On the Performance of Cryptocurrency Funds*

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First draft: December 2019. This draft: April 14, 2021

Abstract

We investigate the performance of funds that specialise in cryptocurrency markets. In doing so, we contribute to a growing literature that aims to understand the value of digital assets as investments. Methodologically, we implement a panel semi-parametric bootstrap approach that samples jointly the cross-sectional distribution of alphas conditional on different benchmark strategies and/or risk factors. Empirically, we show that a small significant fraction of managers are able to generate economically large alphas which are not purely due to sampling variation. However, once we account for the within-strategy correlation of the fund returns, the significance of the alphas substantially decreases below standard threshold confidence levels.

Keywords: Cryptocurrency, Investments, Active Management, Alternative Investments, Bootstrap Methods, Bitcoin.

JEL codes: G12, G17, E44, C58

*We are thankful to Ankush Jain at Aaro Capital for assisting with the data collection on cryptocurrency funds. In addition, we thank Marcin Kacperczyk and participants at the 3rd Cryptocurrency Research Conference at the University of Reading, the 3rd UWA Blockchain, Cryptocurrency and FinTech Conference, and the 2nd Crypto Asset Lab Conference in Milan for helpful comments and suggestions.

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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] A price run up, which is an order of magnitude higher than traditional asset classes, has led to an increasing capital flow into a new category of investment funds, namely cryptocurrency funds. As a result, while much of the total market capitalisation for all cryptocurrencies – which at the time of writing stands roughly at $2 trillion – has been generated by individual traders buying and selling their own private stashes of digital asset, it is possibly also the result of an increasing demand for active investment management by institutional investors.[2]

Beginning with Jensen (1968), the ability of fund managers to create value for investors has become a heavily studied question in the academic literature, especially following the growing popularity of more passive and cheaper investment vehicles 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.

In this paper, we contribute to a further understanding of the value of 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 of the vast majority of cryptocurrency funds for which returns data are available. Although the depth and width of the investment management industry in the cryptocurrency space is not comparable with the mutual fund industry, crypto funds provide a peculiar context in which to understand the role of active asset management for few reasons: first, the fact that cryptocurrency markets have a highly fragmented, multi-platform structure, which is decentralised and granular, adds to the conjecture that

[1] At the time of writing, there are thousands of “alternative coins”, in addition to the most common such as Bitcoin (BTC), Ethereum (ETH), Litecoin (LTC) and Ripple (XRP), with rather different characteristics and features, and that are 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 bewteen 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.

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 when economic downturns are looming such as, for e.g., during the onset of the Covid-19 crisis.[4]

Second, cryptocurrencies is a new and mostly unregulated asset class. This widens the investment landscape to a variety of speculative and arbitrage opportunities (see, e.g., Makarov and Schoar, 2020), which could be ultimately reflected in the managers' decisions and risk taking behaviors.[5] In addition, the regulatory framework fund managers operate in has been shown to play a key role for the value of active asset management. For instance, Novy-Marx and Rauh (2011) and Andonov et al. (2017) provide evidence that regulations can increase the risk of pension fund holdings at the cost of decreasing the risk-adjusted performances.

Third, unlike investing in typical alternative funds, the competition in the crypto fund space still remains mostly non-existent. At the time of writing, the average size of the asset under management is slightly more than \$40mln whereas the total asset under management is estimated to be around \$50bln, indicating these are primarily small funds that operate in a relatively concentrated market. In particular, the limited competition from cheaper investment vehicles, such as ETFs and registered investment advisors, possibly puts less pressure on fund managers in cutting costs, increasing leverage or taking extra risks. Again, these features could ultimately be reflected in the managers' decisions. Last but not least, disentangling "skill" versus "luck" in the crypto fund industry is particularly challenging given the astonishing alphas these funds generated over the last few years. Indeed, when a fund is selected on the *ex-post* performance, with so many outlying returns, without taking into account (1) the heterogeneous risk-taking across funds, (2) the distribution of individual fund alphas, and (3) the massive return volatility and within-strategy correlations, extracting pure funds' skills

[4] 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] This makes crypto funds closer to typical hedge funds, but with the advantage of operating in a much newer and relatively still unknown asset class.

from performances could be quite complicated (see Kosowski et al., 2006 and Fama and French, 2010).

All these aspects combined make cryptocurrency markets a rather unique setting to investigate the fund managers performances and the value generated for investors above and beyond the exposure to market trends, risk factors and the inevitable random component in the realised returns. Indeed, while conventional research has long been debating the value of active management, no study has tested the existence of such value within the context of this new and relatively unregulated industry. This paper fills this gap and conducts what we believe is a first critical and comprehensive examination of the performances of cryptocurrency funds.

Empirically, we look at the performance of 250 funds which specialise in cryptocurrency investments and have been actively managed between March 2015 to January 2021. To avoid survivorship bias, the sample includes not only those funds that are still active, but also the funds that has been 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 1 shows this case in point. The figure reports the value-weighted index of the top 100 cryptocurrencies sorted by market capitalization. A complete description of the data is provided in Section 2. Clearly, the cryptocurrency market experienced a significant boom until December 2017, a major collapse from January 2018 to April 2018 – the so-called ICO bubble burst – and then proceeded to trade sideways until mid-2020. Then, after a major market drop in the early stage of the COVID-19 pandemic – the so-called Black "Thursday" on March 12th 2020, when the market capitalization of cryptocurrencies lost almost 40% of value in a single day – the market experienced an impressive run up with Bitcoin, Ethereum and all other major digital assets reaching all-time high prices. As a result, our sample not only includes different market phases, i.e., boom, bust and flat market, but also captures major regulatory and institutional changes such as the ban by the Chinese government on crypto exchanges and 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. In this respect, it is reasonable to assume that the sample is fairly representative and likely ensure there is sufficient time series variation in the data.

We begin by looking at the aggregate performance of crypto funds in excess of alternative passive investment strategies. 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 evidence of a superior fund performance compared to passive benchmarks 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). However, such performance is not heterogeneous, with the statistical significance of the alphas that is mostly concentrated within long-short and multi-strategy funds. The results are slightly different when replacing the benchmark passive strategies with a set of risk-based portfolios following Liu et al. (2019). Alphas tend to be higher and more significant when using pseudo-tradable risk factors instead of fully traded passive benchmark portfolios. Turning to the funds' betas, the results show that (1) there is a significant market exposures across funds and (2) Bitcoin plays the role of a "level" factor for the performance of crypto funds.

Delving further into the analysis of funds performance, 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-based portfolios – 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 highly correlated within investment strategies. The latter is empirically motivated by the large differences in the performances and the benchmark betas. Across a wide array of statistical tests, our main results show that, after adjusting for passive benchmarks or risk factors, the right tail of the performance distribution can not be simply due to random sampling variation of the returns. In other words, we find that the likelihood that a manager generates positive value for investors cannot be entirely explained by "luck". However, when controlling for commonalities in the fund returns within a given investment strategy, the standardised fund performance becomes substantially weaker, with none of the standardized performances that crosses the conventional 5% significance threshold. Overall, our analysis shows that, although the alphas of best performing funds can not be reconciled simply by sampling variation, the fact that returns are significantly correlated in the cross section substantially dilute the strength of the results.

We further analyse the managers' performance by looking at the period form March 2015 to December 2017 and from January 2018 to August 2020, separately. The cut-off date of December 2017 is chosen to separate the period pre- and post-ICO bubble. This helps to further investigate the benchmark-adjusted performance during different aggregate market trends (see Fig 1). The empirical results show that the strongest funds performance is found in the period of pre-ICO bubble burst, whereas the net-of-fees alphas in the period post January 2018 substantially decrease. Nevertheless, the main results of the paper holds across sub-samples, that is, the statistical evidence in favour of managers' skills weakens when within-strategy correlation of the returns is explicitly considered.

Finally, we test for the persistence in the fund alphas by reconstructing a set of tests as in Carhart (1997). Intuitively, investors could look at the past fund performances to infer the future. Our findings extend some of the results in Kosowski et al. (2006) to the cryptocurrency fund space. To the best of our knowledge, this is something that is new to the literature. Specifically, we document significant persistence in the net-of-fees alphas for the top performing managers. However, once we control for the unobservable heterogeneity and use clustered standard errors, the performance is not statistically significant at conventional confidence levels.

In order to make sure our bootstrap results are not driven by restrictive statistical assumption on the data, we investigate the robustness of the main empirical analysis to both alternative performance measures and different bootstrap procedures. By accounting for either time-series dependencies of fund and benchmark returns, and/or more complex distribution of both realised and unexpected returns in the bootstrap approach; again, the main results of the paper remain unchanged.

1.1 Related literature

As a whole, the empirical results contribute 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.[6] 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 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. The authors use their "value-added" measure of skill instead of the net alpha and show that the average mutual fund generates around $3.2 million per year. Kacperczyk et al. (2016) further provide a new attention allocation theory explaining the existence of managerial skills. 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, 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 often implemented within the context of more traditional asset classes.

In addition, this paper adds to recent literature that aims to understand the investment properties of cryptocurrencies (see Yermack, 2013, Dyhrberg, 2016, Liu and Tsyvinski, 2020, Bianchi, 2020, Bianchi et al., 2020, and Schwenkler and Zheng, 2020, among others).[7] We contribute to this literature by providing a first comprehensive study on the value of active investment management in cryptocurrency markets.

[6]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.

[7]Yermack (2013) and Dyhrberg (2016) investigate the hedging properties of Bitcoin within the context of a diversified portfolio and reach opposite results. In particular, Yermack (2013) argues that Bitcoin is uncorrelated with the majority of fiat currencies and is much more volatile, and therefore is of limited usefulness for risk management purposes and diversification. A similar conclusion is reached by Bianchi (2020) based on a larger set of cryptocurrencies. Similarly, Liu and Tsyvinski (2020) and Bianchi et al. (2020) establish that the risk-return tradeoff of some of the major cryptocurrencies is distinct from those of stocks, currencies, and precious metals.

2 Data

2.1 Fund returns

We obtain data 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, analytics, and insights for alternative investments. Second we complement the data from these sources by hand-collecting information 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 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 average AUM for crypto hedge funds is slightly more than \$40mln, with a distribution that is highly skewed to the left. Indeed, only about a third of the funds in the sample have more than \$20mln of AUM. Second, we focus only on those funds that accept US dollars as the investment currency and likewise report their performances in US dollars, so that FX risk is to a large extent factored in the performance analysis. Third, we consider returns net of all fees, including incentive fees and management fees.[8] By considering net-of-fee returns, the aim is to investigate whether fund managers can generate benchmark-adjusted returns above and beyond the expenses an investor nominally encounters. Fourth, 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 consecutive monthly return history.

