On the Performance of Cryptocurrency Funds*

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Abstract

We investigate the performance of funds that specialise in digital assets. In doing so, we contribute to a growing literature that aims to understand the role of cryptocurrencies and digital assets as investments. Methodologically, we implement a novel bootstrap approach that samples jointly the cross-sectional distribution of alphas and controls for the non-normality of funds returns and their within-strategy correlations. Empirically, we find that a sizable minority of managers are able to cover their costs and generate large alphas compared to benchmark strategies. However, there is weak statistical evidence of managers' skills once within-strategy common variation in returns is considered.

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

JEL codes: G12, G17, E44, C58

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1 Introduction

With the rising prices and public awareness of Bitcoin, investors have been drawn to cryptocurrency markets by the promise of significant returns compared with the paltry or negative yields on offer from cash, bonds or other traditional asset classes.[1] A price increase, which is an order of magnitude higher than for traditional asset classes, has led to the demand for investment in real new money and the establishment of a new category of investment funds, namely cryptocurrency funds, or "crypto funds" for short.[2] As a result, while much of the total market capitalisation for all cryptocurrencies – which at the time of writing stands roughly at $300bn – has been generated by individual traders buying and selling their own private stashes of digital asset, it is also largely the result of active investment management. Yet, achieving those high returns has often proved a bumpy ride, with levels of return volatility and exponential price increase which have been never seen before in traditional asset classes. This ultimately questions the ability of fund managers to actually generate value for investors in risk-adjusted terms and above and beyond the explosive market trend.

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 further understanding the value of active management

[1] At the time of writing, there are more than two thousand "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 number of hedge funds focusing on cryptos has surged from just a handful in 2016 to nearly 120 in 2017 to several hundred active funds at the beginning of 2020 according to a new survey by PWC and Elwood Asset Management Services Ltd. titled "2020 Crypto Hedge Fund Report" (see document here).

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

through the lens of cryptocurrency markets. 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 unique context in which to understand the role of active asset management for five main reasons: first, the fact that cryptocurrency markets have a highly fragmented, multi-platform structure, which is decentralised and granular, adds to the conjecture that they may be separated from traditional, centralized asset market exchanges. Indeed, existing evidence shows that returns on cryptocurrencies are virtually uncorrelated with any other asset class (see Yermack, 2013; Liu and Tsyvinski, 2018; and Bianchi, 2020).[4] This is quite relevant from an investment management perspective since an asset driven by forces and factors that are not common to other assets may offer a considerable hedge, especially during bear regimes.[5]

Second, cryptocurrencies are a new and mostly unregulated asset class. Over the years, regulations have been shown to play a key role in determining 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 performance. As such, the inherent interplay between regulations and the value of active management make cryptocurrency funds a quasi-natural experiment in which we show that, despite the substantial lack of a robust regulatory environment, the average value of active investment management remains low in risk-adjusted terms. Third, professional asset management tools are quickly emerging to assist retail investors with their exploration of the new and rapidly developing cryptocurrency market. For existing companies behind traditional investment funds, the incentive is clear: a more mature market also means that less knowledgeable investors are likely to dip their toes in, requiring in tandem

[4]Recent anecdotal evidence during the COVID-19 crisis showed that cryptocurrency and equity markets were somewhat correlated. However, there are two basic flaws in this "evidence": first, and perhaps more importantly, such correlation is based on a very short time span, whereas the existing empirical evidence of no-correlation between major cryptocurrencies and traditional asset classes is based on years of data sampled at different frequencies (see e.g., Yermack, 2013; Liu and Tsyvinski, 2018; Bianchi, 2020; Bianchi et al., 2020). Second, in the short term, a flight-to-cash reaction to the liquidity shortages due to the COVID-19 lockdown could have plausibly triggered risk-off investment decisions across asset classes, cryptocurrencies included.

[5]Indeed, 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.

platforms that deliver easier and more professional access compared to the fragmentation that currently defines the cryptocurrency trading ecosystem. In this respect, active asset management is at the core of the development of cryptocurrency markets.[6] Fourth, 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 $44mln, indicating these are primarily unregulated small funds. Such limited competition from cheaper investment vehicles, such as ETFs and registered investment advisors, puts much less pressure on fund managers in cutting costs, increasing leverage or taking extra risks. All these aspects should ultimately be reflected in the risk-return tradeoff of actively managed investment vehicles. 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 performances, without taking into account (1) the heterogeneous risk-taking across funds, (2) the distribution of individual fund alphas, and (3) the massive returns volatility and correlations, a separation of skill from luck is difficult to obtain (see Fama and French, 2010).

All these aspects mean that the return dynamics of cryptocurrency funds should in principle reflect the interplay between low competition, low regulation and relatively low entry barriers, conditional on taking into account the inevitable sources of systematic risks. As a result, the implications for the actual value of active management are far from obvious. While conventional research has long been debating the value of active management, no study has tested the existence of such value in the new and relatively unregulated industry of cryptocurrency funds. This paper fills this gap and conducts the first comprehensive and critical examination of active investment management in the cryptocurrency space that explicitly controls for skill versus luck.

Methodologically, we build on Kosowski et al. (2006) and Fama and French (2010) and develop a bootstrap approach that is not only robust to both time-series and cross-sectional correlations, but also takes explicitly into account the unknown forms of time-series and cross-sectional heteroskedasticity as well as the common and idiosyncratic variation in fund

[6] Although, on the surface, the idea of cryptocurrencies as financial assets seems at odds with the conventional wisdom that they mainly represent a medium of exchange, investment value and medium of exchange are two aspects which are inherently interlinked; the intrinsic value of a virtual currency crucially depends on its diffusion as a method of payment and the fact that it attracts a larger number of market operators.

returns. 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 objective of this paper is simple. In the face of crypto funds with ex-post performances that deviate so massively from normality, we investigate how many managers generate alphas simply due to luck – or because they simply follow the aggregate market trend – and how many actually create the value for investors that is not by a random chance. Due to the institutional differences, we view this paper as an "out-of-sample" non-parametric test of existing theories developed and implemented within the context of more traditional active investment funds.

To address this issue, we look at the performance of 153 funds, which specialise in cryptocurrency investments and have been actively managed between March 2015 to July 2020. To avoid any survivorship biases, the sample includes not only those funds that are still actively quoted, but also the funds that disappeared 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 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. Notice, the 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). In this respect, it is reasonable to assume that the sample is fairly representative, ensuring there is sufficient time series variation covering a fair amount of market phases and institutional changes.

We begin by looking at the performance of crypto funds in excess of alternative passive investment strategies at the aggregate level. That is, we look at the alpha generated by equal-weight portfolios aggregated across all funds or groups of funds with respect to their types and investment strategies. The results show that when aggregating funds there is some evidence of a superior fund performance compared to passive benchmarks such as 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 coins traded on Coinbase (one of the major cryptocurrency exchange), and a buy-and-hold investment in Ethereum (ETH).

It is important to note that by looking at the average returns one cannot control for the differences in the risk-taking behavior across funds (see Kosowski et al., 2006 and Fama and French, 2010). Therefore, we focus on the performance of individual funds in the entire cross-section.

Across a wide array of statistical tests, our main results show that, after adjusting for passive benchmarks and controlling for luck, i.e., sampling variability, the right tail of the performance distribution could be simply due to sampling variability, that is by chance. When controlling for time-series and cross-sectional heteroskedasticity as well as residual returns commonalities, i.e., clustered standard errors, we find that despite a large economic magnitude there is no statistical evidence of skills in the cross-section of the fund performance.

Overall, our analysis shows that, although the funds performance tend to be economically large, there is not robust evidence that fund managers provides net-of-fees alphas that are not an artifact of the aggregate market trend or simply due to luck. This is so when controlling for both unobservable heterogeneity across funds as well as fund returns, which are correlated within the same investment strategy.

Further bootstrap results indicate that the strongest benchmark-adjusted performance is found in the period of pre-ICO bubble burst, i.e., from March 2015 to December 2017, whereas the net-of-cost alphas in the period post January 2018 substantially decrease. Nevertheless, the statistical evidence remain rather weak throughout. One possible implication of this result is that the continuing growth of new funds over the 2018-2020 period has not apparently been driven by an increasing number of active fund managers with talent, who do not appear on the right tail of the cross-sectional distribution of alphas by chance alone.

Realistically, most investors look at past performance to infer the future. Thus, we test for the persistence in the fund alphas by reconstructing a test of persistence as in Carhart (1997). Our findings extend some of the results in Kosowski et al. (2006) to the cryptocurrency fund space: specifically, we document significant persistence in the net-of-fees alphas for the top decile of managers. However, once we control for unobservable heterogeneity and use clustered standard errors, the performance is statistically insignificant.

We investigate the robustness of the main empirical analysis to both alternative performance measures and alternative bootstrap procedures. Barber et al. (2016) and Berk and Van Binsbergen (2016) provide evidence that there is substantial uncertainty as to which asset pricing model investors may use to assess the fund performance. Therefore, we construct a series of risk factors that capture the aggregate market returns, market liquidity, volatility, reversal and momentum and re-run the bootstrap analysis used to obtain the main empirical results. When factors instead of benchmarks are used to obtain the fund alphas, the fraction of performing managers slightly increases although again the main results of the paper hold. We extend the baseline bootstrap approach by accounting for either time-series dependencies of returns and benchmarks and/or more complex distribution of both realised and unexpected returns in the bootstrap approach; again, the main results of the paper remain unchanged.

Our results are interesting in light of the existing debate on the value of active investment management. 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). Theoretically, 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.[7] Another argument in favor of the conventional wisdom is the limited number of investment opportunities, which prevent skilled managers from improving fund performance.[8] However, there is an emerging literature now advocating for the existence of a significant and persistent value of active investment management. Bollen and Busse (2001) document stronger timing ability of mutual funds by applying tests to daily returns instead of monthly data. Kothari

[7] 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.

