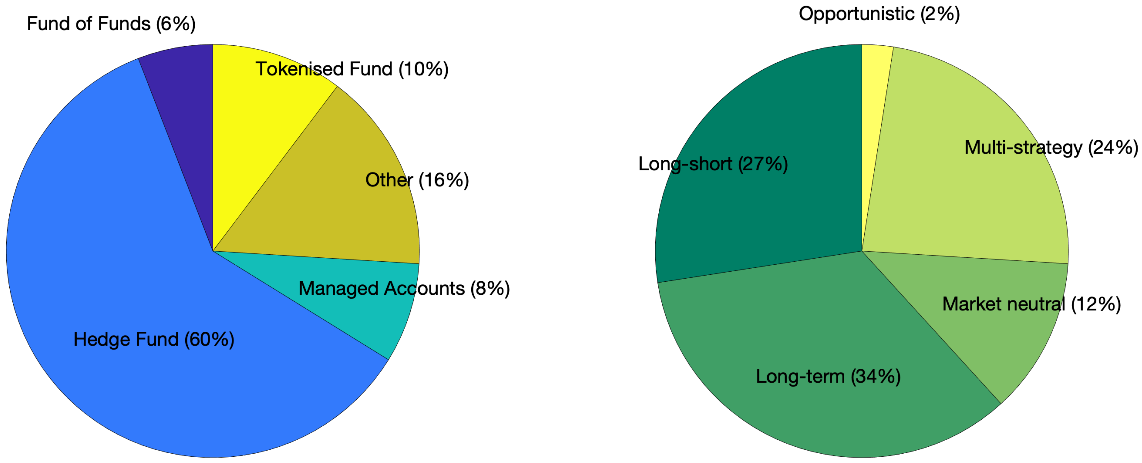


Figure 4: **Classification of funds by type and investment strategy**

This figure plots the distributions of funds per fund type (left panel) and investment strategy (right panel). Funds are clustered by type and labeled as `fund of funds`, `hedge fund`, `managed accounts`, `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.



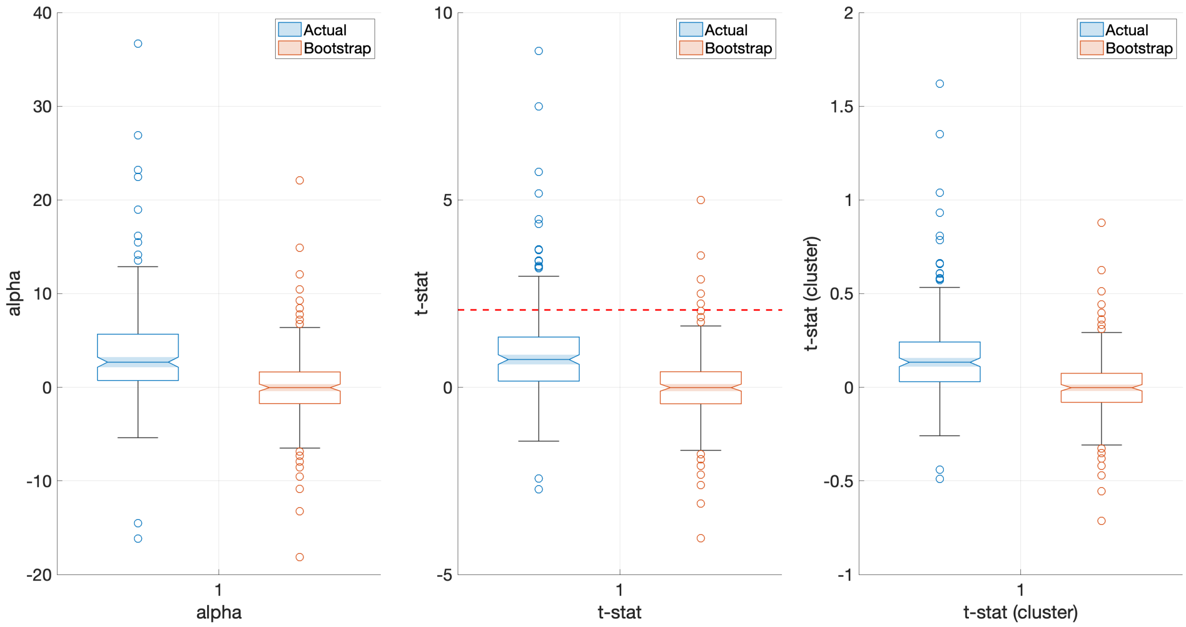
(a) Funds classification by type

(b) Funds 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 (mid 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, e.g., Pástor et al., 2015). The panels report actual (blue box charts) and bootstrapped (red box charts) cross-sectional distributions. The red dashed line in the mid 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