After the filters above have been implemented, the data consist of a maximum of 204 different funds which have been actively managed for at least 12 months between March 2015 to January 2021. Figure 2 provides a snapshot of the data. The left panel shows that the size of the cross-section of

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

funds used in the empirical analysis steadily increases until late 2019 and then tend to be rather stable towards the 2020 and early 2021; virtually no funds after filtering could have been used before March 2015. To the best of our knowledge, at the time of writing this is the largest available data set used in academic research. The estimated assets under management (AUM) steadily increased with the number of funds, with a growth rate of almost 900% within 5 years. The right panel of Figure 2 shows the geographical distribution of the funds; interestingly, the majority of the funds are headquartered either in the US or Europe, Asia – China, Singapore, South Korea and Japan – as well as the UK ranking second. The remaining funds, although a residual part, are located in peripheral countries such as Russia, Brazil and Australia, as well as tax havens such as the Cayman Islands.

Although the number of funds is relatively small, the cross-sectional variation of the fund returns is quite substantial. Figure 3 reports a set of box-plots which summarise the cross-sectional distribution of a variety of descriptive statistics, such as the unconditional Sharpe ratios, the returns skewness and persistence, i.e., AR(1) coefficient, as well as the market beta. The latter is constructed as a value-weighted average of the top 100 cryptocurrencies by market capitalizaion.

Four facts emerge: first, not all of the funds generate positive raw returns, even when not adjusted by risk factors and benchmark strategies. As a matter of fact, a non-trivial fraction of the funds generate negative Sharpe ratios unconditionally. While the average Sharpe ratio is equal to 1.7 on an annualised basis, the median is equal to one, meaning the distribution of Sharpe ratios is positively skewed. Such positive skewness is confirmed by looking at the bottom-right panel of Figure 3 which clearly show the median skewness in the sample is above one. Second, there is very low persistence in the fund returns with the average AR(1) coefficient close to zero 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. Third, the top-right panel shows that there is considerable heterogeneity in the funds exposure to market risk, with the median market beta that is around 0.4.

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). These are the most common forms of active investment management in the cryptocurrency space.

Crypto HF work in the same way of a typical hedge funds, whereby investors' accounts are managed by teams of expert investors, re-balanced on occasion, and constantly analysed. MA, again, are very similar to boutique mutual funds, whereby high-net-worth individuals can access a high degree of customisation and greater tax efficiencies. Instead, TF 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. In this respect, a TF is similar in spirit to a standard mutual fund. The main advantage for investors is liquidity, as shares in the TFs can be freely traded on a secondary market, sometimes even on the blockchain. Finally, FoF take a multi-manager approach and invest in a set of different funds, there is no structural difference between a regular hedge 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. Tokenised funds rank second, whereas only a small fraction of funds are labelled as MA or FoF. There is also a residual category of funds dubbed "other", which consists of those funds for which we cannot find a reliable classification.[9]

Table 1 reports a set of descriptive statistics both at the aggregate level – by taking an equal-weight average of the fund returns in our sample – as well as 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. First looking at the aggregate statistics; the annualised Sharpe ratio of the average fund is in line with the market portfolio (1.28 annualised) and a buy-and-hold investment in Bitcoin (1.26 annualised) as shown later in Table 2. In addition, the returns on the average fund are positively skewed and very low persistent, with an AR(1) coefficient of 0.25.

The picture that emerges by grouping funds according to their type is somewhat more homogeneous. All type of funds show a quite high volatility, which translates in annualised Sharpe ratio between 1.42 (for the Other type) and 1.94 (for managed account funds). Two additional features are worth to notice; first, returns on crypto funds, unlike typical hedge funds, are not persistent, with the highest AR(1) coefficients being equal to 0.32 and 0.42 for managed accounts and tokenized funds while being almost negligible for the other strategy clusters. Second, and perhaps more interestingly, regardless of whether we look at the aggregate crypto fund industry or more granular classifications, the fund returns display a significant and positive skewness. That is, despite the high volatility of

[9]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).

returns, the (unconditional) probability of cashing-in large gains is higher than the probability of suffering large losses.

Panel B of Table 1 shows the correlation between the fund returns and the returns on a set of proxies for global Equity, Bond, Commodity and Real Estate investments, again at the aggregate level and by clustering funds according to their type. Returns on traditional asset classes are approximated by 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. A simple correlation analysis extends to the crypto fund space the conventional wisdom that cryptocurrency returns may offer some diversification benefit to investors within an otherwise standard multi-asset portfolio (see, e.g., Yermack, 2013, Bianchi et al., 2020 and Bianchi, 2020).

2.1.2 Investment strategies. The investment strategies of crypto funds are somewhat comparable to traditional markets. Funds can be grouped into five categories: long-short, long-term, market neutral, multi-strategy, and opportunistic; *Long-short* funds primarily employ a short/medium term systematic quantitative investment process, which seeks to capitalise on the volatile behaviour of cryptocurrencies. 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.[10] *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 most 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. 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 low beta versus its appropriate market index 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-term, long-only investment and in part as a long-short leveraged investment. The right panel

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

of Figure 4 shows that funds adopting so-called opportunistic strategies are the minority. 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 reports the performance of the average fund when grouped by investment strategy. There is a quite significant heterogeneity in the raw performance of funds across different investment strategies; for instance, multi-strategy and long-short funds report a Sharpe ratio that is almost 60% higher than market neutral funds. The latter, however, have the lowest returns volatility, and therefore the lowest with a monthly standard deviation of the returns which is five times smaller than long-term funds. Similar to the market aggregation and the clustering by fund type, Panel B shows that the correlation between the funds returns across different strategies and the returns on proxies of global Equity, Bond, Commodity and Real Estate investments is virtually zero, with the only partial exception of opportunistic funds.

2.2 Benchmark strategies and risk-based portfolios

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 extract funds performance based on both passive benchmarks and risk-based portfolios is twofold: first, within the context of cryptocurrency markets, the use of passive investment benchmarks to extract the fund alphas is arguably more realistic than using factor portfolios. 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. On the other hand, factor portfolios in the cryptocurrency space do not necessarily represent actual alternative investment opportunities since 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 capture the performance of cryptocurrency funds.

2.2.1 Passive benchmarks. To construct the passive benchmarks and risk factors we obtain data on daily prices and trading volumes from CryptoCompare, a website-based data provider that collects data from multiple exchanges. Precisely, the data integrates transactions for over 250 exchanges. Recent work by Alexander and Dakos (2019) suggests that CryptoCompare data is among the most reliable for use in both academic and practical settings.[11] We obtained data on a daily basis for the sample period from March 1st 2015 to January 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, and therefore more sensitive to exogenous shocks, exchanges 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.[12] Second, exchanges are reviewed on a regular basis for each given cryptocurrency pair. Constituent exchanges are excluded if (1) posted prices are too volatile compared to 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 mitigate any bias in selecting 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 in BTC.[13] A second passive benchmark is a simple buy-and-hold investment in ETH, which is widely recognised as the second major digital asset currently trade with a market capitalisation with a $26bn market cap at the time of writing. A third passive investment strategy is a

[11]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).

[12]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.

[13]At the time of writing, BTC represents more than 60% of the total market capitalisation and therefore represents an inexpensive way to capture the aggregate market trend.

simple equal-weight portfolio comprising the top 50 cryptocurrencies in terms of market capitalisation. This is the equivalent of a "dollar risk factor" adapted to cryptocurrencies from Lustig et al. (2011).[14] The fourth and last passive benchmark builds on the so-called "Coinbase Index", which is a passive portfolio giving investors exposure to all digital assets listed on Coinbase and Coinbase Pro exchanges at the end of the sample, weighted by market capitalisation.[15]

The first four columns of Table 2 report a set of descriptive statistics similar to Table 1. Interestingly, compared to the average crypto fund, benchmark strategies earn a lower Sharpe ratio on an annual basis. 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 the realised returns.

2.2.2 Risk factors. The vast majority of the literature on mutual funds uses factor portfolios to disentangle the alpha from simple exposures to sources of systematic risk. Within the context of cryptocurrency markets, a risk-mimicking portfolio often does not represent a feasible investment strategies. In particular, the large investment frictions and costs retailers should face to take short positions make quite prohibitive to implement profitable long-short strategies based on momentum, liquidity, and volatility. In this respect, one may think the use of risk factors within the context of cryptocurrency markets a useful, although not realistic, academic exercise. For this reason, it can still be useful to benchmark fund returns against factor portfolios (see, e.g., Barber et al., 2016; Berk and Van Binsbergen, 2016). 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 mimicking portfolios to proxy risk factors based on the daily returns and volume data for a large cross section of more than 300 cryptocurrencies. Specifically, we first consider the returns on the aggregate market (MKT) calculated as the returns on a value-weighted portfolio of the 100 cryptos by market capitalization. We then consider both the returns on a cross-sectional momentum strategy (MOM) as outlined by Jegadeesh and Titman (2001) and a simple

[14] 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).

[15] 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).

reversal strategy that goes long on past losers and short on past winners (see De Bondt and Thaler, 1985).[16]

In addition, we consider two additional sources of risk that are relevant in cryptocurrency markets: liquidity and volatility (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 300 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 for a given digital asset. 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 equal-weight portfolio of illiquid pairs (fifth quintile) and going short into the liquid pairs (first quintile), again with equal weights. This zero-cost long-short portfolio represents our liquidity factor portfolio.

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 equally 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).

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.

[16] 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.

3 Dissecting the performance of cryptocurrency funds

3.1 Aggregate performance

Table 1 shows that, on average, crypto funds generate quite sizable returns and Sharpe ratios. We now look at the aggregate benchmark- and risk-adjusted fund performances. 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.[17] In addition to the funds performance, we also report a direct test of the difference in the performance between the average fund – first column – and the performance of portfolios grouped by fund 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;

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

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 $\hat{\gamma}$.

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 2.50% (robust t-stat: 2.52) risk-adjusted perfor-

[17] 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 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.

mance 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 6.60% (robust t-stat: 3.40), which is three times larger than the performance of fund of funds (1.98%, robust t-stat: 2.34). In fact, for the residual category "other", the performance is not statistically different from zero. A higher heterogeneity is reported between investment strategies; for instance, while long-short and multi-strategy funds report significant alphas of 3.2% (robust t-stat: 3.01) and 2.28% (robust t-stat: 2.56), respectively, long-term, market-neutral and opportunistic 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 benchmark-adjusted performance for some category of funds not significantly different from zero.

When clustering by fund type, the performance of the average fund is in line with all different fund types, with the only exception of the "tokenized funds" type (γ = 2.98, robust t-stat: 2.27). Managed accounts and tokenized funds both generate a benchmark-adjusted performance which is higher than the average fund. 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 $\gamma = -1.87$ (robust t-stat: -2.13). Both the long-term and the opportunistic funds tend to perform, in benchmark-adjusted terms, below the fund average, although equivalent in statistical terms.