[8] The reduced profitable opportunities are mainly due to increasing market efficiency (Bernstein, 1998; Chordia et al., 2008, 2011; Conrad et al., 2015) and increasing competition among fund managers (Dyck et al., 2013; Pástor et al., 2015; Hoberg et al., 2017).

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. Similarly, Linnainmaa (2013) demonstrates how using the data without survivorship bias gives rise to "reverse survivorship bias", which also underestimates the skills 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 and provides a unique context given its new and unconventional institutional setting.

In addition, this paper adds to recent literature that aims to understand the investment properties of cryptocurrencies. 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 (2018) 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. We contribute to this literature by looking at the value of active investment management.

Our paper proceeds as follows. Section 2 describes our bootstrap procedure, while Section

3 describes the crypto fund database used in our study. Section 4 provides the empirical results. Section 5 investigates the robustness of the main findings to alternative performance measures and bootstrap procedures. Section 6 concludes.

2 Bootstrap Estimate of Fund Alphas

We apply a bootstrap procedure to evaluate the performance of cryptocurrency funds over the period from March 2015 to July 2020. There are many 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 and/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 (see Kosowski et al., 2006 and Fama and French, 2010). Second, with a relatively limited investment opportunity set compared to traditional equity funds, crypto funds operating within a given strategy could show overlapping investments, which in turn transmits to correlated returns. Clustering standard errors at the strategy level allows us to account for comovements in fund returns within a given investment strategy. 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). Comparing fund returns with passive investment strategies helps to better disentangle the fund managers' skills since risk factor portfolios do not represent actual, exploitable investment opportunities as they do not incorporate trade impact, trading restrictions and transaction costs (see, e.g., Huij and Verbeek, 2009).

We follow Pástor et al. (2015) and estimate the historical alphas by a panel regression of the form

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

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 $\boldsymbol{\beta}$ is the corresponding set of slope parameters. 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.[9] 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 by employing information on the dynamic behavior of the whole set of funds jointly. Third, and perhaps more importantly, by pooling information from different funds, we can obtain precise estimates of the fund performance despite their short life span. Fourth, by clustering standard errors at the strategy level, we take into account returns commonalities when evaluating the significance of the fund performances.

2.1 Main bootstrap implementation

We now illustrate the main bootstrap implementation. For each fund i, the historical, meaning the actual alpha estimates $\hat{\alpha}$ as well as the corresponding t-statistics $\hat{t}_{\hat{\alpha}}$ and the

[9] 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.

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. For each fund i, we draw a sample with replacement from both the fund residuals *and* the benchmark investment returns $\left\{\hat{\epsilon}^b_{it},\ \boldsymbol{x}^b_t;\ t = s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}\right\}$, where $b = 1, \ldots, B$ is the bootstrap index and $s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}$ are drawn randomly from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for this fund i as

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

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. Notice the t-statistics are calculated based on clustered standard errors where clustering is made at the strategy level.

We estimate the bootstrapped alphas and t-statistics based on clustered standard errors via the panel regression for the constructed panel of pseudo fund returns at a bootstrap iteration b. Repeating for all bootstrap iterations $b = 1, \ldots, B$ we then build the distribution of cross-sectional draws of alphas $\hat{\alpha}^b_i$ and t-statistics $\hat{t}^b_{\hat{\alpha}_i}$ 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 genuine skills 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 obvious 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 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 differentiator of our approach is that we rely on a panel regression bootstrap approach 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 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, 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 within-strategy performance correlation by clustering fund-specific standard errors at the strategy level.

2.2 Bootstrap extensions

We extend the baseline bootstrap approach in two main directions: first, we explicitly take into account the possibility of time-series dependence in both the benchmark returns and the return residuals by applying a block-bootstrap approach whereby benchmark returns and residuals from the panel regression are sampled in blocks (see, e.g., Politis and Romano, 1994). Such persistence could arise due to time-series patterns of fund returns or simply because fund returns are not properly captured by our performance model. Second, we implement a bootstrap with independent resampling of benchmark returns and the residuals. This allows us to break a correlation structure between fund and benchmark returns by randomizing the latter.

3 Data

3.1 Fund returns

We obtain data on the monthly returns for a variety of cryptocurrency funds from Crypto Fund Research, a website-based data provider that collects in-depth crypto fund data. We manually cross-check and complement the data from Crypto Fund Research by looking at the public prospectus and websites of each company. Managers report fund returns on a voluntary basis since there is no legal obligation to disclose the fund 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 initially reported 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 $5mln of assets under management and five employees. That is, we exclude micro funds which often escape any kind of regulatory oversight. The threshold seems low in absolute value, but in relative terms it is not considering the average AUM for crypto hedge funds is $44mln, 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, with the only exception of tokenised funds, which escape any reliable currency tracking for the reasons expressed above, 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 factored in the performance to a large extent. Third, we consider returns net of all fees, including incentive fees, management fees, sales/commission fees, and other fees. In this respect, we investigate whether active management in the cryptocurrency space can generate any actual value for investors above and beyond the expenses an investor nominally encounters.[10] Fourth, we include in the sample only those funds that explicitly state their investment strategy through public prospectus and/or provide such information directly to the data provider. Fifth, to avoid survivorship bias, the sample includes not only those funds that are still actively quoted, but also the funds that disappeared before the end of the sample. In this respect, the only requirement is that a fund should have at least twelve months of consecutive monthly return history.

The filters and checks leave us with a maximum of 123 funds that are actually active in a given month. Figure 2 provides a snapshot of the data.

[Insert Figure 2 here]

The left panel shows that the size of the cross-section of funds used in the empirical analysis steadily increases until early 2019 and then drops until early 2020; virtually no funds after

[10]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 to account for the aggregate fees.

filtering could have been used before March 2015. Although the number of funds considered seems low compared to a typical study in more traditional markets, this number is fairly representative of the active management industry in the cryptocurrency landscape.[11]

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.

3.1.1 Fund types. We focus on Crypto Hedge Funds (HF), Tokenised Funds (TF) and Managed Accounts (MA). These are the most common forms of active investment management in the cryptocurrency space.

Crypto Hedge Funds work in the same way of a typical HF, whereby investors' accounts are managed by teams of expert investors, re-balanced on occasion, and constantly analysed. Managed Accounts in the cryptocurrency space, again, are very similar to boutique mutual funds, whereby high-net-worth individuals can access a high degree of customisation and greater tax efficiencies. Tokenised Funds are peculiar to the cryptocurrency space; participating in a TF is similar to buying shares of a regular fund except that quotas are bought in the form of crypto-coins or tokens. In this respect, a TF is similar in spirit to a standard mutual fund, except that investments in cryptocurrencies and shares are held in the form of tokens. The main advantage for investors is liquidity, as shares in the TFs can be freely traded on a secondary market, often on the blockchain.

[Insert Figure 3 here]

The left panel of Figure 3 shows a breakdown of the funds by type; the HF category constitutes the vast majority of funds in our sample. Tokenised funds rank second, while only a small fraction of funds are classified as "managed accounts". 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

[11] A recent report by PricewaterhouseCoopers (PwC) argues that at the end of 2019 the actual number of cryptocurrency hedge funds is around 150. See the full report here.

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 direct long-term investments in ICOs, whereas the 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).

3.1.2 Investment strategies. The investment strategies of crypto funds are somewhat comparable to regular hedge funds. Funds can be divided into six categories: fund of funds, long-short, long-term, market neutral, multi-strategy, and opportunistic. We describe each strategy within the crypto space in turn; *fund of funds* avoid the risks of investing directly in digital assets, such as high volatility, lack of regulatory oversight and market manipulation, by taking a multi-manager approach and investing in a set of different crypto funds. In essence, there is no structural difference between a regular hedge fund of funds and a crypto fund of funds.

Long-short funds primarily employ a short/medium term systematic quantitative investment process, which seeks to capitalise on the volatile behaviour of cryptocurrencies by potentially going long in bull markets and short in bear ones. 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.[12]

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 zero beta versus its appropriate market index to hedge out systematic risk. Such global factor is typically BTC or a basket of top cryptocurrencies selected by market capitalisation.

[12] 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.

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.

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 of Figure 3 shows that while funds that adopt so-called opportunistic strategies and fund of funds are the minority, the other investment styles are somewhat evenly split in the cross-section. We also consider a category labeled "Other", which includes funds that do not specify their investment strategy. These can be classified as multi-strategy but we kept a separate labeling for the sake of transparency.

Although about a half of the funds implement either a long-short or a long-term strategy, Figure 3 shows that the composition of the sample of funds is quite heterogeneous in terms of investment styles.

3.2 Benchmark strategies

Our main methodology is based on comparing fund returns with a set of alternative passive investment strategies (see, e.g., Berk and Van Binsbergen, 2015 and Dyakov et al., 2020). 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. The reason is twofold: first, passive investment strategies, such as a buy-and-hold investment in BTC, ETH, a basket of major cryptocurrencies, or a market index, are the actual benchmarks used by the vast majority of the funds in our sample to calculate performance fees. Second, factor portfolios in the cryptocurrency space do not necessarily represent actual alternative investment opportunities. Indeed, factor portfolios hardly incorporate transaction costs and trading restrictions and often imply long-short strategies that are rather complex to implement within the context of cryptocurrency markets. In fact, in the early part of our sample it was not even possible to take large short positions. 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).