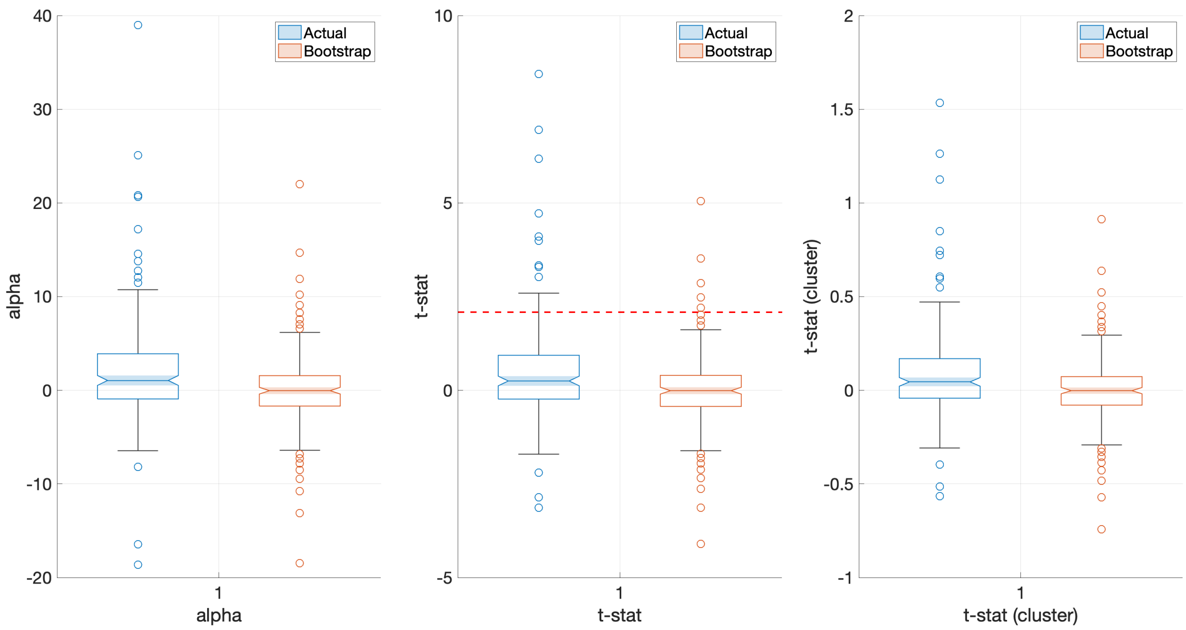
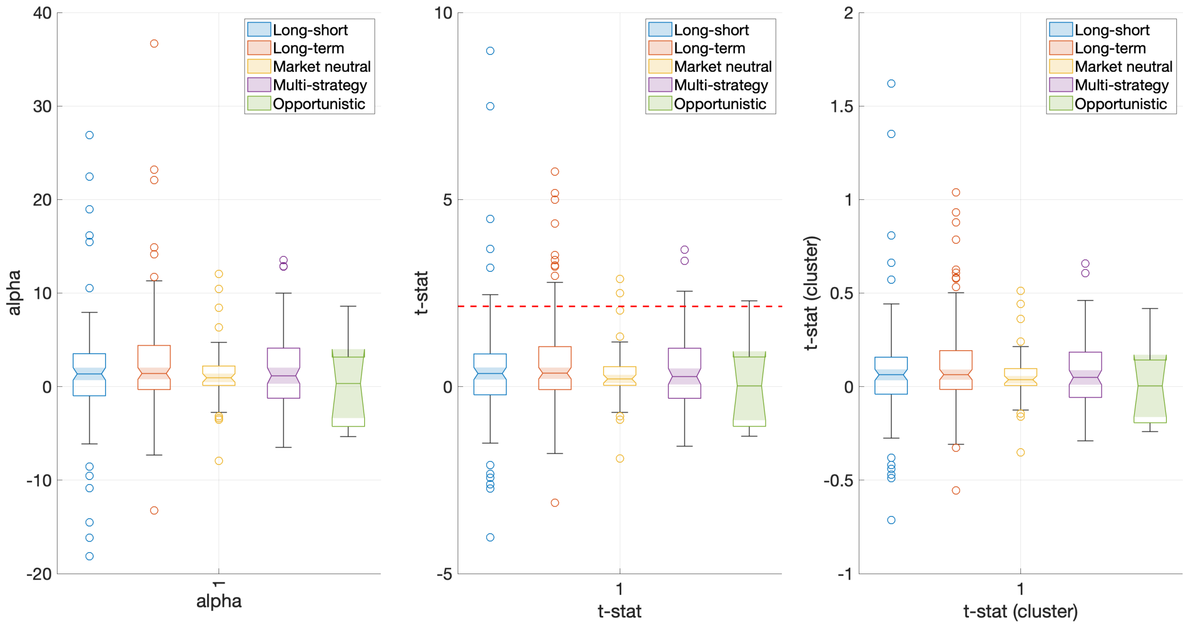


Figure 6: **The cross-section of alphas for different investment strategies**

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, e.g., Pástor et al., 2015). The red dashed in the mid 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

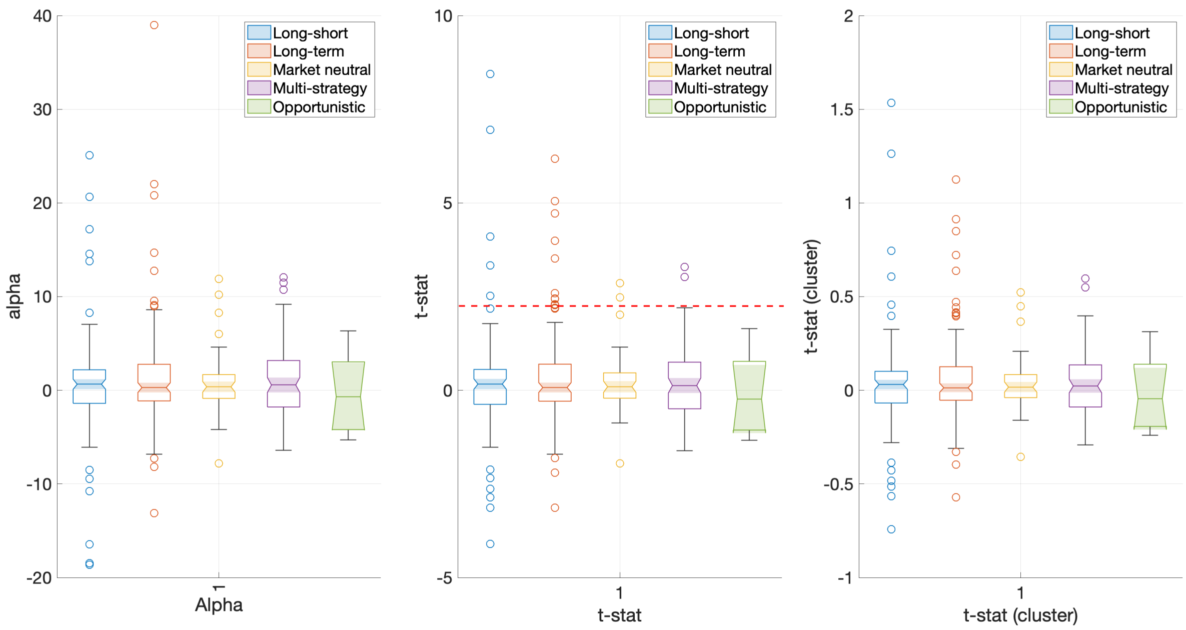
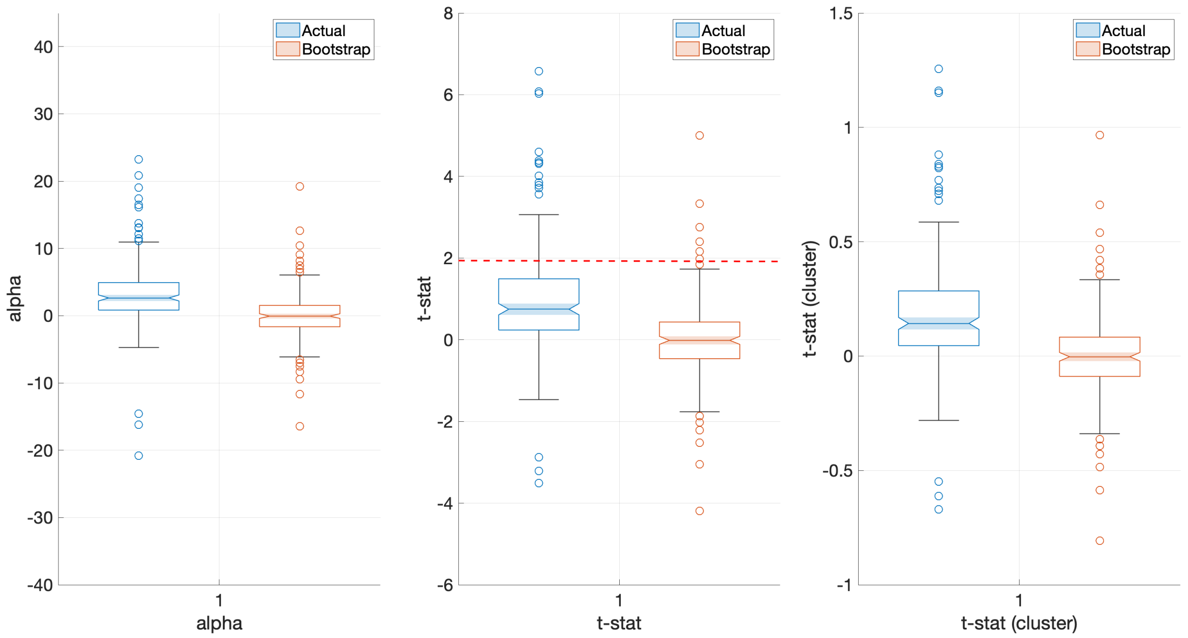