Panel B of Table 3 suggests that the heterogeneity in the benchmark-adjusted performance primarily comes from the heterogeneous exposure to the returns on passive investment strategies. As far as the more granular fund classification is concerned, two interesting facts emerge: first, with the exception of managed accounts and tokenized funds, the exposure to BTC returns is positive and significant. A similar path is shown by β_{ETF}, that is, funds are positively and significantly exposed to the ETF passive benchmark. Second, by looking at the strategy-based clustering we can see that both long-short and market neutral strategies tend to be uncorrelated with BTC returns, while both long-term and multi-strategy are significantly exposed to the BTC performance. As a whole, both BTC and ETF, of which BTC is a considerable component, seem to affect the majority of funds when classified by type and/or strategy, with the exception of more actively managed long-short and market neutral funds.

3.1.2 Risk-adjusted alphas.

3.1.2 Risk-adjusted alphas. We repeat the analysis by replacing the passive benchmark portfolios with the set of risk factors outlined in Section 2. Table 4 reports the results. Again, the dependent variable is an equal-weight aggregation of all funds or funds clustered by type and strategy, and the independent variables are the long-short portfolios of cryptos sorted on liquidity or volatility, as well as 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. When clustered by type, the risk-adjusted alphas are slightly higher than the benchmark-adjusted performances. For instance, the alpha of the "other" funds increases by 0.6% on a monthly basis with respect to the benchmark-adjusted equivalent (robust t-stat: 2.00). Similarly, the results for the funds clustered by investment strategy also slightly change. For example, the risk-adjusted alpha for the long-term strategy is now positive and significant (3.07%, robust t-stat: 2.69), whereas for its benchmark-adjusted equivalent was still positive but not statistically significant. Despite few nuances, the risk-adjusted performance of the funds is largely positive and significant, which is somewhat in line with Panel A of Table 3.

Panel B of Table 4 reports the risk factor loadings. Two interesting facts emerge: first, regardless of the type and investment strategy all funds load positively and significantly to market risk. In fact, the market beta is possibly the only slope parameter that is consistently significant, as suggested by the robust t-statistics on the other risk factors across fund types and strategies. Second, the magnitude of the market beta substantially change especially across investment strategies; for instance, while market neutral strategies show a modest $\beta_{MKT} = 0.14$ (robust t-stat: 2.77), long-term strategies show a highly positive and significant exposure to market risk ($\beta_{MKT} = 0.82$, robust t-stat: 12.93). This result suggests that the market trend represents the primary, if not the major, source of risk for active management in cryptocurrency funds.

3.2 Individual fund performances

Although instructive, given the substantial cross-sectional heterogeneity in the fund returns, by simply looking at the average performance may give a misleading picture as the individual as one cannot control for the differences in managers' risk-taking behaviors/skills (see, e.g., Kosowski et al., 2006). In addition, the returns of individual funds exhibit non-normality, that is the cross-section of alphas represents a complex mixture of non-normal distributions and aggregation at the type or strategy level may dilute important sources of cross-sectional heterogeneity.

To address these issues, we apply a panel bootstrap procedure to evaluate the performance of individual cryptocurrency funds. There are several reasons why a bootstrap approach is helpful for statistical inference within the context of cryptocurrency markets. For instance, the returns of individual funds exhibit large departures from normality, such as large positive skewness and massive kurtosis, with the cross-section of alphas effectively representing a complex mixture of these non-normal distributions.

We follow Kosowski et al. (2006) and Fama and French (2010) and consider two key parameters to measure the fund performance, 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. 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 be small in assets under management, have a short life span, and engage in a relatively high risk asset class such as digital assets. Thus, the cross-sectional distribution of alpha estimates tend to show spurious outliers. The t-statistics provides a correction to these outlying funds by normalising the alpha estimates by their standard errors. Second, with a relatively limited investment opportunity set compared to traditional equity funds, crypto funds operating within a given strategy framework could embark in overlapping investments, which in turn may generate highly correlated returns. By clustering standard errors at the strategy level, the resulting t-statistics explicitly take into account within-strategy returns comovement. For these reasons, we implement a bootstrap both for $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ and comment the bulk of the empirical results based on the t-statistic rather than the alpha estimates.

To prepare for our bootstrap procedure, we estimate the alphas by comparing the historical net-of-fees fund returns with a set of alternative investment opportunities as represented by low-cost passive funds (see, e.g., Berk and Van Binsbergen, 2015 and Dyakov et al., 2020) or risk factors. We build upon Pástor et al. (2015) and estimate the historical alphas by a panel regression of the form

$$y_{it} = \alpha_i + \sum_{j=1}^{J} \boldsymbol{\beta}_j^{\prime} \boldsymbol{x}_t + \epsilon_{it}, \qquad i = 1, \ldots, N \qquad t = 1, \ldots, T \tag{1}$$

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

A panel regression of the form in Eq.(1) 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 soak up 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.[18] 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 t-statistics, by employing information on the behavior of the whole set of funds jointly. Perhaps more importantly, by pooling information from different funds, we can obtain more precise estimates of the fund performances despite their short life span.

For each fund i, the historical, meaning the actual alpha estimates $\hat{\alpha}_i$ as well as the corresponding t-statistics $\hat{t}_{\hat{\alpha}_i}$ and the residuals $\hat{\epsilon}_{it}$ obtained from the panel regression (1), 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 $\{\hat{\epsilon}^b_{it},\ \boldsymbol{x}^b_t;\ t = s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}\}$, where $b = 1, \ldots, B$ is the bootstrap index and $s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}$ are drawn randomly from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for this fund i as

$$y^b_{it} = \sum_{j=1}^{J} \hat{\boldsymbol{\beta}}_j \boldsymbol{x}^b_t + \hat{\epsilon}^b_{it}, \qquad b = 1, \ldots, B. \tag{2}$$

Notice that the sequence of returns y^b_{it} has a true alpha (and the t-statistic of the alpha) that is zero by construction. However, when we regress the alpha-adjusted returns on the bootstrap factors $\boldsymbol{x}^b_t$ for a given bootstrap sample b, a positive alpha (and t-statistic) may still arise from pure sampling variation; that is, by luck. In order to take into account the within-strategy returns correlation for the standardised returns, the t-statistics are calculated based on clustered standard errors where

[18] Although in Berk and Green's model investors cannot observe the skills of the fund manager i, which corresponds to α_i in Eq.(1), 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.

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 $b = 1, \dots, B$ 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.

Two differences between our empirical setting and the existing literature are (1) departure from normality is much more pronounced in crypto fund returns (see descriptive statistics below) and (2) the average life span, assets under management, and the number of funds are much lower than within the context of traditional equity funds. Yet, these issues likely justify even more the use of bootstrap methods instead of standard asymptotic inference.

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. To summarise, by considering the joint estimates of alphas and betas within a panel regression context possibly leads to more conservative estimates of the fund performance. Section 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 fund performances. Figure 5 compares the distribution of actual $\hat{\alpha}$ and the corresponding $\hat{t}_{\hat{\alpha}}$ with the distribution of bootstrapped values. For the sake of completeness, we report the results with both classic standard errors (middle panel) and standard errors clustered by investment strategy (right panel). The left panel confirms some of the previous intuition and shows that there is a significant cross-sectional variation in the $\hat{\alpha}$ estimates. Actual individual fund alphas (a light-blue histogram) range from -15% to an impressive +35% on a monthly basis. This suggests that some of the aggregate performance reported in Section 3 can be driven by a small number of outlying funds. Nevertheless, compared to the bootstrapped alphas, the probability mass of the fund performances is much more pronounced on the right tail, that is, the economic value of the actual alphas is larger than the one that could have been generated only by sampling variation, i.e., by luck.

The middle panel shows the cross-sectional distribution of the actual and bootstrap t-statistics obtained without clustering standard errors by strategy. Two main facts emerge: first, only a small fraction of funds show a positive and significant $\hat{t}_{\hat{\alpha}}$. More precisely, only 24 of the total 204 funds in our sample show an alpha that is significant at the conventional 5% confidence level. Second, similar to the alpha estimates, the probability mass of actual t-statistics is shifted to the right side compared to the distribution generated by the bootstrap. However, if we explicitly acknowledge that the performance of funds can be correlated within a given strategy, the statistical significance of the alphas significantly decreases. As a matter of fact, the right panel shows that, although the probability mass is still tilted more to the right compared to the returns generated by sampling variation, none of the individual standardised performances is above the typical 5% significance threshold.

As a whole, Figure 5 suggests that 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 quite weak. 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 returns (see McNemar, 1947).

We now replace the passive benchmark portfolios with the risk factors describe in Section 2 to calculate the individual risk-adjusted fund performances based on our bootstrap procedures. Figure 6 reports the actual values (light-blue bars) as well as the bootstrap values (light-red bars) of both $\hat{\alpha}$ (left panel) and $\hat{t}_{\hat{\alpha}}$ with (right panel) and without (mid panel) standard errors clustered by investment strategy. The economic magnitude of $\hat{\alpha}$ is rather similar to that obtained using the benchmark strategies. The bulk of alphas are concentrated around an average value of 3.5% on a monthly basis; however, there is a sizable amount of outlying funds with performance well above 10% on a monthly basis.

Turning to the standardised performance $\hat{t}_{\hat{\alpha}}$, the picture that emerges is marginally different from the main benchmark-adjusted returns. In particular, the left panel in Figure 6 shows that the fraction of funds with significant alphas is slightly bigger when using factor portfolios rather than benchmark strategies. As show in the middle and right panels, sampling variation, or luck, cannot explain the performance of the few outlying funds. However, there is still overall weak statistical significance of the individual fund performances.

3.3 Sub-sample analysis

Figure 1 shows that cryptocurrency markets were marked by a massive 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 and 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.

To further investigate such assumption, we repeat our analysis of individual fund performances for two subsamples: the pre-ICO bubble and the post-2017 periods (see the vertical dashed black line in Figure 1). The reason why considering the cut-off of the sample in December 2017 can enrich the empirical results is twofold. First, there is a clear separation between overwhelmingly bullish and bearish markets before and after December 2017. Thus, we are able to disentangle the performance of funds between favourable and more adverse investment scenarios. Second, the second part of 2017 was characterised by the so-called ICO boom due to increasing BTC prices, whereby hundreds of new crypto-assets and cryptocurrencies were introduced into the market primarily for speculative purposes. This allows us to further investigate the value of active investment management within the context of a drastically changing investment opportunity set.

We first look at the simple descriptive statistics for the raw returns across sub-samples. Table 5 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 an order of magnitude 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 1.00 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. Finally, 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.

We now turn our focus on the individual fund performances across sub-samples. For the ease of exposition we report only the benchmark-adjusted alphas.[19] The top panels of Figure 7 show $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ for the pre-2017 period. Similar to Figure 5, we report the alphas (left panel), the t-statistics from a simple OLS estimate of the panel regression (1) (middle panel) and the same fixed-effect estimates with robust t-statistics using standard errors clustered by investment strategy (right panel).