To construct the passive benchmarks, we obtain data on cryptocurrency prices and trading volumes from CryptoCompare, a website-based data provider that collects real-time data from multiple exchanges. Specifically, the data integrates transactions for over 250 exchanges.[13] We follow the approach in Bianchi and Dickerson (2019) and implement a variety of filters to mitigate the effect of erratic and fraudulent trading activity on market prices and volume. First, trade outliers are automatically excluded from the calculation of trading volume and therefore from the volume-weighting scheme. For a trade to be considered an outlier, it must deviate significantly either from the median of the set of exchanges, or from the previous aggregate price.[14] Second, we filter out exchanges with suspicious trading activity; exchanges are reviewed based on a month's worth of hourly data for all exchanges on a given cryptocurrency pair. Constituent exchanges are excluded if (1) posted prices are too volatile compared to the market average, (2) suspended trading, (3) verified user or social media reports false data provision, or (4) malfunctioning of their public API.[15]

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. At the time of writing, BTC represents more than 65% of the total market capitalisation and therefore represents an inexpensive way to capture the aggregate market trend. 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 simple equal-weight portfolio comprising the top 30 cryptocurrencies in terms of market capitalisation. This is the equivalent of a "dollar risk factor" adapted to cryptocurrencies from Lustig et al. (2011). Equal-weight portfolios have

[13]Recent work by Alexander and Dakos (2019) suggests that CryptoCompare data is among the most reliable for use in both academic and practical settings. Note that 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).

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

[15]Note that when a large exchange is excluded it could affect the aggregate market price of a given pair. To ensure that exchanges that are excluded in a given month have an expiring price impact, a time penalty is introduced. That is, the aggregate market price takes the last trade time into account, and therefore the last price on a given exchange expired with time and the aggregation moved with the market without being affected significantly by the changes in the exchange composition.

been proved to be a rather difficult benchmark to beat once fees and expenses are considered (see, e.g., DeMiguel et al., 2009). 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 a given point in time, weighted by market capitalisation.[16] The time series of the hypothetical fund returns can be found on the Fred database held by the St.Louis Fed.[17]

4 Empirical analysis

4.1 A first look at the funds and benchmark returns

Table 1 provides a set of descriptive statistics for both the aggregate set of funds as well as for a more granular classification based on fund type and investment strategy. The first column reports descriptive statistics for an equal-weight portfolio of all crypto funds. Consistent with the conventional wisdom, crypto funds on average have quite significant returns (7.85%) and even larger volatility (15.66%), which nevertheless translate into a remarkable 1.74 Sharpe ratio in annualised terms. Interestingly, there is no evidence of crash risk unconditionally since the skewness of the returns is high and positive and there is also weak evidence of persistence in the realised returns, with an AR(1) coefficient equal to 0.27.

[Insert Table 1 here]

From the second to the fourth column of Table 1, we report the same descriptive statistics but now aggregating funds based on their type (see Section 3.1.1 for a description). As far as the Sharpe ratios are concerned, there are no large differences across types of funds. This implies that the heterogeneity, which may be interesting to look at, is not necessarily determined by the fund type but rather the investment strategy.

This is confirmed by the last seven columns of Table 1. There is quite a substantial difference in average returns and volatility across strategies, with a Sharpe ratio that goes

[16] Taken together, Coinbase and Coinbase Pro exchanges represent one of the largest, if not the largest, market place to trade cryptocurrencies.

[17] Note that although the fund is not directly investable, it can be easily replicated by investing in the digital assets currently available on Coinbase proportionally to their market capitalisation. The list of digital assets tradable on Coinbase can be found here. The data on the index can be found here.

from 3.42 for the market neutral strategy to a much lower 1.16 (0.35) for the opportunistic (other) funds. Two aspects are worth to notice here; first, returns on crypto funds, unlike typical hedge funds, are not really persistent with the highest AR(1) coefficient being equal to 0.55 for market neutral funds. This makes our bootstrap approach less exposed to time-series dependence when resampling the fund returns. 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 returns, the (unconditional) probability of cashing-in large gains is higher than the probability of suffering large losses. Such a significant departure from normality makes the use of our bootstrap approach almost unavoidable compared to more traditional OLS-based asymptotic inference.

Table 2 shows the same set of descriptive statistics for the passive benchmark strategies (first four columns) used to extract the fund alphas. We label the equal-weight investment in the top 30 cryptocurrencies by market capitalisation as "DOL" and the Coinbase Index, which is constructed as a value-weighted passive investment on the digital assets available for trading on Coinbase and Coinbase Pro, as "ETF".

[Insert Table 2 here]

Interestingly, compared to the average crypto fund (the first column in Table 1), all benchmark strategies have 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.[18] Also, with the only exception of BTC, all benchmark strategies show a positive skewness and exhibit weak persistence in the realised returns.

The last five columns show the descriptive statistics for the factor portfolios, which are used in the robustness check whereby we use crypto-specific risk factors instead of benchmark strategies to extract the fund alphas. We refer the reader to Section 5.2. for a full description of the factor portfolios construction.

[18]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=1here).

With the only exception of a pure reversal strategy, all factor portfolios deliver lower Sharpe ratios than average funds. Similarly, and with the only exception of a cross-sectional momentum strategy, returns skewness is positive. Finally, the return persistence is virtually zero, adding to the conjecture that our main bootstrap approach may not require a block-based resampling of returns and benchmarks/factors.

Table 1 shows that, on average, crypto funds generate quite sizable returns and Sharpe ratios. We now look at the aggregate fund performance adjusted for a set of passive investment strategies. The benchmark-adjusted alpha $\hat{\alpha}$ of a group of funds is calculated as the intercept of a univariate time-series regression where the dependent variable is an equal-weight portfolio of crypto funds and the independent variables are the benchmark returns outlined in Section 3.1.[19]

In addition to aggregating the whole set of funds, we also look at a more granular classification based on the fund type and the disclosed investment strategy. Table 3 reports the results.

[Insert Table 3 here]

Notice that despite the cross-sectional aggregation the fund returns show significant outliers in the time series. To mitigate the weight of outlying observations, 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.[20] This translates into a set of robust standard errors, which account for heteroskedasticity in the model residuals. The t-statistics reported are based on those residuals.

[19]More precisely, we estimate a univariate 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 within a particular group, $\hat{\alpha}$ is the estimated performance, and $\hat{\boldsymbol{\beta}}'$ is the exposure to the benchmark returns $\boldsymbol{x}_t = (\mathrm{BTC}_t, \mathrm{ETH}_t, \mathrm{ETF}_t, \mathrm{DOL}_t)'$.

[20]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 $6m$.

In addition to the aggregate alphas, we also report a test of the difference in the performance between the average fund performance and the performance of portfolios aggregated across fund types or investment strategies.[21] Again, to account for outlying returns, we implement a robust regression with a bi-square weighting function.

On average, crypto fund returns show a positive and significant benchmark adjusted return of 3.6% on a monthly basis (robust t-stat: 3.81). The aggregate performance is in line with the performance of the average hedge fund (3.25%, robust t-stat: 3.46). Interestingly, tokenised funds perform better than the average fund by almost 2% monthly, however, this outperformance is not statistically significant. Further, those funds, which are labeled as managed accounts, significantly underperform the average fund by almost 3% on a monthly basis (robust t-stat: -2.14).

Interestingly, when looking at the performance across different investment strategies, the picture that emerged is that a good fraction of managers tend to perform below average, while some do not show a significant benchmark-adjusted performance. Indeed, fund of funds, opportunistic, and "other" funds do not generate an alpha that is significantly different from zero, despite a large economic magnitude. This result shows on the one hand that despite the stellar nominal performance, the possibly high volatility of the returns make the risk-adjusted performance not significantly different from zero, whereas on the other hand suggests that an even more granular look at the cross-section of fund performances is needed in order to investigate the true value of active investment management in cryptocurrency markets.

4.2 Individual fund alphas

The summary statistics and the aggregate fund performances reported in Tables 1-3 suggest there is a significant heterogeneity across fund types and investment strategies. Figure 4 reports the full cross-sectional distribution of monthly mean and volatility of fund returns

[21]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 $\hat{\gamma}$.

as well as their annualised SRs, skewness, and autocorrelation.

[Insert Figure 4 here]

Four facts emerge: first, there is a significant heterogeneity in the cross-section of fund returns in terms of their average values and volatilities, which in turn result in a significant heterogeneity in the SRs. Second, although the annualised SRs for the average fund is lower than of a buy-and-hold investment in BTC, there is a considerable mass of funds that generate much higher SRs, i.e., SRs are more than twice as large as BTC or ETF. Third, although the overwhelming majority of funds have positively skewed returns, there is a non-trivial mass of funds for which the probability of a large loss is actually higher than the probability of a large gain as proxied by a negative skewness. Fourth, 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 0.6. 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.

Given the substantial cross-sectional heterogeneity in the fund returns, simply looking at the average performance may be misleading. As a matter of fact, Kosowski et al. (2006) argue that the evaluation of the average performance cannot explicitly control for the differences in the risk-taking behavior across funds within the same type and/or strategy.

To address this issue, we delve further into the cross section of fund returns and apply our bootstrap approach to understand whether the performance of superior funds is merely due to luck and/or exposure to the overall market trend, or there is ultimately some skill involved.

One comment is in order; the panel regression specification in Eq.(1) implies that the exposure of funds pertaining different investment strategies is the same. This is a fairly restrictive assumption; for instance, it make sense to assume that market-neutral funds should have a different exposure to BTC (which is the dominant market player) compared to, say, to long-term funds, which may actively seek exposure to long-run market trends. In order to mitigate this issue, we explicitly incorporate the heterogeneity in the betas across investment strategies and extend Eq.(1) as follows

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

for $j = 1, \ldots, J$ the number of strategies, and with $\boldsymbol{\beta}_j^{'}$ the vector of exposures to benchmark/factor returns $\boldsymbol{x}_t$ for the funds in the jth investment class.

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 standard errors clustered by investment strategy (right panel) and plain-vanilla OLS estimates (middle 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 -12% to an impressive +30% 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 actual alphas is much more pronounced on the positive axis, that is, the economic value of the actual alphas is larger than the one that could have been generated by luck as measured by our bootstrap approach.