Figure 7: **The cross-section of alphas for the post ICO-bubble period**

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 (mid 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, e.g., Pástor et al., 2015). The panels report actual (blue box charts) and bootstrapped (red box charts) cross-sectional distributions. The red dashed line in the mid 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

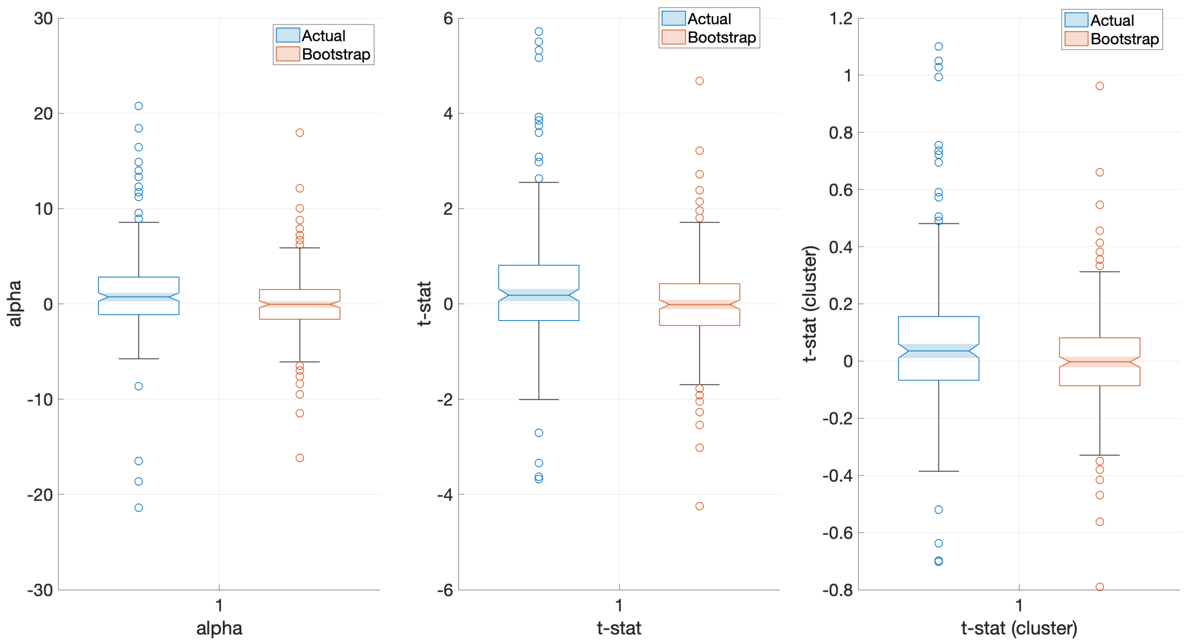
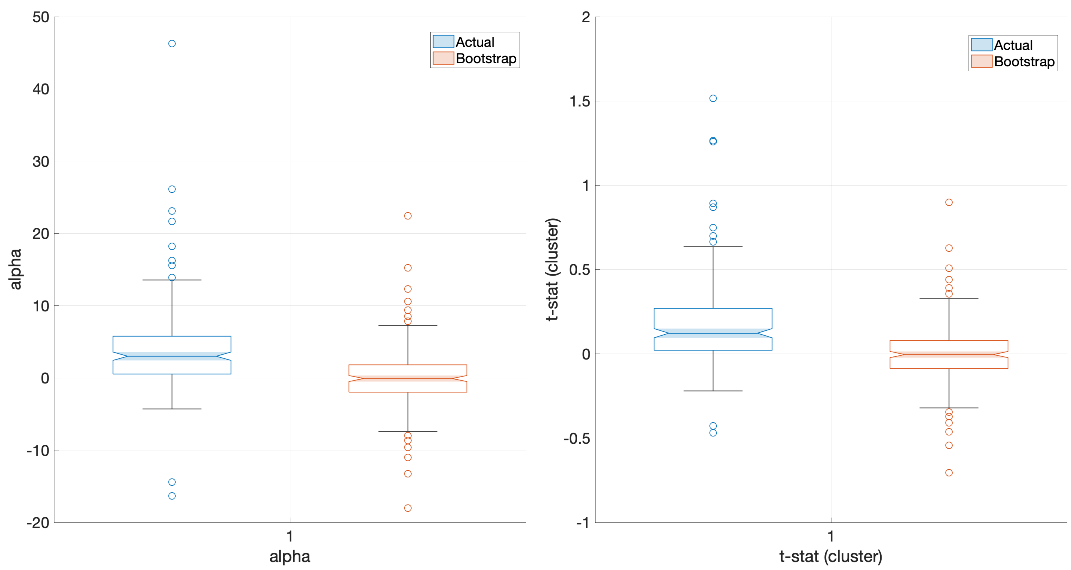