Few interesting aspects emerge; first, the estimated alphas are much higher than those based on the whole sample (see Figure 5), with outlying alphas greater than 50% on a monthly basis. Second, the bootstrap t-statistics with clustered standard errors show that one fund appears to show

[19]The sub-sample results for the risk-adjusted alphas are qualitatively similar to the bechmark-adjusted results and are available upon request.

a significant performance. Third, and similar to the full-sample evidence, when the within-strategy correlations are ignored, a larger fraction of funds now generate significant performance. Overall, managers have superior performance during the market run up early in the sample with some sign of statistical significance. The bottom panels of Figure 7 provide the evidence of a substantial drop in managers' performances after the price collapse in early 2018. The left panel shows that the economic value of the performance is almost an order of magnitude smaller than during the pre-ICO bubble period, whereas the right panel shows that the set of "skilled" funds is empty based on within-strategy clustered standard errors. Yet, if the correlation between the fund returns within strategy buckets is ignored, there is some evidence of significant performance.

In sum, Table 5 and Figure 7 provide some evidence of managers' skills across sub-samples. As a matter of fact, the right tail of the actual distribution of alphas is more skewed to the right than the bootstrapped performances. That is, the fund alphas cannot be simply explained by pure sampling variation. However, when within-strategy correlation in the returns is considered, there is little statistical significance of the alphas across both samples, with slightly stronger evidence during the massive price run up until the end of 2017.

3.4 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. Although there is weak evidence of skills in the cross section of individual funds based on the above bootstrap results, we evaluate the short-term and long-term persistence of fund performance.

Specifically, we first estimate the panel regression defined by Eq.(1) using the actual historical data from March 2015 to the "formation" month and sort all funds into three portfolios based on the estimated individual fund alphas. 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 formation and report the average alphas and t-statistics in each of the three portfolios constructed at the formation period. We perform this analysis for the portfolio groups sorted in August 2019 and February 2020 to check for a persistence in the 12-month and 6-month alpha-sorted fund portfolios, respectively.

Figure 8 reports the results. The left panels show the short-term (top panel) and long-term (bottom panel) persistence of the historical economic 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.

Turning to the standardized performance $\hat{t}_{\hat{\alpha}}$, similar to the main cross-sectional analysis there is no significant evidence of persistent skills in fund managers when controlling for within-strategy correlations in the regression residuals, both in the short and in the long term as shown in the right panels of Figure 8.

4 Further results

In this section, we provide a set of additional results and robustness checks to show the sensitivity of the main empirical analysis to a variety of different modeling choices.

4.1 Constant betas and time-series regressions

Our main bootstrap approach is based on a panel regression with fund fixed effects, within-strategy clustered standard errors and strategy-dependent loadings on passive benchmark returns (see Eq.1). Such an approach allows to (1) increase the power of the test as fund returns can be pooled together, (2) acknowledge unobserved fund-specific heterogeneity, (3) control for correlations between individual fund performances within a given investment strategy, and (4) assume that betas on benchmark strategies/factors may differ across investment mandates.

In this section we relax these assumptions to assess the marginal contribution of each of the testing ingredients. First, we restrict $\boldsymbol{\beta}_j^{'} = \boldsymbol{\beta}^{'}$ for $j = 1, \ldots, J$. Figure 9 shows the results. The left panel reports the alphas, whereas the right and middle panel report the t-statistics with and without clustered standard errors, respectively. Except for few nuances, the results of the main empirical analysis hold. Specifically, although most successful managers generate net-of-fees performances which cannot be reconciled purely by random sampling variation, such economic value is not statistically significant when within-strategy return correlation is explicitly considered.

Next, we relax assumptions from (1) to (3) and estimate alphas for each fund separately based on a simple time-series regression with Newey and West (1986) robust standard errors. That is, β_i' is fund-specific and we do not assume correlation within strategies and/or fund types. Figure 10 shows the results.

[Insert Figure 10 here]

Two interesting facts emerge; first, the estimated alphas are significantly larger than the fixed-effects 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 univariate OLS estimates. Second, the cross-sectional distribution of the t-statistics shows some evidence of skill vs. luck, that is, the distribution of actual t-statistics is shifted above a standard 5% significance threshold. Interestingly, this result is similar to the one obtained from a panel regression without clustered standard errors. This suggest that taking into account the cross-correlation of the fund returns turn out to be crucial to assess the managers' performance. By coupling together the mid panel of Figure 5 and the right panel of Figure 10, one can assume that when simple time-series regressions are considered, the fund managers skills tend to be overestimated.

4.2 Block bootstrap and independent resampling

Our main bootstrap procedure assumes that the residuals are only weakly autocorrelated. Tables 1-5 and the bottom-left panel of Figure 3 show that the persistence of fund returns is low compared to traditional equity mutual funds. 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.

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 history of data, we set the length of the blocks equal to three months (if the length of the historical data for a specific fund is not a divisor of 3, one of the blocks will contain one or two observations only). With the only exception of market neutral funds, this is largely consistent with the small auto-correlation of returns shown in Figure B.1.

Panel A of Figure 11 presents the fund alphas and their t-statistics for the block-bootstrap approach. The left panel confirms that the right tail of actual fund alphas does not reconcile with pure sampling variation. That is, there is some evidence of skills vs luck as far as the economic value of active management is concerned. However, as for the main empirical results, when the within-strategy correlation is explicitly considered (right panel), there is no statistical evidence of fund performances. All of the standardised performances $\hat{t}_{\hat{\alpha}}$ are below conventional significance values. Overall, allowing for a short-term autocorrelation in our bootstrap procedure, the results are largely in line with the main empirical analysis.

We next 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.

The extended bootstrap approach works as follows; let T_{0i} and T_{1i} represent the dates of the first and the last available returns for the fund i, respectively. For each fund i, we draw one sample with replacement from the fund residuals $\left\{\hat{\epsilon}_{it}^{b};\ t_{\epsilon} = s_{T_{0i}}^{b}, \ldots, s_{T_{1i}}^{b}\right\}$, and one *separate* sample with replacement from the benchmark returns $\left\{\boldsymbol{x}_{t}^{b};\ t_{x} = \tau_{T_{0i}}^{b}, \ldots, \tau_{T_{1i}}^{b}\right\}$. Note that the indicators $s_{T_{0i}}^{b}, \ldots, s_{T_{1i}}^{b}$ and $\tau_{T_{0i}}^{b}, \ldots, \tau_{T_{1i}}^{b}$ are drawn independently from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for the fund i as

$$y_{it}^{b} = \hat{\boldsymbol{\beta}}' \boldsymbol{x}_{t_x}^{b} + \hat{\epsilon}_{it_{\epsilon}}^{b}, \qquad b = 1, \ldots, B \tag{3}$$

Note that the sequence of returns y_{it}^{b} has a true alpha (and the t-statistic of the alpha) that is zero by construction. More details on the procedure can be found in Appendix A.2.

Panel B of Figure 11 report the estimates for both $\hat{\alpha}$ (left panel) and $\hat{t}_{\hat{\alpha}}$ with and without clustered standard errors (right and mid panel, respectively). The results are virtually the same as in the main empirical analysis, that is there is some evidence of economic value for the best performing funds, but such evidence is not statistically significant when within-strategy returns correlation is explicitly acknowledged.

5 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 January 2021. We investigate the performance of funds both at the aggregate level through a set of different regression analysis and at the individual through a bootstrap approach which takes 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 a sizable minority of managers can generate benchmark- and risk-adjusted returns which cover their cost and possibly could create a positive value for investors. However, once within-strategy correlations among fund returns is taken into account, there is weak statistical significance in favour of managers' performance, that is there is weak evidence of significant and positive alphas even for the best performing funds.

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 net of both management and performance fees. We report 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). The top panel reports the sample mean and standard deviation (%, monthly), the annualized Sharpe ratio, the skewness and autocorrelation of returns of fund portfolios. The bottom panel reports the correlations of aggregate fund returns with the returns of global ETFs from traditional asset classes: equity, corporate bond, commodity, and real estate markets. We use the data for Vanguard Total World Stock Index Fund ETF, iShares Global Corporate Bond UCITS ETF, S&P GSCI Commodity Index ETF, and iShares Global REIT ETF for four traditional asset classes, respectively. The sample period is from March 2015 to January 2021.

Panel A: Descriptive statistics

		Fund type					Fund strategy				
	Agg	Fund of funds	HF	Managed acc	Other	Token fund	Long-short	Long-term	Market neutral	Multi-strategy	Opportunistic
Mean (%)	7.96	4.98	7.35	9.72	8.98	12.38	6.89	10.29	1.86	6.65	2.84
Std (%)	16.26	11.46	15.53	17.36	21.89	24.11	14.31	24.65	5.95	13.1	7.77
SR (annualized)	1.7	1.5	1.64	1.94	1.42	1.78	1.67	1.45	1.09	1.76	1.27
Skewness	1.48	1.19	1.22	1.49	1.92	2.04	1.91	1.76	4.38	0.68	1.7
AR(1)	0.25	0.08	0.17	0.32	0.19	0.42	0.45	0.22	0.12	0.07	0.24

Panel B: Correlation with 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
Equity	0.04	-0.07	0.03	-0.15	0.09	-0.18	0.15	0.03	0.13	0.08	0.55
Bond	0.09	0.02	0.07	0.01	0.14	-0.12	0.16	0.08	0.08	0.08	0.20
Commodity	-0.12	-0.09	-0.11	-0.08	-0.16	0.03	-0.11	-0.11	-0.06	-0.16	-0.28
Real Estate	0.02	0.06	0.01	0.05	-0.02	0.09	0.01	0.02	-0.02	-0.01	-0.19

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. We consider four passive benchmarks in the cryptocurrency market: the returns of a buy-and-hold investment in Bitcoin (BTC), the returns on 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) (DOL), the returns on a value-weight average of the coins traded on Coinbase (ETF), and the returns of a buy-and-hold investment in Ethereum (ETH). We also consider five risk factors in the cryptocurrency market in the spirit of the Fama-French risk factors. We construct the returns on a value-weight portfolio of the same top 300 cryptocurrencies (MKT). In addition, we consider the returns of a cross-sectional momentum strategy (MOM) as introduced by Jegadeesh and Titman (2001) as well as the returns on a pure reversal strategy (REV) without a hold-back period. Finally, we consider the returns of both liquidity (LIQ) and volatility (VOL) timing portfolios; liquidity exposure is proxied by a long-short portfolio constructed by going long into illiquid pairs (fifth quintile) and going short into the liquid cryptocurrency pairs (first quintile). The out-of-sample return is then computed by taking the equally weighted mean of each decile. Similarly, volatility exposure is constructed via long-short portfolio whereby a short position is initiated in the sub-portfolio with the pairs which have the lowest volatility and a long position is taken in the sub-portfolio with the pairs which have the highest volatility. Liquidity for each cryptocurrency pair is approximated by using the Abdi and Ranaldo (2017) bid-ask spread approximation. Volatility is computed using the volatility estimator of Yang and Zhang (2000) (a rolling period of 30-days is used). 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 January 2021.