[Insert Figure 5 here]

The middle panel shows the cross-sectional distribution of the actual and bootstrap t-statistics obtained without clustering standard errors at the strategy level. Two main facts emerge: first, only a small fraction of funds show a positive and significant performance as measured by actual $\hat{t}_{\hat{\alpha}} > 2$. Indeed, only 18 of the total 153 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. In particular, the bootstrap results show that only a small number of funds could generate a positive and significant alpha, which is not due to luck. However, if we explicitly acknowledge that the performance of funds can be correlated within a given strategy, the evidence in favour of manager skills disappears. The right panel shows that, with the exception of a couple of funds with alpha being significant at the conventional 10% confidence level, none of the individual managers seem to deliver economic value per unit of risk, which cannot be explained by sampling variation, i.e., by luck.

As a whole, Figure 5 suggests that although there is strong evidence of economic performance, such performance may not be necessarily significant from a statistical perspective. 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 inflating the t-statistics (see McNemar, 1947).

4.2.1 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 and investors in search of yields. It is fair to assume 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 furhter investigate this evidence, we repeat our analysis of individual fund performances for the two subsamples: the pre-2017 and 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 somewhat 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.

Table 4 reports the descriptive statistics for fund returns at the aggregate level (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 seven columns). Few interesting 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 and order of magnitude higher, consistent with the idea that investment opportunities were much more favourable during the BTC price run up.

[Insert Table 4 here]

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 3.76 in the pre-ICO bubble period and 4.6 from January 2018 to the end of the sample. This suggests that while these funds may not be neutral with respect to market trends in terms of actual returns, they are stable once the performance is adjusted for risk. Third, and with the only exception of market neutral funds, Sharpe ratios are substantially lower during the second sub-sample; that is, average returns decrease more than proportionally to realised volatility.

We now turn our focus on the fund performances across sub-samples. The top panels of Figure 6 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 (3) (middle panel) and the same fixed-effect estimates with robust t-statistics using standard errors clustered by the investment strategy (right panel).

[Insert Figure 6 here]

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 a small fraction, i.e., 3 out of 125, of funds do now show a significant performance which is not due to luck, that is by sampling variation only. This contrasts the evidence related to the entire sample provided in Figure 5. Third, and similar to the full-sample evidence, when the within-strategy correlations are ignored, the significance of the alphas significantly increases with a larger fraction of funds, i.e., 14 out of 125, that now generate significant performances. Overall, managers have higher performance during the market run up early in the sample with some sign of statistical significance.

The bottom panels of Figure 6 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 o magnitude smaller than in 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 beyond sampling variation.

In sum, Table 4 and Figure 6 provide an interesting evidence on the performance of cryptocurrency funds. Specifically, the large economic performance produced over the whole sample is primarily driven by the massive price run up until the end of 2017. When isolating the performance from January 2018 onward, fund managers look much less skilled, with the fund performance which cannot significantly be disentangled from pure sampling variation, i.e. from luck.

4.2.2 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 March 2019 and October 2019 to check for a persistence in the 12-month and 6-month alpha-sorted fund portfolios, respectively.

Furthermore, we implement our bootstrap to determine the significance and to distinguish luck from skills in the performance persistence of alpha-sorted portfolios. In particular, we construct zero-alpha pseudo-returns as outlined in Section A.1 and simulate the distribution of bootstrapped alphas and t-statistics (with and without within-strategy clustered standard errors) at each sorting period. We then report the average bootstrapped alphas and t-statistics for funds belonging to the top and bottom deciles as well as to the second to ninth decile in each period. The average bootstrapped statistics of the three portfolios do not actually show the persistence in fund performance under the null of zero true alphas. Indeed, one fund could possibly belong to the top decile in simulations during one month, but then could turn out to be the worst performing fund in the next period. Instead, the bootstrapped values show the average statistics of the distribution of the three portfolios if they were formed in a particular month.

[Insert Figure 7 here]

Figure 7 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 (see right top and bottom panels).

5 Further results and robustness checks

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.

5.1 Time-series regressions and constant betas

Our main bootstrap approach is based on a panel regression with fund fixed effects, within-strategy clustered standard errors and strategy-dependent loading on passive benchmark returns (see Eg.(3)). Such an approach allows to (1) increase the power of the test as funds returns can be pooled together, (2) acknowledge unobserved fund-specific heterogeneity, (3) control for correlation of managers' 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 investigate what is the marginal contribution of each of the testing ingredients. First, we relax assumption (4) that is, we assume $\boldsymbol{\beta}_j^{'} = \boldsymbol{\beta}^{'}$ for $j = 1, \ldots, J$. Figure 8 shows the results. The left panel reports the alphas whereas the middle and right panels report the t-statistics without and with clustered standard errors, respectively.

[Insert Figure 8 here]

Except few nuances, the main results of Section 4 hold, that is despite there is considerable economic value in active fund management, such value is consistent with the dynamics implied by pure sampling variability, especially when considering within-strategy returns correlation.

Next, we relax both (1) and (3) above such that the bootstrapped alphas and t-statistics are estimated for each fund separately based on a simple time-series regression with Newey and West (1986) robust standard errors. That is, $\boldsymbol{\beta}_i^{'}$ is fund-specific and we do not assume correlation within strategies and/or fund types. Figure 9 shows the bootstrap results.

[Insert Figure 9 here]

Two interesting facts emerge; first, the estimated alphas are significantly larger than the ones obtained as fixed-effects with a panel regression (see Figure 5). This suggests that the short time series available for some of the funds may generate upward small-sample bias in univariate OLS estimates. Second, the cross-sectional distribution of the t-statistics show some evidence of skill vs. luck, that is the distribution of actual t-statistics is more shift to the right and above a standard 5% significance threshold. To some extent this is similar to the results obtained from a panel regression without clustered standard errors. Again, by coupling together the mid panel of Figure 5 and the right panel of Figure 9, one can assume that indeed the possibly overlapping investment opportunities sets within a given strategy makes within-strategy correlations particularly relevant to disentangle skill vs luck in cryptocurrency funds.

5.2 Using factor portfolios

The vast majority of the mutual fund literature uses factor portfolios when attempting to disentangle the alpha from simple exposures to sources of systematic risk. As outlined in Section 3.2., within the context of cryptocurrency markets, factor portfolios do not necessarily represent feasible investment strategies. However, one may argue that there is ambiguous evidence on which asset model investors may use to assess fund performances so that it can still be useful to benchmark funds returns agains factor portfolios (see, e.g., Barber et al., 2016; Berk and Van Binsbergen, 2016). In other words, by using risk factors we can nevertheless compare our main results with a more common approach, which involves the use of hypothetical risk factor portfolios.

To address these issues, we also implement our bootstrap approach replacing the set of benchmark returns with a set of risk factor portfolios. In particular, we construct a series of proxies for sources of risk factors based on the daily returns and volume of the top 300 cryptocurrencies in terms of market capitalisation. The data are obtained from CryptoCompare (see Section 3.1 for a complete description of the data source).

Specifically, we first consider the returns on the aggregate market (MKT) calculated as the value-weighted average returns of the top 300 cryptocurrencies in terms of market capitalisation. We then consider both the returns on a cross-sectional momentum strategy (MOM) as introduced by Jegadeesh and Titman (2001) and a simple reversal strategy that goes long on past losers and short on past winners (see De Bondt and Thaler, 1985).[22]

[22] 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

In addition, we consider two additional sources of risk that are typical in cryptocurrency markets: liquidity and volatility (see Bianchi and Dickerson, 2019).

A relatively easy 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. Indeed, bid-ask spreads on a single currency, at a given point in time, could massively 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 OHLC 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 currency. Next, we single sort each pair into quintiles based on the average measure. A risk factor is then constructed by going long into illiquid pairs (fifth quintile) and going short into the liquid pairs (first quintile). This zero-cost long-short portfolio is the liquidity risk factor.

As far as the volatility tradable portfolio is concerned, at each time t, a rolling volatility estimate is computed using the volatility estimator of Yang and Zhang (2000) (a rolling period of 30-days is used). 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. The average value and standard deviation of a pure reversal strategy are, respectively, 102.95% and 69.59% on a monthly basis. The remaining risk factors have substantially lower average values. In particular, a value-weight market portfolio return and liquidity risk factors are, on average, positive, but both earn a much lower monthly return of 5.78% and 6.62%, respectively.

Figure 10 reports the actual values (light-blue bars) as well as the bootstrap values (light-

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.

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 5% on a monthly basis; however, there is a sizable amount of outlying funds with performance well above 10% on a monthly basis.

[Insert Figure 10 here]

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 fraction of funds with significant alphas is slightly higher when using factor portfolios rather than benchmark strategies. However, the overall weak statistical evidence that sampling variation, or luck, cannot explain the performance of the few outlying funds remains intact.

5.3 Time-series dependence in fund returns

Our main bootstrap procedure assumes that the residuals are only weakly autocorrelated. Tables 1-4 and bottom panel of Figure 4 show that indeed the persistence of funds returns is low compared to, say, traditional equity mutual funds. The persitence of funds 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.

Nevertheless, we further explore the sensitivity of our results to the possibility of 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.

[Insert Figure 11 here]

The top panels of Figure 11 present the fund alphas and their t-statistics for a modified version of the bootstrap procedure. When standard errors are clustered by investment strategy, the set of funds with a positive and significant alpha, with a t-statistic higher than 1.96, remains empty as in the main empirical results. On the other hand, with typical OLS estimates there is evidence of few funds reaching significance performance which cannot be simply explained by sampling variation. As a whole, even by considering short-term auto-correlation in our bootstrap procedure the results are largely in line with the main empirical analysis.

5.4 Independent resampling of factors and residuals

We next implement an alternative bootstrap approach whereby the benchmark returns and the residuals are sampled independently. By construction, this approach breaks any possible correlation between explanatory returns and unexpected returns. As outlined in Kosowski et al. (2006), such a correlation could arise if the performance model specified does not fully capture the set of possible explanatory factors.