Figure 8: **Constant betas and time-series regressions**

Panel A plots the box charts for the benchmark-adjusted alphas (left) and the t-statistics obtained with clustering the standard errors by investment strategy (right). Unlike the main empirical analysis the betas on 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, e.g., 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 bootstrapped (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

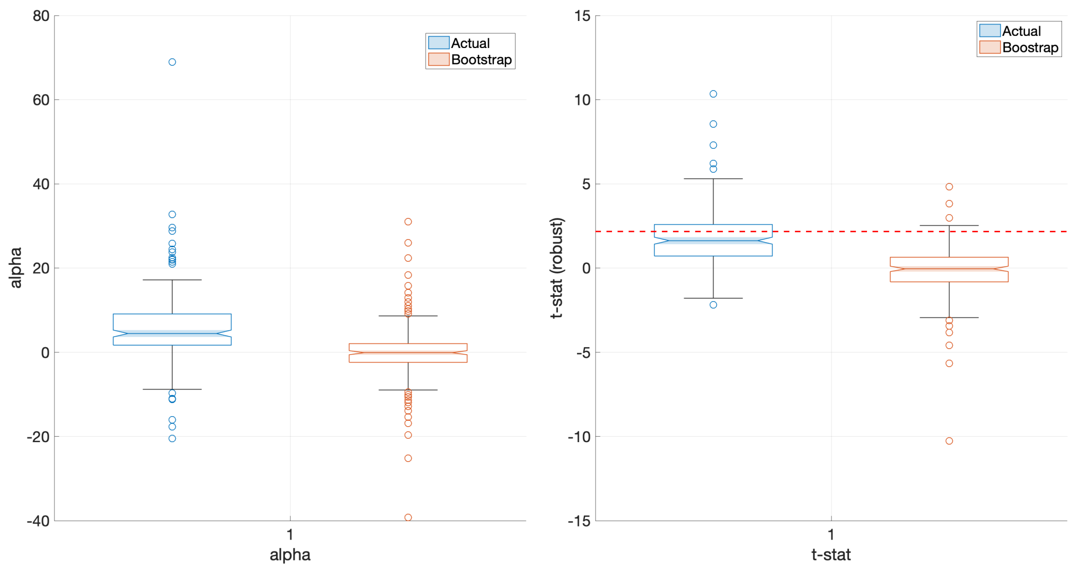
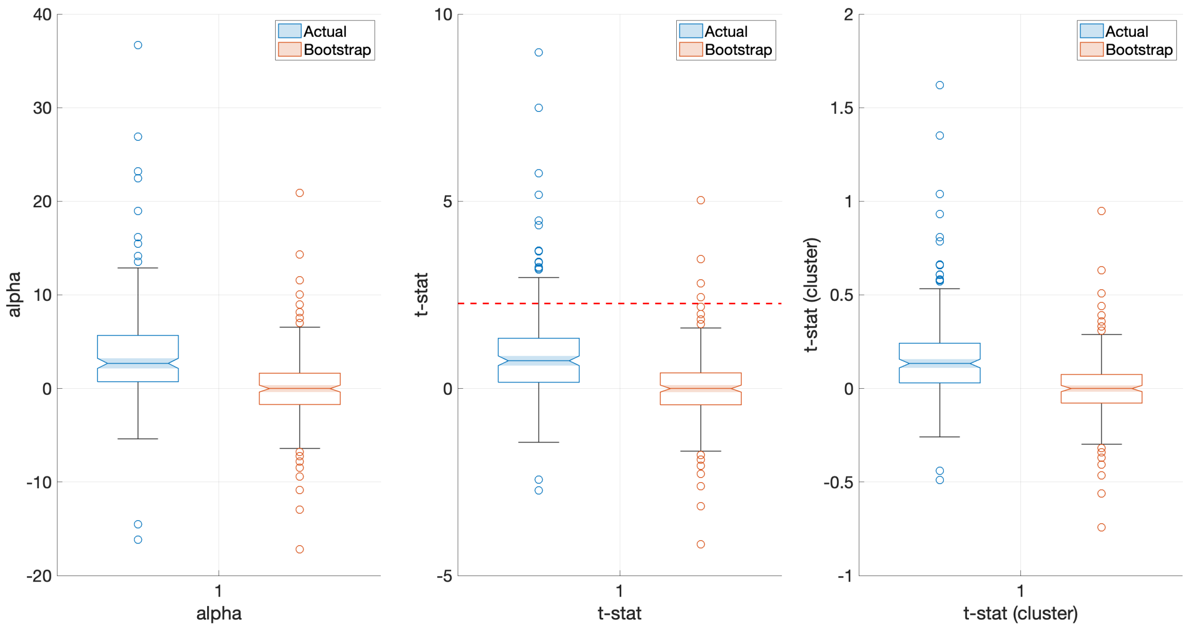