	Passive benchmarks				Risk factors				
	BTC	DOL	ETF	ETH	LIQ	MKT	MOM	REV	VOL
Mean (%)	7.43	5.65	7.70	10.65	15.64	10.17	-0.25	51.20	14.68
Std (%)	20.14	33.83	23.13	36.94	53.34	28.06	64.40	86.87	54.50
SR (annualized)	1.28	0.58	1.15	1.00	1.02	1.26	-0.01	2.04	0.93
Skewness	-0.06	1.34	1.14	0.60	3.49	1.00	0.47	1.34	3.44
AR(1)	0.11	0.16	0.27	0.23	0.07	0.13	0.14	0.45	0.07

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). 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;

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

where $\alpha_{t,k} = y_{t,k} - \hat{\boldsymbol{\beta}}_k^{\prime} \boldsymbol{x}_t$. Testing for the difference in the performance boils down to a test for the significance in $\hat{\gamma}$. The top panel also reports the estimate and robust t-statistics (in parenthesis) for the difference in alphas. The bottom panel reports the estimates and robust t-statistics (in parenthesis) of passive benchmark loadings (betas) and the adjusted R^2 of the regressions. The sample covers the period from March 2015 to January 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	2.50	1.98	2.14	4.76	2.03	6.60	3.17	2.09	0.49	2.28	1.92
	(2.52)	(2.34)	(2.30)	(3.37)	(1.42)	(3.40)	(3.01)	(1.45)	(1.09)	(2.56)	(1.92)
Difference		-0.52	-0.36	1.14	-0.47	2.98	0.66	-0.41	-1.87	-0.22	-1.70
		(-0.49)	(-1.21)	(1.36)	(-0.61)	(2.27)	(0.90)	(-0.76)	(-2.13)	(-0.31)	(-1.13)

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}	0.28	0.19	0.34	0.16	0.34	-0.07	0.12	0.40	0.05	0.43	0.11
	(3.34)	(3.08)	(5.63)	(0.97)	(2.69)	(-0.37)	(1.07)	(3.27)	(1.36)	(8.79)	(2.22)
β_{DOL}	0.09	0.01	0.11	-0.02	0.10	0.03	0.13	0.13	0.03	0.04	0.03
	(1.27)	(0.22)	(1.69)	(-0.47)	(0.89)	(0.29)	(2.24)	(1.16)	(0.80)	(0.75)	(0.92)
β_{ETF}	0.19	0.08	0.16	0.17	0.22	0.26	0.11	0.28	0.11	0.10	-0.08
	(3.13)	(1.19)	(2.70)	(3.30)	(2.31)	(1.98)	(1.77)	(2.85)	(1.58)	(1.67)	(-1.23)
β_{ETH}	0.13	0.08	0.08	0.25	0.21	0.38	0.11	0.22	0.00	0.01	0.06
	(1.74)	(1.25)	(1.59)	(1.73)	(1.74)	(2.02)	(1.21)	(1.97)	(0.10)	(0.35)	(1.32)
Adj. R^2	0.78	0.39	0.80	0.69	0.69	0.60	0.60	0.77	0.40	0.72	0.23

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). In particular, we regress the difference in the factor-adjusted returns for a given fund type/strategy j, $\alpha_{t,j}$, and the aggregate crypto fund market, $\alpha_{t,m}$, onto a constant;

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

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 $\hat{\gamma}$. The top panel also reports the estimate and robust t-statistics (in parenthesis) for the difference in alphas. The bottom panel reports the estimates and robust t-statistics (in parenthesis) of risk factor loadings (betas) and the adjusted R^2 of the regressions. The sample covers the period from March 2015 to January 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	2.80	2.35	2.12	4.80	2.61	6.55	2.47	3.07	0.27	2.10	0.69
	(3.77)	(1.76)	(2.96)	(3.60)	(2.00)	(3.28)	(2.33)	(2.69)	(0.66)	(2.23)	(0.74)
Difference		-0.45	-0.68	1.53	-0.18	3.29	-0.33	0.27	-2.34	-0.70	-2.57
		(-0.30)	(-1.83)	(1.73)	(-0.20)	(2.15)	(-0.41)	(0.49)	(-3.01)	(-0.69)	(-2.09)

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}	-0.01	0.00	-0.03	0.07	-0.01	0.05	0.04	-0.05	-0.02	0.01	-0.06
	(-0.38)	(0.05)	(-0.94)	(1.30)	(-0.24)	(0.58)	(1.09)	(-0.99)	(-0.83)	(0.17)	(-1.54)
β_{MKT}	0.55	0.27	0.53	0.45	0.69	0.60	0.43	0.82	0.14	0.39	0.09
	(18.12)	(6.10)	(22.16)	(8.31)	(10.32)	(6.71)	(11.08)	(12.93)	(2.77)	(10.67)	(2.86)
β_{MOM}	-0.01	-0.02	-0.01	0.01	-0.01	-0.03	-0.02	-0.02	-0.01	0.01	0.00
	(-1.15)	(-2.00)	(-0.88)	(0.84)	(-0.40)	(-1.03)	(-1.33)	(-1.35)	(-1.17)	(0.87)	(0.00)
β_{REV}	-0.01	0.00	0.00	-0.02	-0.01	-0.05	-0.01	-0.02	0.00	0.01	0.04
	(-1.24)	(-0.35)	(-0.41)	(-1.54)	(-0.68)	(-1.90)	(-0.76)	(-1.60)	(0.33)	(0.90)	(1.93)
β_{VOL}	0.02	0.01	0.03	-0.03	0.00	0.00	-0.01	0.04	0.02	0.00	0.02
	(0.53)	(0.13)	(1.20)	(-0.63)	(0.03)	(-0.02)	(-0.29)	(0.91)	(0.98)	(-0.02)	(0.74)
Adj. R^2	0.87	0.37	0.88	0.70	0.77	0.62	0.68	0.87	0.42	0.69	0.27

Table 5: **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: "fund of funds", "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 January 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 (%)	3.20	1.68	2.88	3.63	4.57	3.47	3.88	3.27	0.98	3.56	3.25
Std (%)	11.87	7.95	12.12	10.09	17.72	10.46	10.25	17.43	3.42	11.43	8.92
SR (annualized)	0.93	0.73	0.82	1.25	0.89	1.15	1.31	0.65	1.00	1.08	1.26
Skewness	0.47	0.34	0.37	0.92	1.07	0.52	0.77	0.38	0.14	0.34	1.37
AR(1)	0.07	0.08	0.05	0.23	0.03	0.08	0.11	0.02	0.32	0.09	0.24

Figure 1: **Cryptocurrency market**

This figure plots the value-weighted index of digital assets expressed normalized at 100 in January 2015. The index is constructed as a value-weighted portfolio of the top 100 digital assets in terms of market capitalization. The sample period is from March 2015 to January 2021. The black line indicates the end of December 2017, a time stamp which coincides with the burst of the so-called ICO bubble. The red solid line indicates the March 12th 2020, the so-called "Black Thursday" when market prices of major cryptocurrencies drop by 40% in a single day, on average.

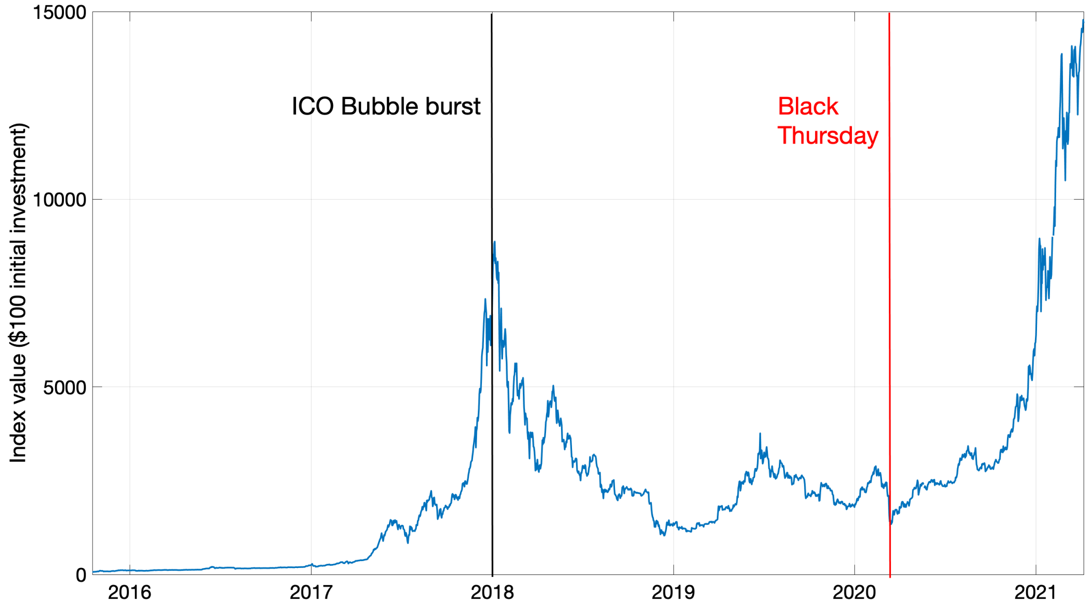
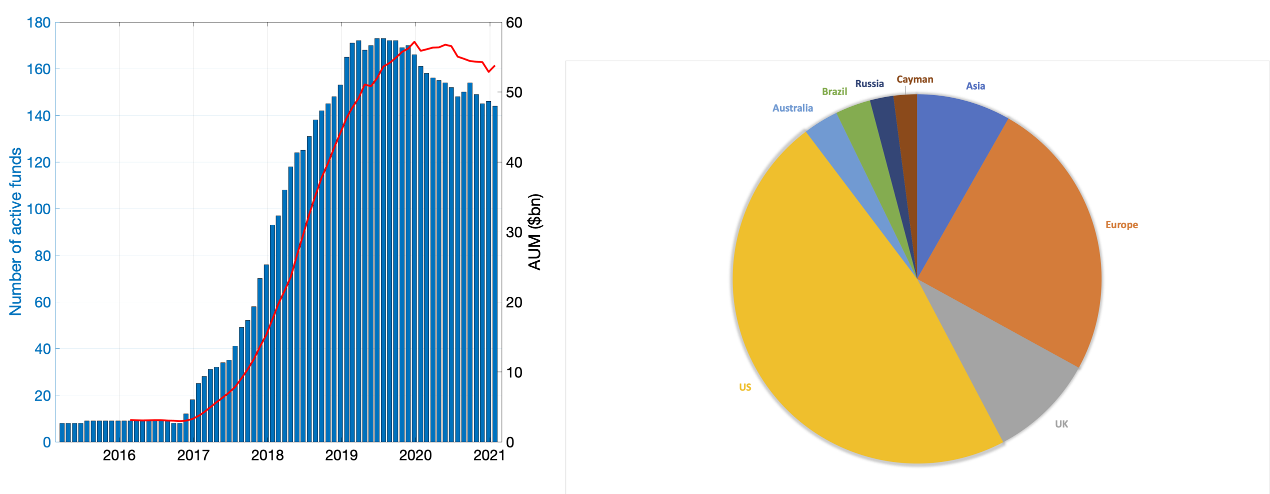


Figure 2: **A snapshot of the sample of funds**

The left panel of the figure plots the number of active funds (blue bar) and the asset under management (AUM) in $bn for the sample of funds used in the main empirical analysis. The sample period is from March 2015 to January 2021. The right panel of the figure reports the geographical distribution of the funds. The sample period is from March 2015 to January 2021.