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

$$y_{it}^{b} = \hat{\boldsymbol{\beta}}' \boldsymbol{x}_{t_x}^{b} + \hat{\epsilon}_{it_{\epsilon}}^{b}, \qquad b = 1, \ldots, B \tag{4}$$

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.

The bottom panels of Figure 11 report the estimates for both $\hat{\alpha}$ (left panel) and $\hat{t}_{\hat{\alpha}}$ (right panel). Again, the results are virtually the same as the main empirical analysis in Section 4.2.

6 Conclusion

This article provides the first examination of the value of active asset management in the new class of digital assets. We begin by constructing a novel dataset of 153 actively managed funds over the period from March 2015 to July 2020. We then empirically examine the performance of funds through a novel bootstrap approach. In our empirical investigation, we measure the value of fund managers through their ability to generate positive alphas.

We consider a set of benchmark strategies to extract the active investment performance. Our results show that a sizable minority of managers can generate performances which cover their cost, therefore value for investors. However, once within-strategy correlations among funds is taken into account there is weak statistical significance in favour of managers skill vs luck, that is, there is weak evidence of significant positive performance which is not due to sampling variation.

While conventional research has long been debating the value of active management, no study has tested the existence of such value in the new and relatively unregulated industry of cryptocurrency funds. This paper fills this gap and conducts the first comprehensive and critical statistical examination of active investment management in the cryptocurrency space that explicitly controls for skill versus luck extending the approach of Kosowski et al. (2006) and Fama and French (2010).

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Table 1: **A first look at crypto funds returns**

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: "hedge fund", "managed accounts", and "tokenized fund" (from column two to column four), and each investment strategy: "fund of funds", "long-short", "long-term", "market neutral", "multi-strategy", "opportunistic", and "other" (the last seven 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 July 2020.

		Fund type			Investment strategy						
	Agg	HF	Managed acc	Token fund	Fund of funds	Long-short	Long-term	Market neutral	Multi-strategy	Opport	Other
Mean (%)	7.85	7.55	4.89	10.01	3.80	9.25	10.70	3.45	10.35	2.06	3.19
Std (%)	15.66	15.20	10.93	24.59	8.43	17.46	27.55	3.49	21.90	6.15	31.53
SR (annualized)	1.74	1.72	1.55	1.41	1.56	1.83	1.35	3.42	1.64	1.16	0.35
Skewness	1.95	1.82	0.68	2.69	1.20	1.49	2.07	1.78	1.68	1.02	2.67
AR(1)	0.27	0.19	0.14	0.47	0.10	0.36	0.24	0.55	0.11	0.02	-0.06

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 July 2020.

	Passive benchmarks				Risk factors				
	BTC	DOL	ETF	ETH	LIQ	MKT	MOM	REV	VOL
Mean (%)	7.34	4.35	7.70	7.01	6.91	5.13	-36.9	105.21	-2.70
Std (%)	19.35	30.75	22.97	33.02	24.33	27.94	26.56	68.42	20.08
SR (annualized)	1.31	0.49	1.16	0.74	0.98	0.64	-4.81	5.33	-0.47
Skewness	-0.06	0.61	1.36	0.71	1.95	0.77	-0.19	2.97	0.17
AR(1)	0.11	0.19	0.32	0.18	-0.11	0.18	-0.01	0.09	-0.08

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

This table reports the benchmark-adjusted performance of aggregate funds across all crypto funds, each fund type and strategy. Specifically, we run a set of time-series regressions in which the dependent variable is the equal-weight portfolio returns aggregated across all funds (first column), each type of funds: "hedge fund", "managed accounts", and "tokenized fund" (from column two to column four), and each investment strategy: "fund of funds", "long-short", "long-term", "market neutral", "multi-strategy", "opportunistic", and "other" (the last seven 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 $\alpha_{t,k} = y_{t,k} - \hat{\boldsymbol{\beta}}_k' \boldsymbol{x}_t$. Testing for the difference in the performance boils down to a test for the significance in $\hat{\gamma}$. The bottom panel reports the estimate and robust t-statistics (in parenthesis). The sample covers the period from March 2015 to July 2020.

		Fund type			Investment strategy						
	Agg	HF	Managed acc	Token funds	Fund of funds	Long-short	Long-term	Market neutral	Multi-strategy	Opport	Other
Alpha	3.59	3.25	1.83	5.47	1.65	4.46	3.60	2.55	5.88	0.93	4.05
t-stat	(3.81)	(3.46)	(1.69)	(3.17)	(1.85)	(2.94)	(2.50)	(8.27)	(3.02)	(1.04)	(1.33)
Difference		-0.34	-2.79	1.88	-2.96	0.86	0.01	-1.05	1.27	-3.69	-0.71
t-stat		(-1.36)	(-2.14)	(1.53)	(-2.87)	(0.99)	(0.01)	(-1.20)	(1.05)	(-2.51)	(-0.29)

Table 4: **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: "hedge fund", "managed accounts", and "tokenized fund" (from column two to column four), and each investment strategy: "fund of funds", "long-short", "long-term", "market neutral", "multi-strategy", "opportunistic", and "other" (the last seven 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 July 2020.

Sample until Dec 2017

		Fund type			Investment strategy						
	Agg	HF	Managed acc	Token fund	Fund of funds	Long-short	Long-term	Market neutral	Multi-strategy	Opport	Other
Mean (%)	13.49	13.10	10.82	17.20	10.94	15.24	20.62	4.63	30.56	1.59	24.41
Std (%)	17.93	17.22	9.99	30.51	10.05	21.04	31.30	4.27	27.70	0.85	75.27
SR (annualized)	2.61	2.64	3.75	1.95	3.77	2.51	2.28	3.76	3.82	6.45	1.12
Skewness	1.75	1.62	0.92	2.11	0.90	0.89	1.99	1.11	1.00	0.54	0.93
AR(1)	0.26	0.16	-0.27	0.44	-0.25	0.31	0.23	0.46	-0.11	0.25	0.05

Sample from Jan 2018

		Fund type			Investment strategy						
	Agg	HF	Managed acc	Token fund	Fund of funds	Long-short	Long-term	Market neutral	Multi-strategy	Opport	Other
Mean (%)	1.67	1.46	2.60	2.12	1.03	2.67	-0.18	2.16	2.53	2.24	-0.23
Std (%)	9.70	9.68	10.55	11.97	5.85	8.84	17.52	1.62	12.80	7.25	17.82
SR (annualized)	0.59	0.52	0.85	0.61	0.61	1.05	-0.03	4.60	0.68	1.07	-0.04
Skewness	0.85	0.98	0.82	0.59	0.20	0.94	0.65	1.46	0.48	0.80	0.46
AR(1)	-0.05	-0.09	0.18	-0.12	-0.18	0.04	-0.11	0.30	-0.30	0.02	-0.01

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 300 digital assets in terms of market capitalization. The sample period is from March 2015 to July 2020. The black dashed line indicates the end of December 2017, a time stamp which coincides with the burst of the so-called ICO bubble.

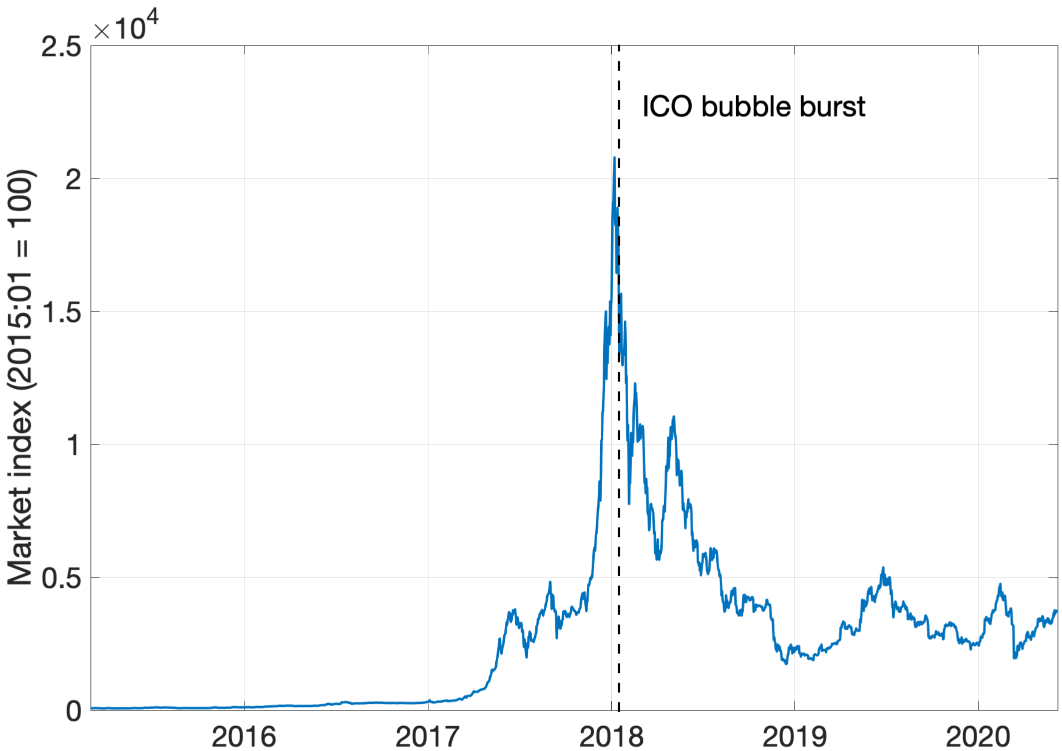
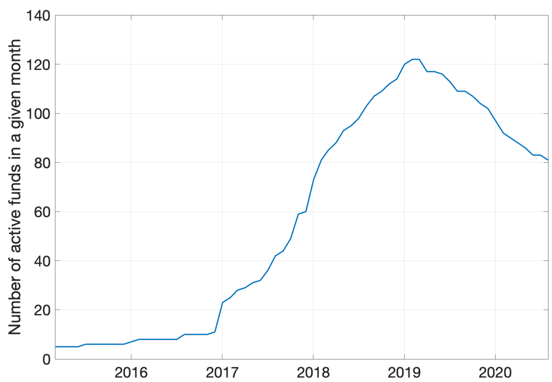
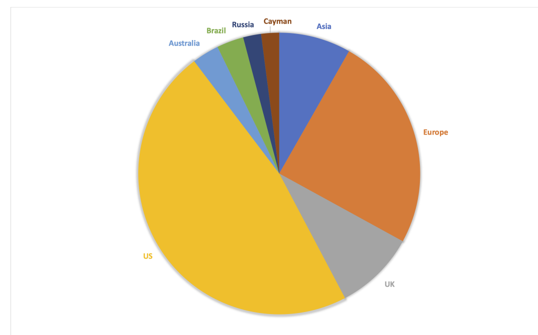


Figure 2: **A snapshot of the sample of funds**

This figure plots the time series of the number of funds considered in the sample (left panel) and the geographical distribution of the funds (right panel). The sample period is from March 2015 to July 2020.