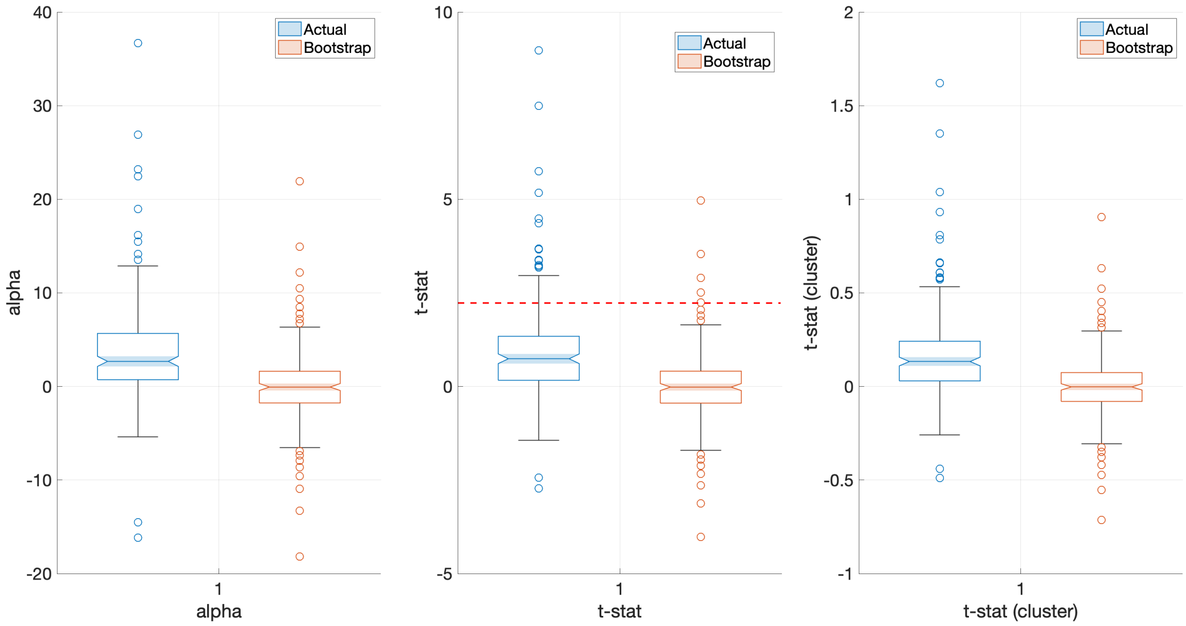
Figure 9: **Alternative bootstrap procedures**

This figure plots the box charts of the benchmark-adjusted alphas (left panels) and the corresponding t-statistics. The latter are calculated without (mid 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, e.g., Pástor et al., 2015). The figure reports the actual (blue box charts) and bootstrapped (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 mid 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



Appendix

A Bootstrap methods

In this section, we provide details on both the baseline bootstrap procedure and the two extensions proposed to investigate the robustness of the main results to alternative assumptions on the data generating process.

A.1 Baseline bootstrap approach

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 bootstrapped 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.

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 $\{\varepsilon^b_{i,t} : t = s^b_{T_{0,i}}, ..., s^b_{T_{1,i}}\}$
- Generate a time-series of "synthetic" zero-alpha returns as

$$y^b_{it} = \hat{\boldsymbol{\beta}}' \boldsymbol{x}^b_t + \hat{\epsilon}^b_{it},$$

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:

$$y^b_{it} = \hat{\alpha}^b_i + (\hat{\beta}^b)' \boldsymbol{x}^b_t + \varepsilon^b_{i,t}$$

end

Output: The bootstrapped individual fixed effects $\{\hat{\alpha}_i^b : b = 1, ..., B\}$ and the corresponding t-statistics $\{\hat{t}_{\hat{\alpha}_i}^b : b = 1, ..., B\}$.

A.2 Bootstrap extensions

A.2.1 Block bootstrap. The baseline bootstrap procedure 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.1.

A.2.2 Independent bootstrap of residuals and explanatory returns. The second bootstrap extension allows for independent draws of the benchmark 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 $\{s_{T_{0,i}}^b, ..., s_{T_{1,i}}^b\}$, and a sample of month for the benchmark returns $\{\tau_{T_{0,i}}^b, ..., \tau_{T_{1,i}}^b\}$, 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 $\{\varepsilon_{i,t_\varepsilon}^b : t_\varepsilon = s_{T_{0,i}}^b, ..., s_{T_{1,i}}^b\}$
- Construct a time-series of resampled benchmark returns $\{\boldsymbol{x}_{i,t_x}^b : t_x = \tau_{T_{0,i}}^b, ..., \tau_{T_{1,i}}^b\}$
- Generate a time-series of "synthetic" zero-alpha returns as

$$y_{it}^b = \hat{\boldsymbol{\beta}}' \boldsymbol{x}_{t_x}^b + \hat{\varepsilon}_{it_\varepsilon}^b,$$

in which $\boldsymbol{x}_{t_x}^b$ 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:

$$y_{it}^b = \hat{\alpha}_i^b + (\hat{\beta}^b)' \boldsymbol{x}_{t_x}^b + \varepsilon_{i,t_\varepsilon}^b$$

end

Output: The bootstrapped individual fixed effects $\{\hat{\alpha}_i^b : b = 1, ..., B\}$ and the corresponding t-statistics $\{\hat{t}_{\hat{\alpha}_i}^b : b = 1, ..., B\}$.

B Additional results

B.1 Performance persistence

The existing literature provides controversial evidence on the performance persistence. On the one hand, a number of studies present evidence of some persistence, especially among winning funds (see, e.g., Lynch and Musto, 2003; Kosowski et al., 2006). On the other hand, the early theoretical and empirical evidence shows that performance persistence is weak to nonexistent (see, e.g., Carhart, 1997; Berk and Green, 2004).

Other things equal, if fund managers possess some cryptocurrency-picking skills, the best performing crypto funds should persistently generate higher alphas compared to their peers. We have already presented evidence of manager skill in the cross section of individual funds based on the bootstrap results. We now evaluate the short-term and long-term persistence of fund performance.

Specifically, we first estimate the panel regression defined by Eq.(3) using the historical data from March 2015 to December 2020. Then, we sort all funds into three portfolios based on the estimated individual fund alphas. These portfolios are formed only once in December 2020, which is labeled as the "formation" month. The first two groups consist of the top and bottom deciles of funds with the highest and lowest alphas, respectively. The third group comprises the remaining funds in the second to ninth deciles. Next, we reestimate the individual fund alphas in each month after the "formation" month using the new data (for instance, the alphas in January 2020 are based on the panel regression estimated from the data from March 2015 to January 2020). We report the average alphas and t-statistics in each of the three portfolios constructed at the "formation" period to illustrate a short-term persistence in alphas over the 6-month horizon. We replicate this analysis for the portfolio groups sorted in the "formation" month of June 2020 to evaluate a long-term persistence in alphas over the 12-month horizon.