(a) Active funds

(b) Geographical distribution

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

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 as of January 2021. The sample period is from March 2015 to January 2021.

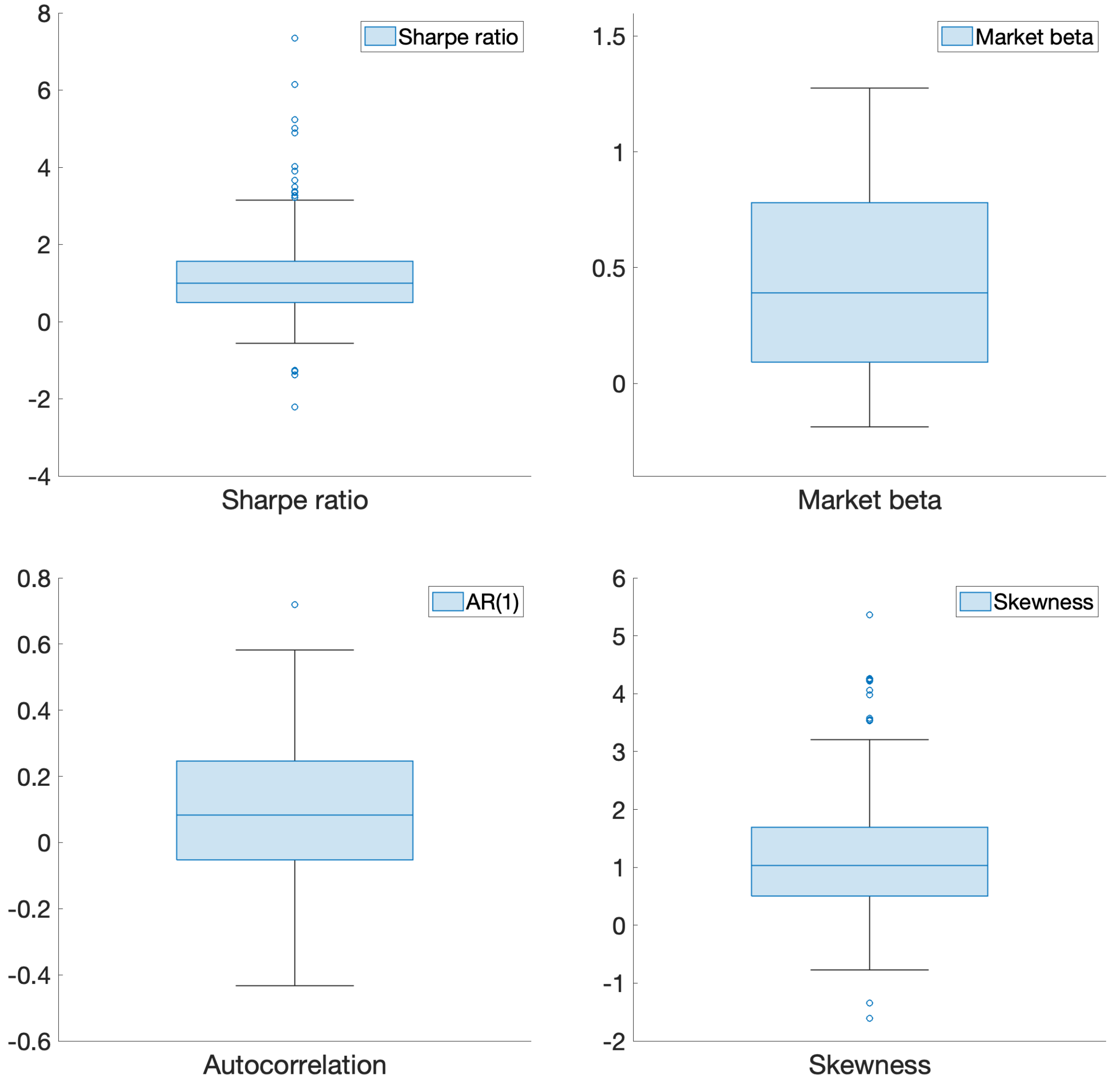
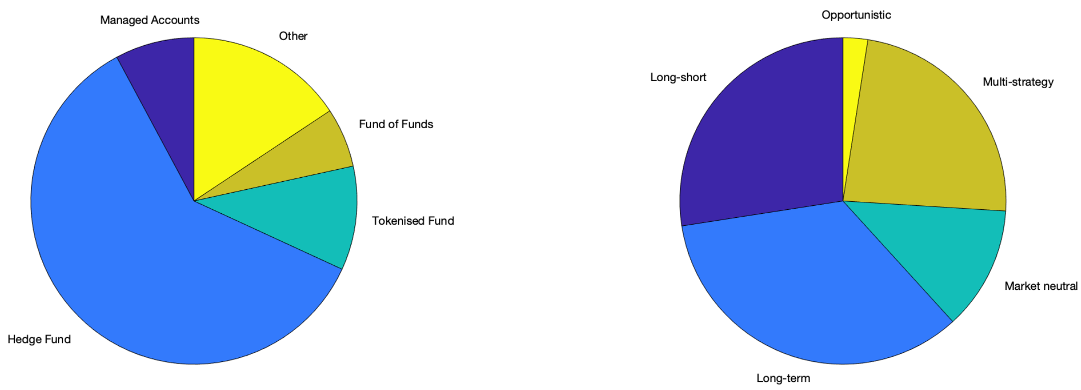


Figure 4: **A breakdown of fund types and strategies**

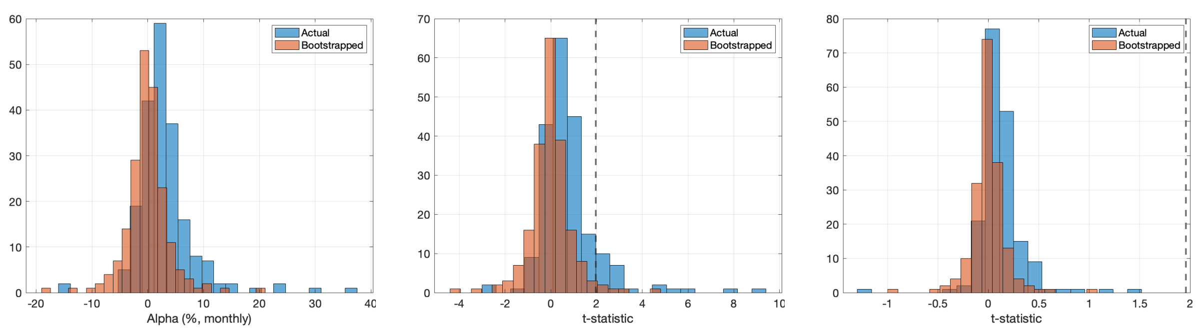
This figure plots the distributions of funds per type of fund (left panel) and investment strategy (right panel). Funds are clustered by type and labeled as "fund of funds", "hedge fund", "managed accounts", "tokenised fund", and "other". Classification by investment strategy is defined as "long-short",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



(a) Funds by type (b) Funds by investment strategy

Figure 5: **The cross-section of benchmark-adjusted alphas**

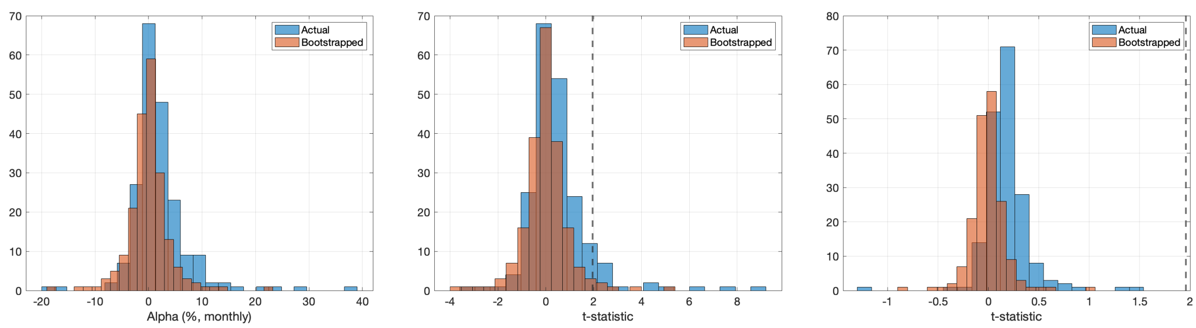
This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The four passive benchmarks — buy-and-hold investments in Bitcoin (BTC) and Ethereum (ETH), an equal-weight market portfolio (DOL), and a value-weight average of the coins traded on Coinbase (ETF) — represent an investor's alternative investment opportunity set. 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 bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and t-statistic of fund alphas as in Kosowski et al. (2006). The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.



(a) Alpha (b) Standard t-statistics (c) Clustered standard errors

Figure 6: **The cross-section of risk-adjusted alphas**

This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The five factor portfolios — a value-weight market portfolio (MKT), liquidity (LIQ), momentum (MOM), reversal (REV), and volatility (VOL) long-short portfolios — are considered as proxies for systematic sources of risk. 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 bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and t-statistic of fund alphas as in Kosowski et al. (2006). The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.



(a) Alpha

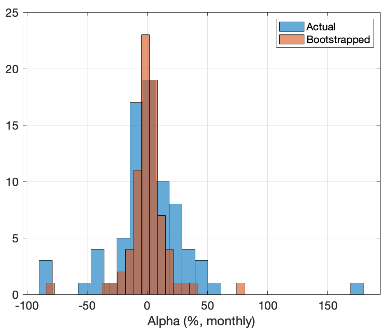
(b) Standard t-statistics

(c) Clustered standard errors

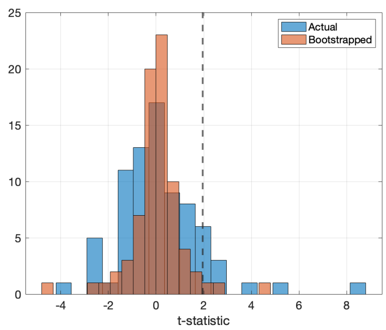
Figure 7: **The cross-section of benchmark-adjusted alphas across sub-samples**

This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The data is split before and after the peak of the market prices in December 2017 where the monthly price of BTC reached its highest point. The top panels report the results for the period until December 2017, whereas the bottom panel reports the results for the period after January 2018. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. 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 bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and t-statistic of fund alphas as in Kosowski et al. (2006). The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.