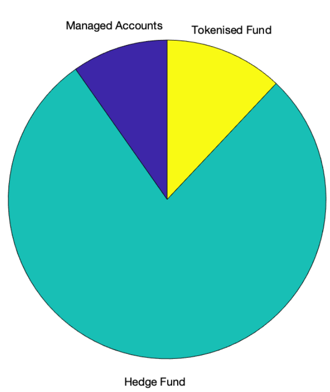
(a) Number of funds



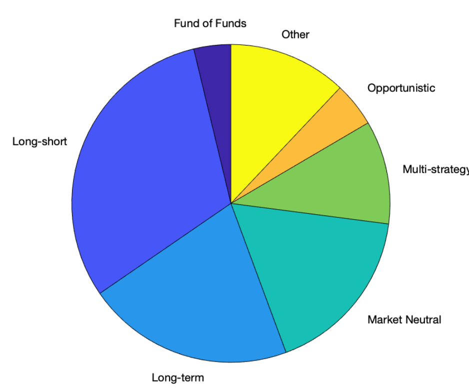
(b) Geographical distribution

Figure 3: **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 "hedge fund", "managed accounts", and "tokenised fund". Classification by investment strategy is defined as "fund of funds", "long-short", "long-term", "market neutral", "multi-strategy", "opportunistic", and "other". The sample period is from March 2015 to July 2020.



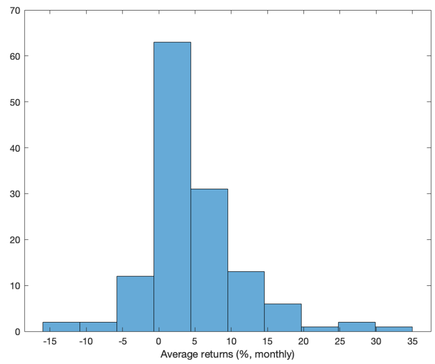
(a) Funds by type



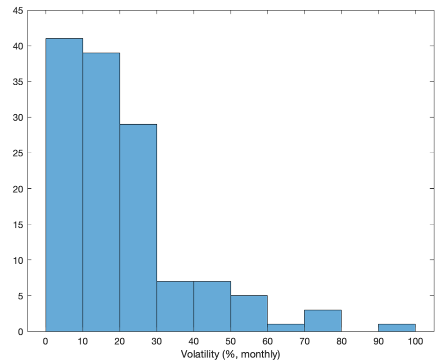
(b) Funds by investment strategy

Figure 4: **The cross-sectional distribution of funds descriptive statistics**

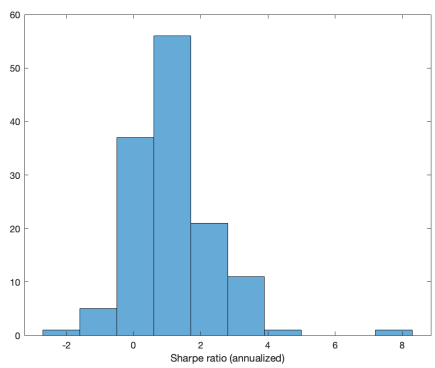
This figure plots the cross-sectional distribution of mean (%, monthly), volatility (%, monthly), Sharpe ratios (annualised), skewness and first-order autoregressive coeffcient (AR(1)) of the fund returns in our sample. The sample period is from March 2015 to July 2020.



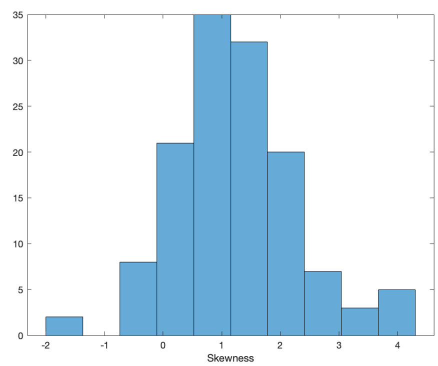
(a) Average returns



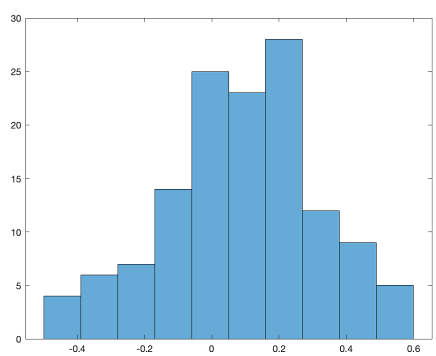
(b) Volatility



(c) Sharpe ratio



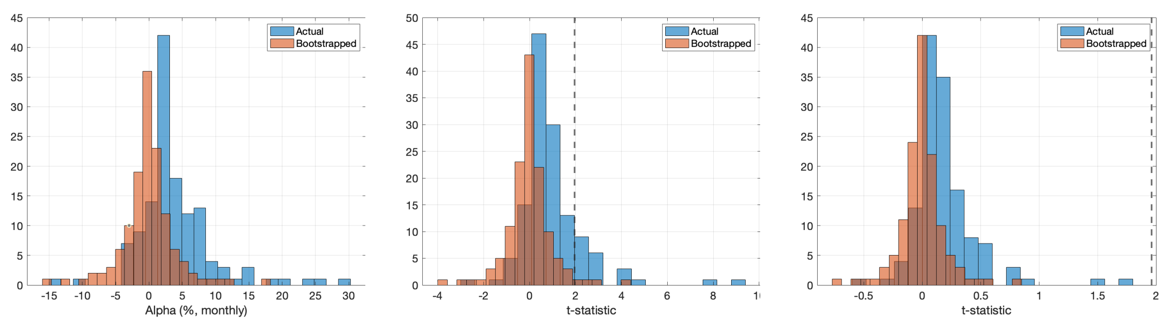
(d) Skewness



(e) AR(1)

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 July 2020.

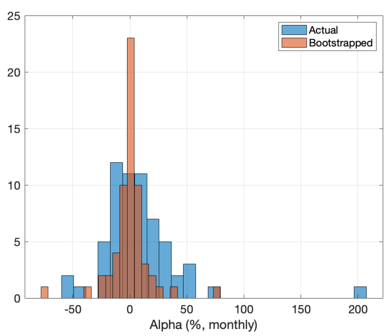


(a) Alpha (b) Standard t-statistics (c) Clustered standard errors

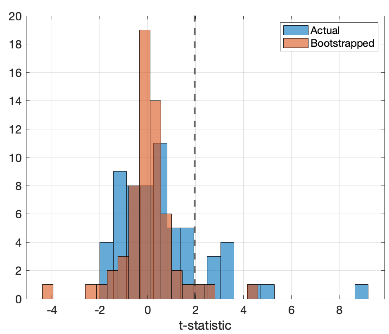
Figure 6: **The cross-section of benchmark-adjusted alphas across sub-samples**

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 July 2020.

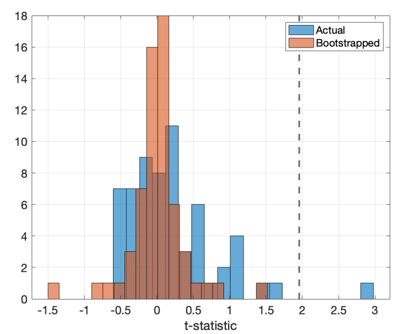
Sample until Dec 2017



(a) Alpha

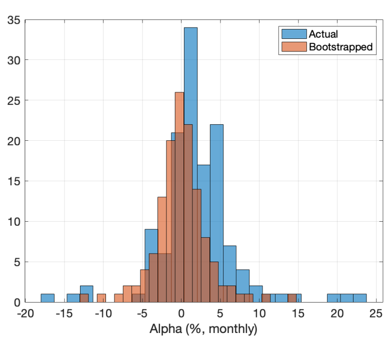


(b) Standard t-statistics

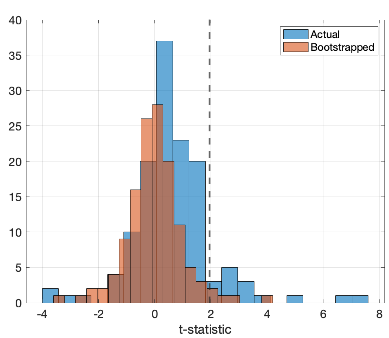


(c) Clustered standard errors

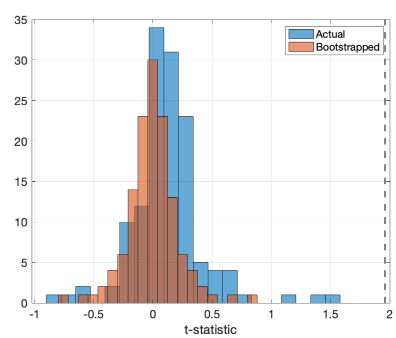
Sample from Jan 2018



(d) Alpha



(e) Standard t-statistics

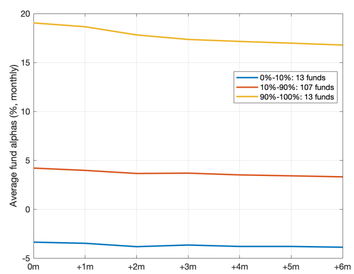


(f) Clustered standard errors

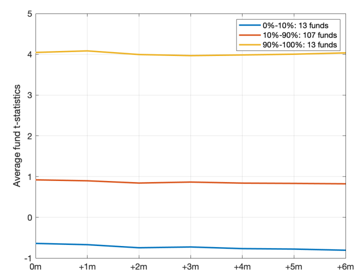
Figure 7: **Persistence of benchmark-adjusted alphas**

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 January 2020 to the end of the sample whereas the bottom panels show the results for the post-formation alphas from July 2019 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 July 2020.