Figure A.1 reports the results. Panels A and B show the short-term and long-term persistence of the historical performance. The evidence suggests that the economic value produced by the successful managers has some persistent over time, both in the short term and in the long term. The fund performance of past "successful" and "unsuccessful" funds tends to persist in the future, i.e. the best and worst funds continue to, respectively, over-perform and under-perform in the subsequent six and twelve months after their original formation. It is worth noting that this result might not be very surprising given the overlapped estimation procedure to obtain the individual fund alphas.

B.2 Persistence of the average fund returns

The returns of hedge funds and other alternative investments are often highly serially correlated. Such strong autocorrelation could be due to illiquidity exposure and smoothed returns (see, e.g., Getmansky et al., 2004). Figure B.1 shows that this may not be the case for cryptocurrency funds. The figure shows the autocorrelation function up to 20 lags of the average returns across different types of funds (first row) and different investment strategies (second and third row). There is no strong evidence of a long-lasting persistence in the return dynamics, which may require to "clean" the raw net-of-fees returns from autocorrelation.

[Insert Figure B.1 here]

Figure B.2 further confirms that there is not actually momentum, i.e., persistence, in the dynamics of raw returns, that is, a high return today does not necessarily predict a high return next month. In particular, the figure shows the post-formation returns from February 2020 (left panel) and from August 2019 (right panel) to the end of the sample.

[Insert Figure B.2 here]

The lines in the graph depict the average returns of funds in each of the three portfolios in the month of initial ranking (the "formation" month) and in each of the next months after formation. The first portfolio consists of funds in the top decile with the highest six-month returns, the second portfolio – funds in the bottom decile with the lowest six-month returns, and the third portfolio – remaining funds with the six-month returns in the second to ninth deciles. Clearly, there is not much evidence of momentum in raw returns, especially in the long term.

B.3 Cumulative returns

For the sake of completeness, in this section we look at the dynamics of the cumulative returns of cryptocurrency funds vs. passive benchmark returns, as well as the dynamics of the cumulative returns across different fund types and investment strategies.

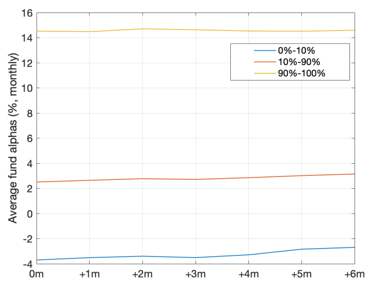
B.3.1 Crypto funds vs. benchmark returns. Figure C.1 illustrates the cumulative sum of log returns of an equal-weight average of the fund returns and compares it against a buy-and-hold investment in Bitcoin, an equal-weight (DOL) and a value-weight (Market) portfolio of top 300 cryptocurrencies in terms of market capitalisation, as well as a value-weighted portfolio of the digital assets available on Coinbase (ETF). The data covers the period from March 2015 to August 2020. Two observations are noteworthy. First, there is strong comovement around the dynamics of BTC across all passive investment strategies. That is, there is evidence of a "level" effect of BTC on cryptocurrency markets. Second, despite the dramatic decline in Bitcoin in later periods considered, the cumulative return of all funds only slightly declined during 2018 and in fact manages to recover by the end of 2019.

B.3.2 Returns across fund type and investment strategies. Figure C.2 shows that the compounded returns across different fund groups share a similar time variation during the considered period. An equal-weight average return for each fund type and strategy dramatically increases in the first half of the sample before starting to decline in 2018. The compounded returns then stabilise and start to recover towards the end of 2019. In relative terms, the `market neutral` funds are the best among other investment strategy funds.

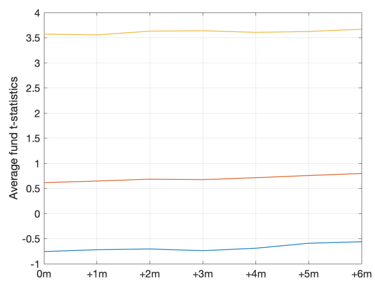
Figure A.1: **Persistence of benchmark-adjusted alphas**

This figure plots the benchmark-adjusted fund alphas (left panels) and the t-statistics obtained without (mid panels) and with (right panels) clustering the standard errors by investment strategy. Panel A shows the results for the post-formation alphas obtained from December 2020 to the end of the sample, whereas Panel B shows the results for the post-formation alphas from June 2020 to the end of the sample. The lines in the graphs depict the average alphas or t-statistics of funds in each of the three portfolios in the month of initial ranking (the "formation" month) and in each of the next months after formation. The three portfolios are formed once according to the estimated alphas from March 2015 to the "formation" month. The first portfolio consists of funds in the top decile with the highest alphas, the second portfolio – funds in the bottom decile with the lowest alphas, and the third portfolio – remaining funds with the alphas in the second to ninth deciles. The benchmark strategies consist of a buy-and-hold investments in Bitcoin (BTC) and Ethereum (ETH), an equal-weight market portfolio (DOL), and a value-weight average of the coins traded on Coinbase (ETF). The individual alphas are calculated as the individual fund fixed effects from a panel regression with varying beta coefficients across investment strategies (see, e.g., Pástor et al., 2015). The sample period is from March 2015 to June 2021.