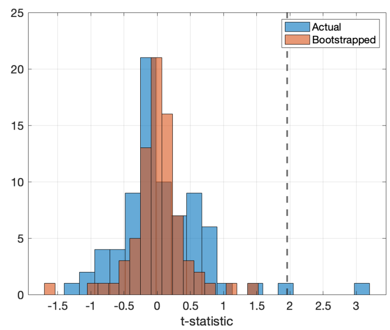
Panel B: Sample until Dec 2017



(a) Alpha

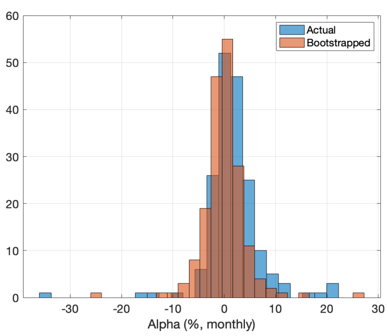


(b) Standard t-statistics

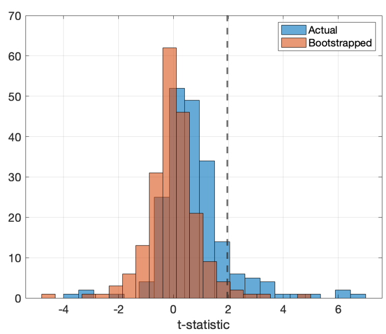


(c) Clustered standard errors

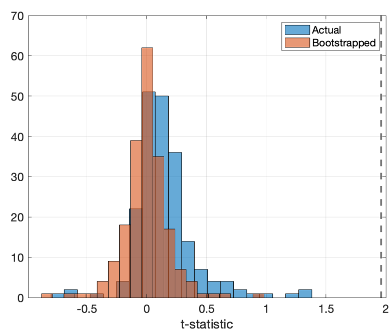
Panel B: Sample from Jan 2018



(d) Alpha



(e) Standard t-statistics

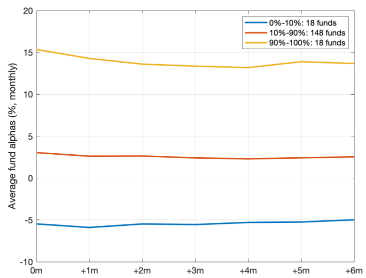


(f) Clustered standard errors

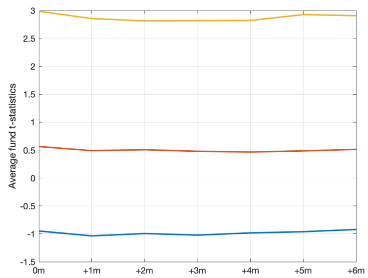
Figure 8: **Persistence of benchmark-adjusted alphas**

This figure plots the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The top panels show the results for the post-formation alphas obtained from July 2020 to the end of the sample whereas the bottom panels show the results for the post-formation alphas from January 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 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 January 2021.

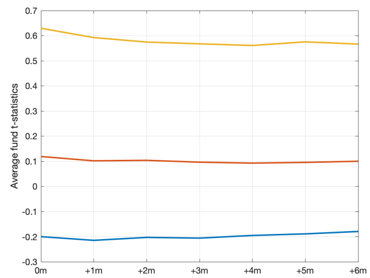
Panel A: Short-term persistence



(a) Alpha

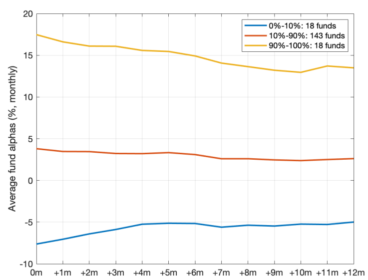


(b) Standard t-statistics

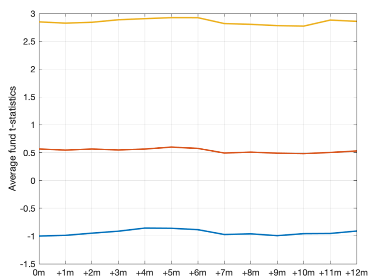


(c) Clustered standard errors

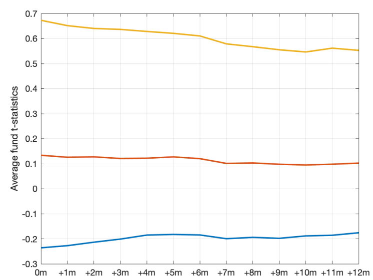
Panel B: Long-term persistence



(d) Alpha



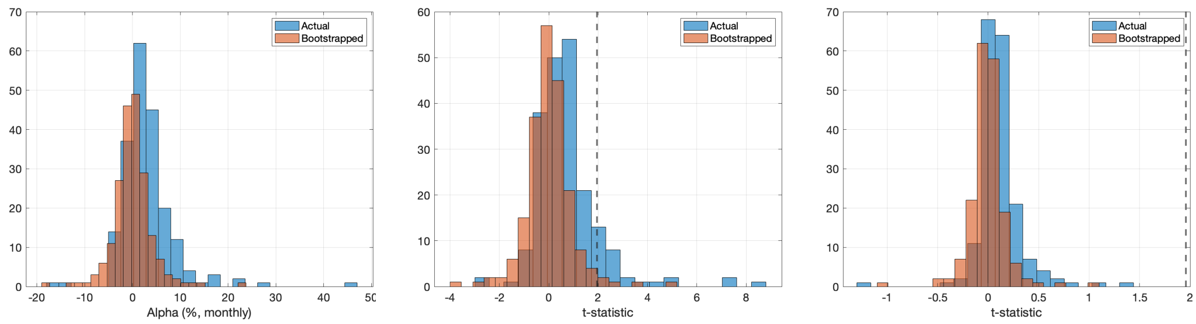
(e) Standard t-statistics



(f) Clustered standard errors

Figure 9: **The cross-section of benchmark-adjusted alphas: constant betas**

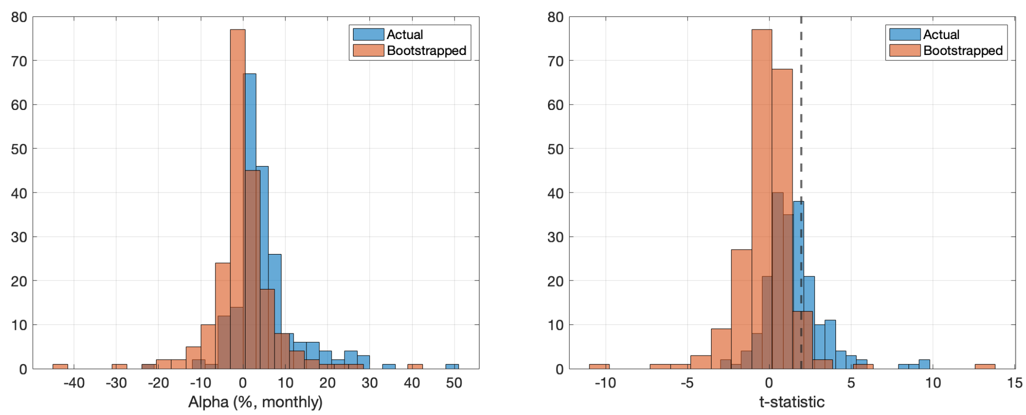
This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. Unlike the main empirical analysis the betas on the benchmark portfolios are restricted to be constant in the whole cross section of funds. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. 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 bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and t-statistic of fund alphas as in Kosowski et al. (2006). The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.



(a) Alpha (b) Standard t-stats (c) Clustered t-stats

Figure 10: **The cross-section of benchmark-adjusted alphas: time-series analysis**

This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics (right panel) obtained from time-series regressions performed for each individual fund separately. The t-statistics are based on the Newey and West (1986) robust standard errors. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. The individual alphas are calculated as the intercept from a time-series regression. The panels report actual (blue bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and the robust t-statistic of fund alphas. The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.

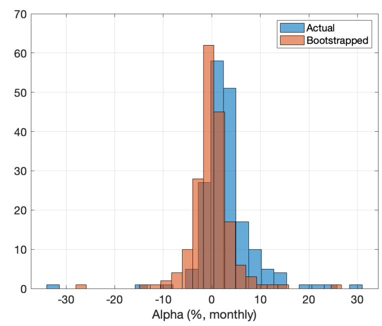


(a) Alpha (b) Robust t-stats

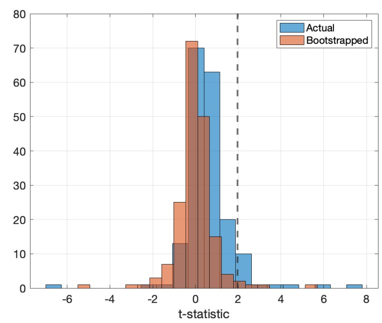
Figure 11: **The cross-section of fund alphas using alternative bootstrap procedures**

This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. 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 bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and t-statistic of fund alphas as in Kosowski et al. (2006). The top and bottom panels report the results for the two bootstrap extensions: a block bootstrap procedure and a bootstrap independently resampling benchmark returns and residuals. The vertical dashed line represents a threshold of 1.96 for the t-statistic. The sample period is from March 2015 to January 2021.

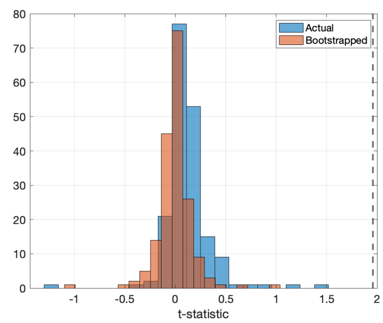
Panel A: Block bootstrap



(a) Alpha

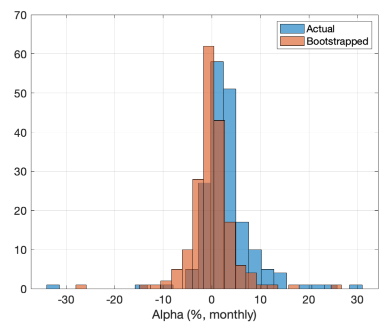


(b) Standard t-statistics

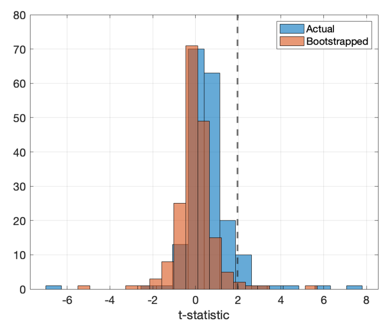


(c) Clustered standard errors

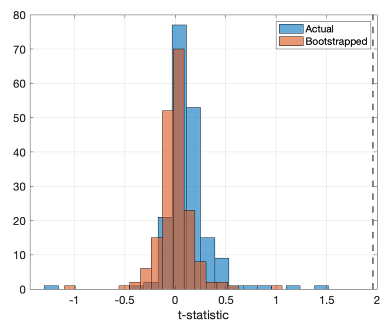
Panel B: Independent resampling of benchmark returns and residuals



(d) Alpha



(e) Standard t-statistics



(f) Clustered standard errors

Appendix

A Bootstrap methods

In this section we provide details on both the baseline bootstrap procedure as well as 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. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. The five-factor model includes a value-weight market portfolio (MKT) as well as liquidity (LIQ), momentum (MOM), reversal (REV) and volatility (VOL) long-short portfolios as proxies for systematic sources of risk.