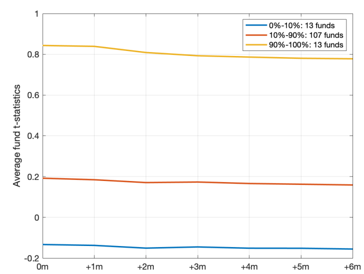
Panel A: Short-term persistence



(a) Alpha

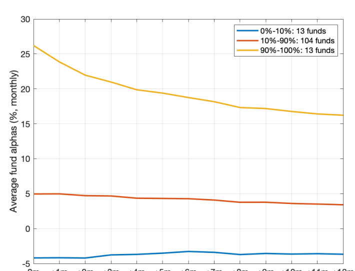


(b) Standard t-statistics

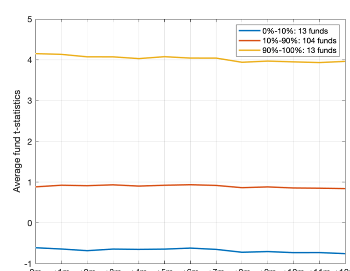


(c) Clustered standard errors

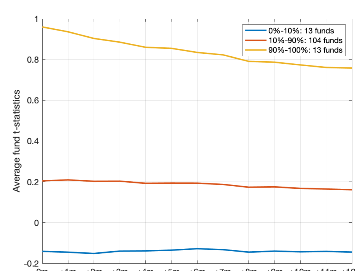
Panel B: Long-term persistence



(d) Alpha



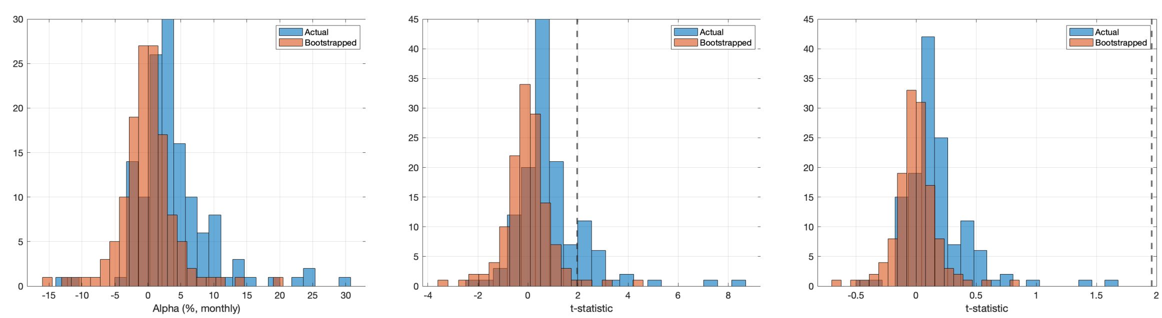
(e) Standard t-statistics



(f) Clustered standard errors

Figure 8: **The cross-section of benchmark-adjusted alphas: constant betas**

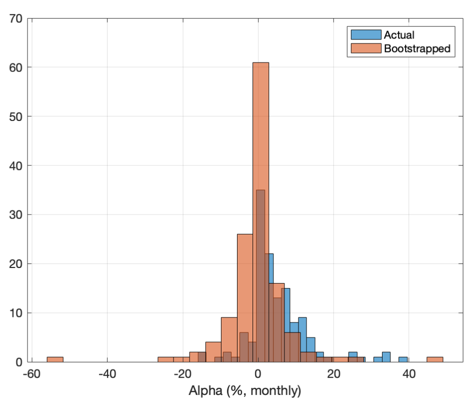
This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. Unlike the main empirical analysis the betas on the benchmark portfolios are restricted to 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 July 2020.



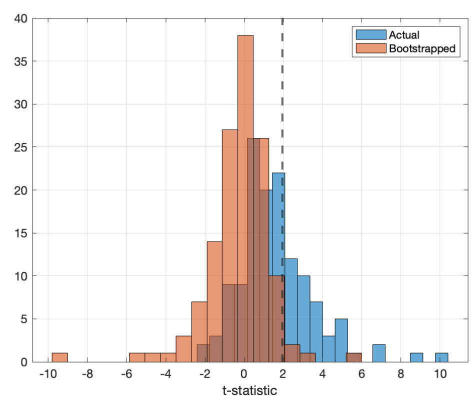
(a) Alpha (b) Standard t-stats (c) Clustered t-stats

Figure 9: **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 July 2020.



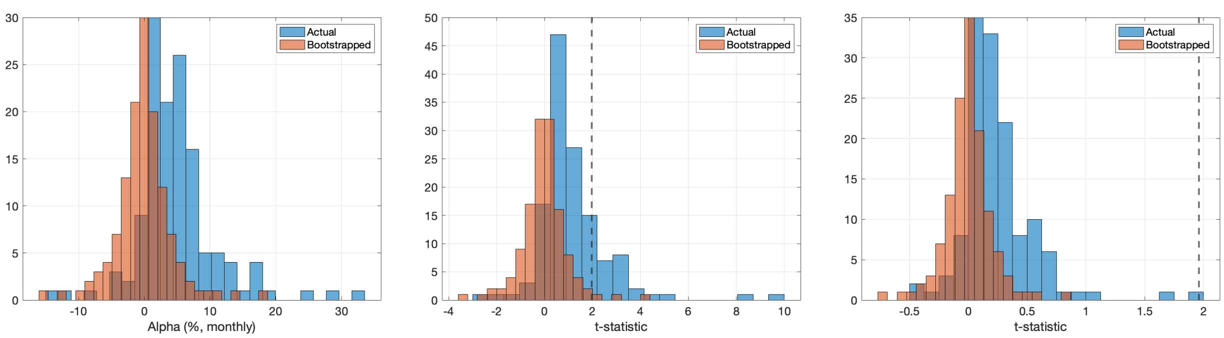
(a) Alpha



(b) Robust t-stats

Figure 10: **The cross-section of factor-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 July 2020.

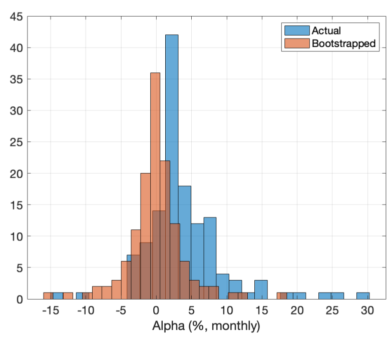


(a) Alpha (b) Standard t-statistics (c) Clustered standard errors

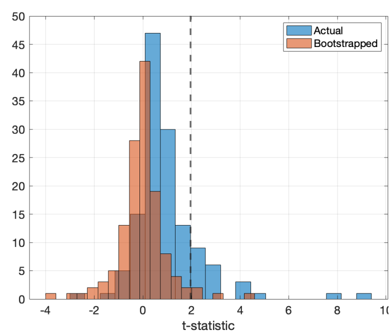
Figure 11: **The cross-section of fund alphas using alternative bootstrap procedures**

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 July 2020.

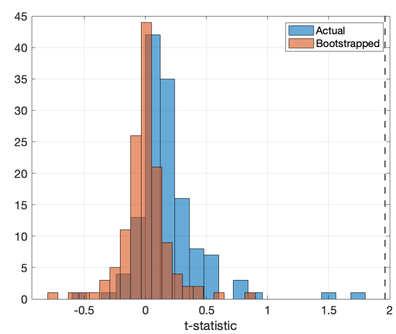
Panel A: Block bootstrap



(a) Alpha

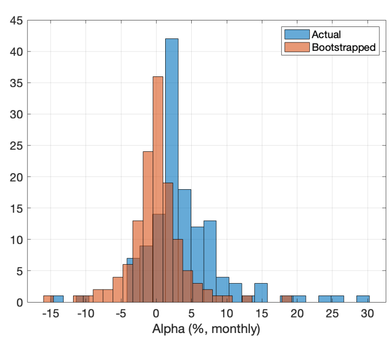


(b) Standard t-statistics

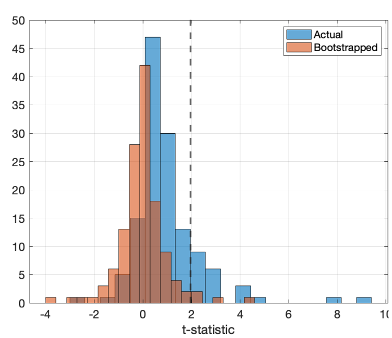


(c) Clustered standard errors

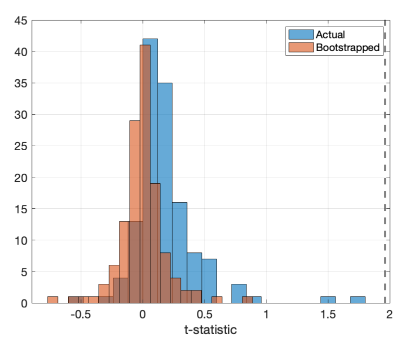
Panel B: Independent resampling of benchmark returns and residuals



(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:

$$y^b_{it} = \hat{\alpha}^b_i + \hat{\beta}^{b\prime} \boldsymbol{x}^b_t + \varepsilon^b_{i,t}$$

end

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

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

$$y^b_{it} = \hat{\boldsymbol{\beta}}' \boldsymbol{x}^b_{t_x} + \hat{\varepsilon}^b_{it_\varepsilon},$$

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

end

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

$$y^b_{it} = \hat{\alpha}^b_i + \hat{\beta}^{b\prime} \boldsymbol{x}^b_{t_x} + \varepsilon^b_{i,t_\varepsilon}$$

end

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

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). With the only mild exception of market neutral strategy, 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 September 2019 (left panel) and from March 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.