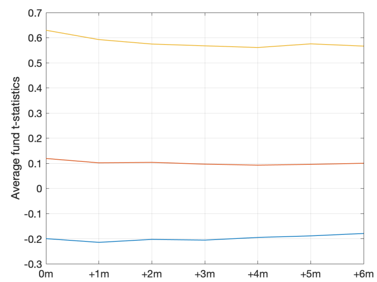
Panel A: Short-term persistence



(a) Alpha

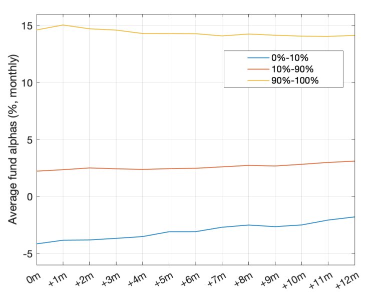


(b) Standard t-statistics

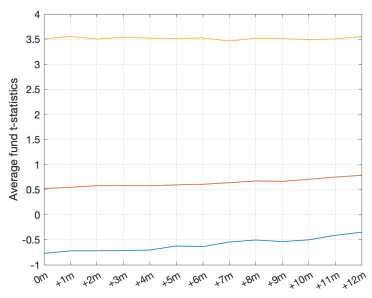


(c) Clustered standard errors

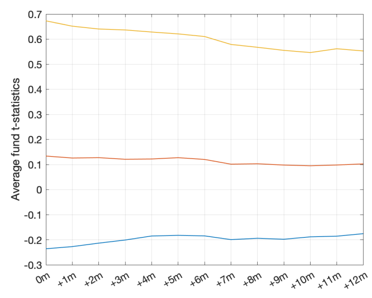
Panel B: Long-term persistence



(d) Alpha



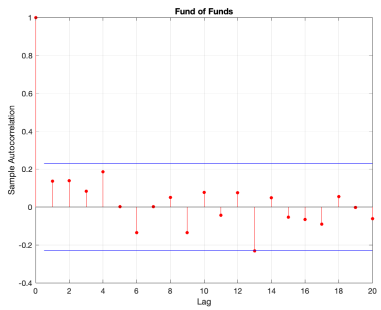
(e) Standard t-statistics



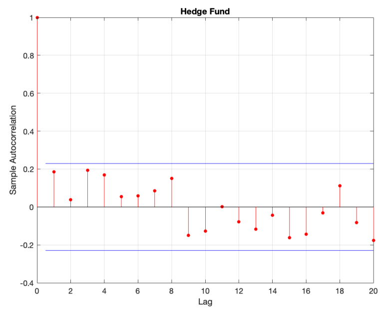
(f) Clustered standard errors

Figure B.1: **Autocorrelation function per fund type or investment strategy**

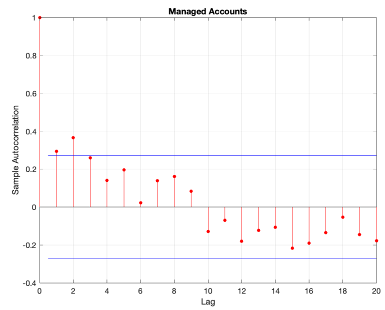
This figure shows the autocorrelation function up to 20 lags of equal weight portfolio returns aggregated across each type of funds and the investment strategy. The sample period is from March 2015 to June 2021.