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:

$$y_{it}^b = \hat{\alpha}_i^b + \hat{\beta}^{b\prime} \boldsymbol{x}_t^b + \varepsilon_{i,t}^b$$

end

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

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. The four passive benchmarks — 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) — represent an investor's alternative investment opportunity set. The five-factor model includes a value-weight market portfolio (MKT) as well as liquidity (LIQ), momentum (MOM), reversal (REV) and volatility (VOL) long-short portfolios as proxies for systematic sources of risk.

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:

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

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 Persistence of 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.2 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.

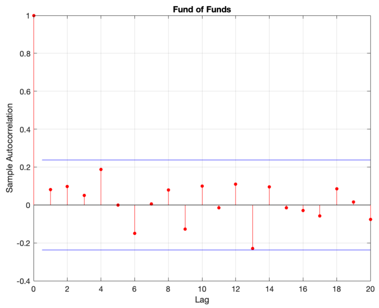
B.2.1 Crypto funds vs. benchmark returns. Figure C.1 illustrates the cumulative sum of log returns of an equal-weight average of the fund returns and compares it against a buy-and-hold investment in Bitcoin, an equal-weight (DOL) and a value-weight (Market) portfolio of top 300 cryptocurrencies in terms 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 Returns across fund type and investment strategies

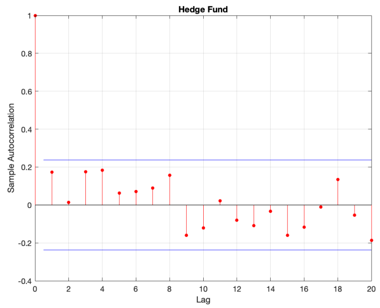
Figure C.2 shows that the compounded returns across different fund groups share a similar time variation during the considered period. An equal-weight average return for each fund type and strategy dramatically increases in the first half of the sample before starting to decline in 2018. The compounded 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 B.1: **Autocorrelation function per fund type or investment strategy**

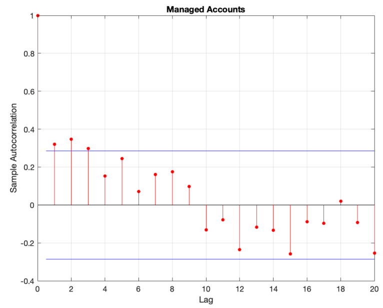
This figure shows the autocorrelation function up to 20 lags of equal weight portfolio returns aggregated across each type of funds and the investment strategy. The sample period is from March 2015 to January 2021.



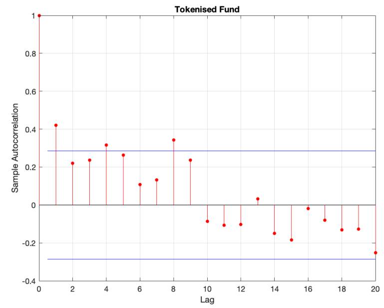
(a) Fund of funds



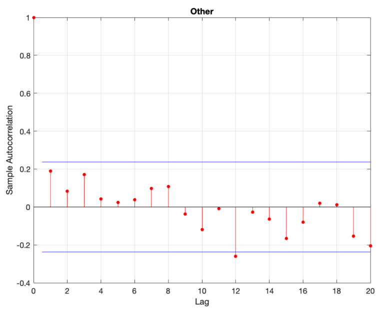
(b) Hedge fund



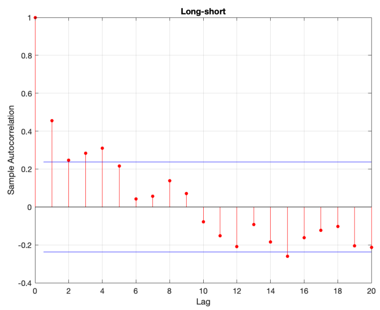
(c) Managed accounts



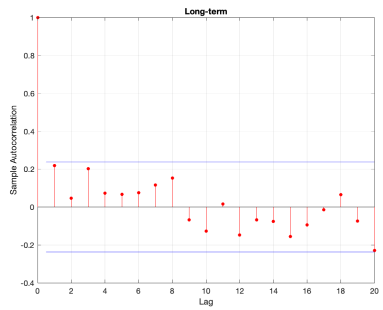
(d) Tokenized fund



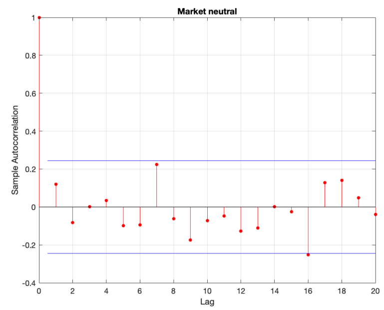
(e) Other Types



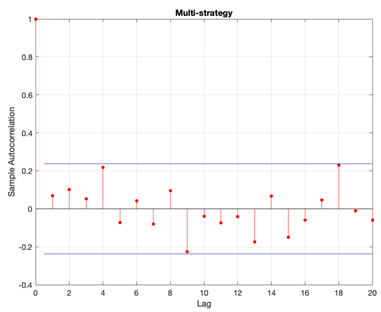
(f) Long-short



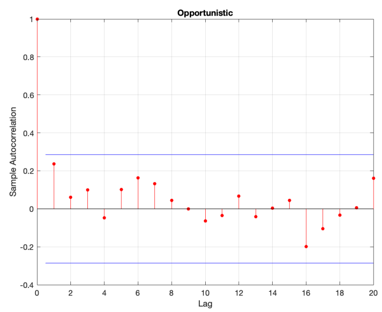
(g) Long-term



(h) Market neutral



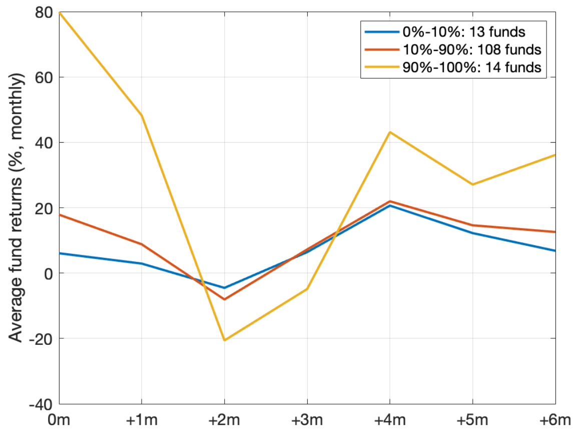
(i) Multi-strategy



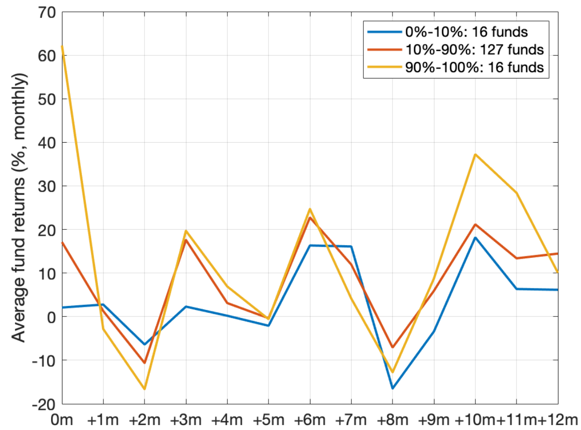
(j) Opportunistic

Figure B.2: **Persistence of the fund performance**

This figure plots the post-formation returns from July 2020 (left panel) and from January 2020 (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 January 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 January 2021.

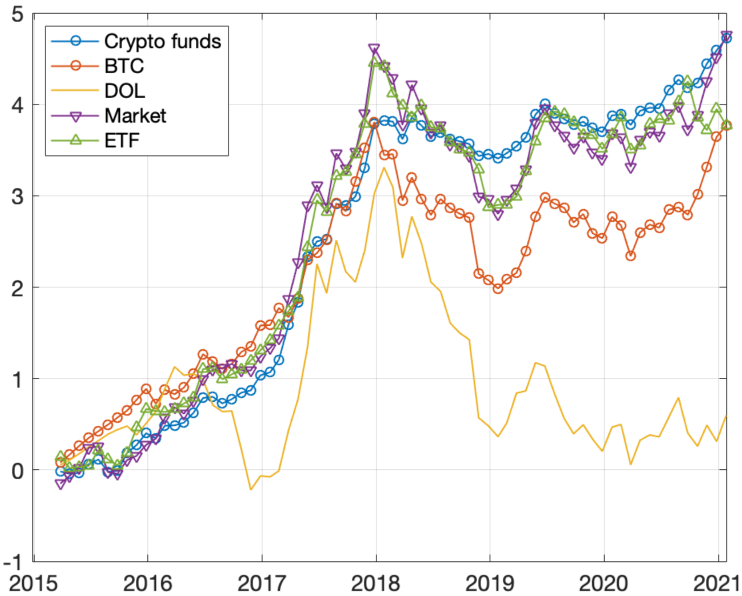
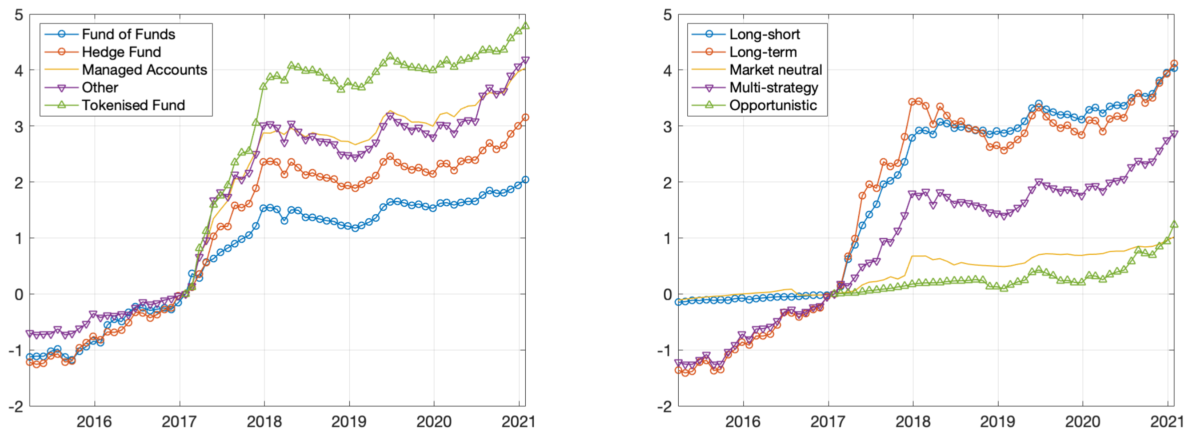


Figure C.2: **Compounded returns per fund type or investment strategy**

This figure plots the time series of fund returns for each type of fund (left panel) and investment strategy (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 January 2021.



(a) Cumulative log returns per fund's type

(b) Cumulative log returns per strategy