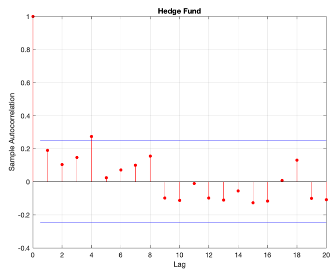
B.2.1 Crypto funds vs. benchmark returns. Figure C.1 illustrates the simple compounded return (starting with an initial investment of 1$) of an equal-weight average of the fund returns and compares it against a buy-and-hold investment in Bitcoin, an equal-weight (DOL) and a value-weight (Market) portfolio 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 March 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 average 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

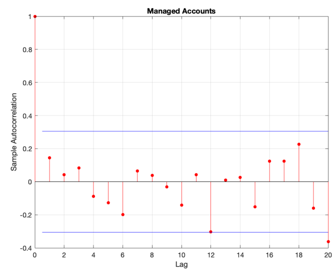
Figure C.2 shows that the compounded returns across different fund groups share a similar time variation during the considered period. An equal-weight average return for each fund type and strategy dramatically increases in the first half of the sample before starting to decline in 2018. The compounded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

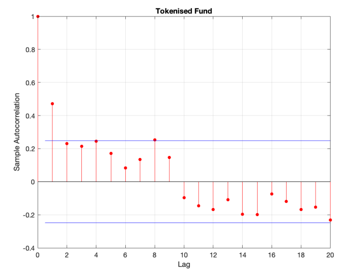
This figure shows the autocorrelation function up to 20 lags of equal weight portfolio returns aggregated across each type of funds and the investment strategy. The sample period is from March 2015 to July 2020.



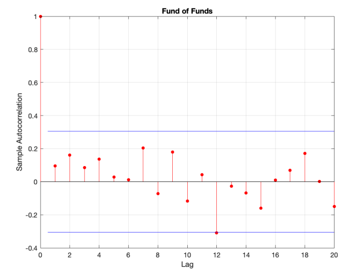
(a) Hedge fund



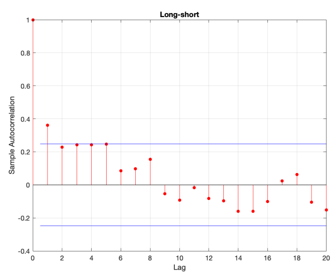
(b) Managed accounts



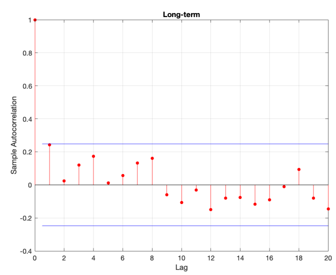
(c) Tokenized fund



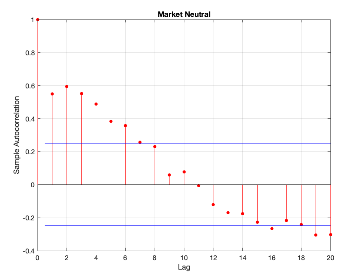
(d) Fund of funds



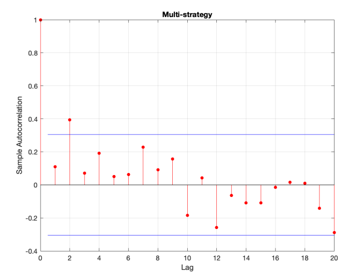
(e) Long-short



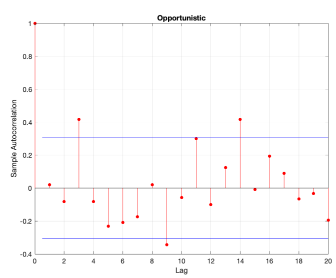
(f) Long-term



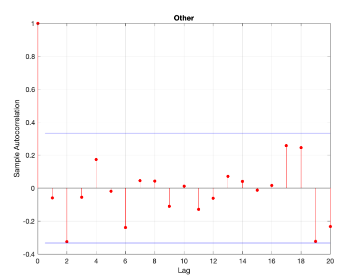
(g) Market neutral



(h) Multi-strategy



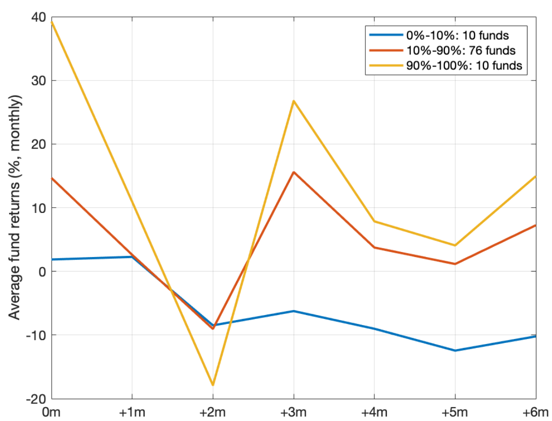
(i) Opportunistic



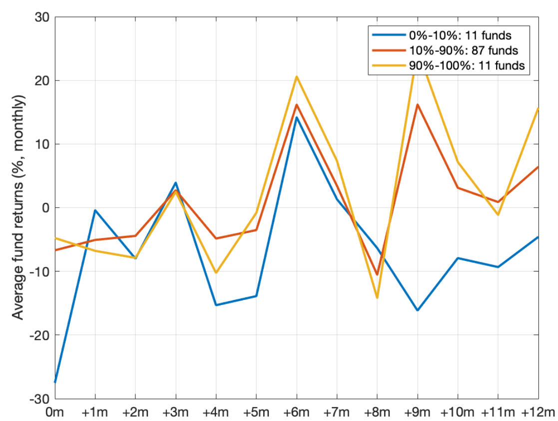
(j) Other

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

This figure plots the post-formation returns from January 2020 (left panel) and from July 2019 (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 July 2020.



(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 July 2020.

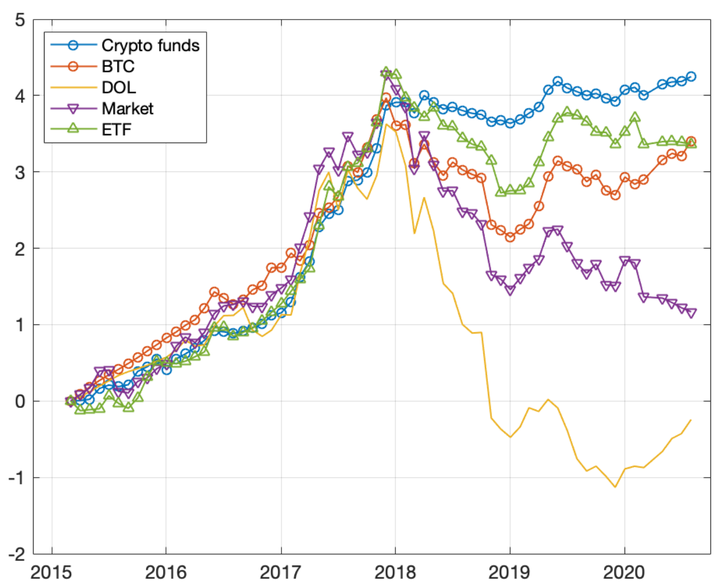
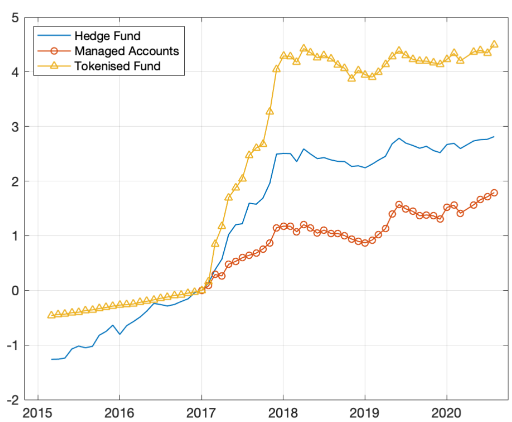
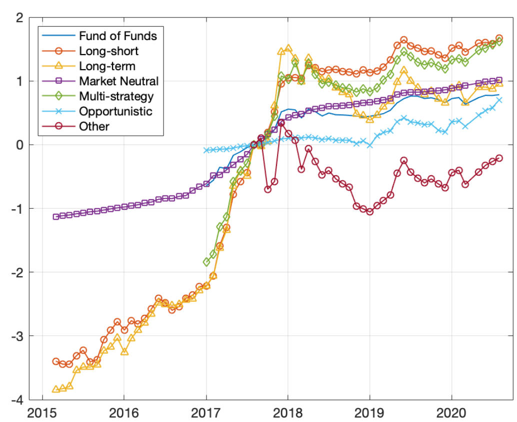


Figure C.2: **Compounded returns per fund type or investment strategy**

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 were introduced. The cumulative log returns per investment strategy are normalised to 0 in August 2017 when the first fund with the "Other" strategy was introduced. The sample period is from March 2015 to July 2020.



(a) Cumulative log returns per fund's type



(b) Cumulative log returns per strategy