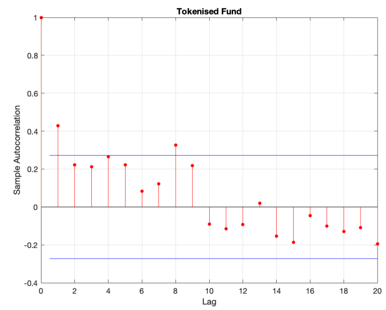
(a) Fund of funds



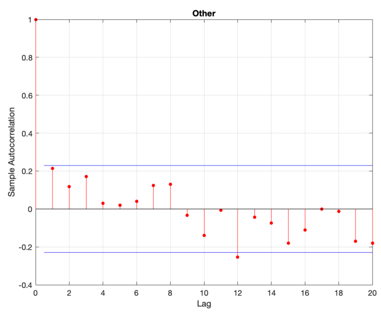
(b) Hedge fund



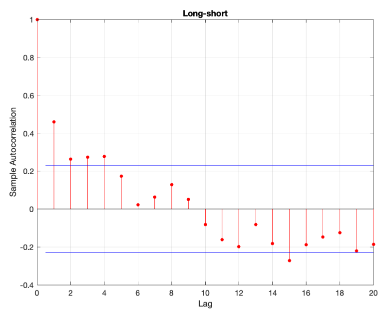
(c) Managed accounts



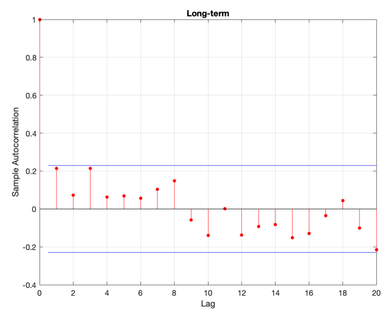
(d) Tokenized fund



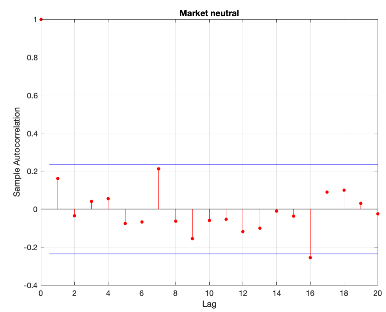
(e) Other



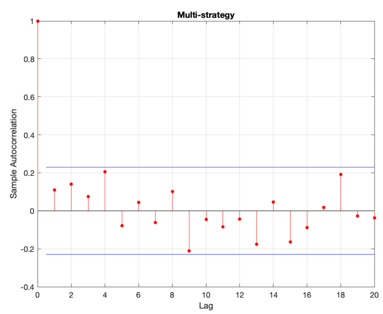
(f) `Long-short`



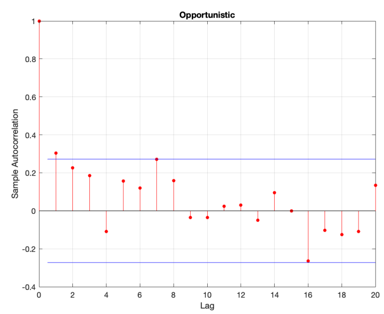
(g) `Long-term`



(h) `Market neutral`



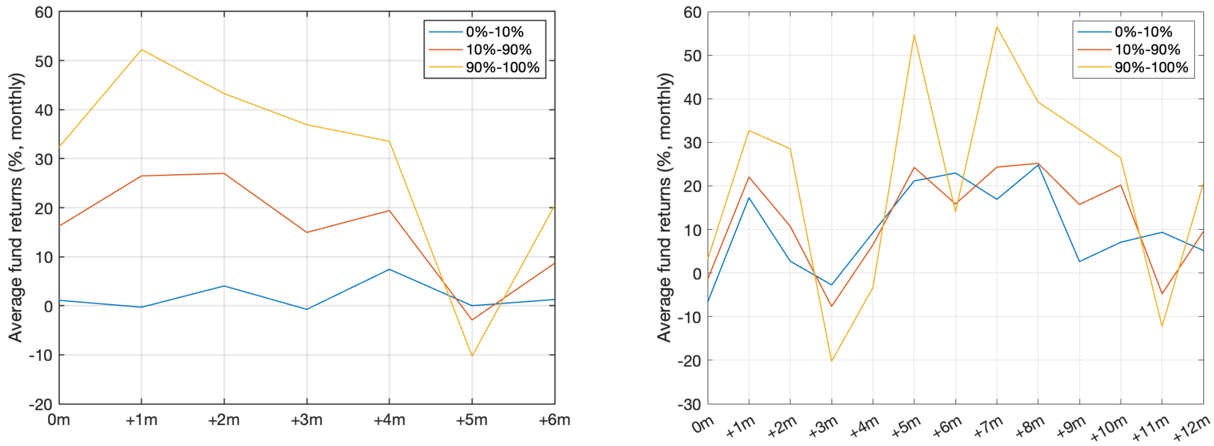
(i) `Multi-strategy`



(j) `Opportunistic`

Figure B.2: **Persistence of the raw fund returns**

This figure plots the post-formation returns from December 2020 (a left panel) and from June 2020 (a right panel) to the end of the sample. The lines in the graph depict the average returns of funds in each of the three portfolios in the month of initial ranking (the "formation" month) and in each of the next months after formation. The first portfolio consists of funds in the top decile with the highest six-month returns, the second portfolio – funds in the bottom decile with the lowest six-month returns, and the third portfolio – remaining funds with the six-month returns in the second to ninth deciles. The sample period is from March 2015 to June 2021.



(a) Short-term return persistence

(b) `long-term` return persistence

Figure C.1: **Fund returns vs. cryptocurrency returns**

This figure plots the time series of the fund returns proxied as an equal-weight average of each fund performance. The fund performance is calculated as the cumulative sum of log returns and is compared against a simple buy-and-hold investment in BTC, an investment in both an equal-weight and a value-weight portfolio of the major cryptocurrency pairs in terms of market capitalisation, and an investment in a value-weight average of the coins traded on Coinbase. The sample period is from March 2015 to June 2021.

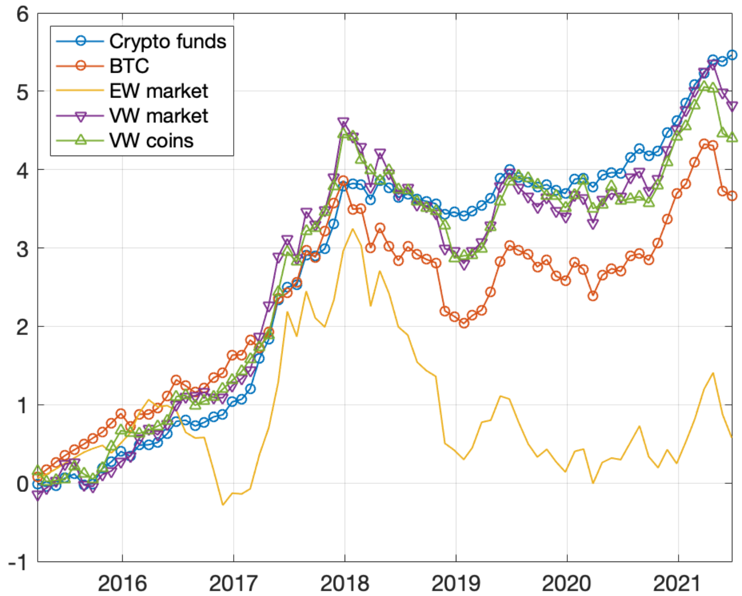
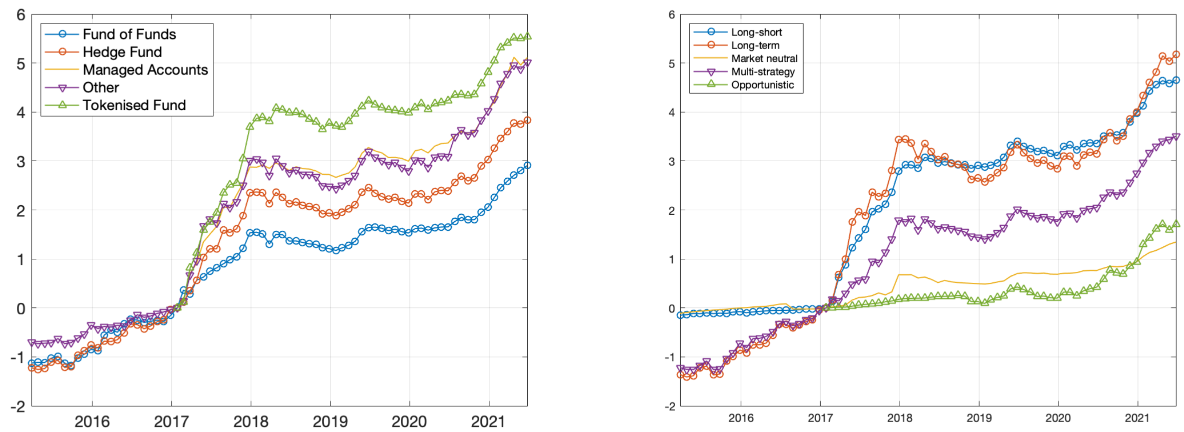


Figure C.2: **Compounded returns per fund type or investment strategy**

This figure plots the time series of fund returns for each type of funds (a left panel) and investment strategy (a right panel). The returns on each fund are aggregated as an equal-weight average of the returns within a given type/strategy. The fund performance is calculated as the cumulative sum of log returns. The cumulative log returns per fund type are normalised to 0 in January 2017 when the managed accounts and tokenised funds were introduced. The cumulative log returns per investment strategy are normalised to 0 in January 2017 when the first fund with the "`opportunistic`" strategy was introduced. The sample period is from March 2015 to June 2021.



(a) Cumulative log returns per fund's type

(b) Cumulative log returns per strategy

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