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On the Performance of Cryptocurrency Funds*

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Abstract

We investigate the performance of funds that specialise in cryptocurrency markets. In doing so, we contribute to a growing literature that aims to understand the role of digital assets as an investment. Methodologically, we implement a novel bootstrap approach that samples jointly the cross-sectional distribution of alphas and controls for the non-normality of fund 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. However, there is weak statistical evidence of managers' skills once within-strategy common variation in returns is taken into account.

Keywords: Cryptocurrency, Investments, Active Management, Alternative Investments, Boot-strap 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 which have never been seen before in traditional asset classes.

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.

[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.

In this paper, we contribute to further understanding the value of active management 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. Related to that, existing research 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 others 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 makes cryptocurrency funds a quite unique environment given the substantial lack of a robust regulatory environment. Third, professional asset management tools are quickly emerging to assist retail investors. The incentive is clear: a more mature and widespread market also means that less knowl-

[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]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.

edgeable investors are likely to dip their toes in, requiring in tandem 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 the new and rapidly developing cryptocurrency market. 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 slighltly more than $40mln whereas the total asset under management is around $2bln indicating these are primarily small funds that operate in a relatively concentrated market and that escape major regulatory ties. The limited competition from cheaper investment vehicles, such as ETFs and registered investment advisors, possibly puts less pressure on fund managers in cutting costs, increasing leverage or taking extra risks. 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 a new and relatively unregulated industry such as cryptocurrency markets. This paper fills this gap and conducts the first comprehensive and critical examination of crypto funds performance 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 robust to both time-series and cross-sectional correlations while also taking explicitly into account the unknown forms of time-series and cross-sectional heteroskedasticity as well as the common and idiosyncratic variation in fund 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 latter is empirically motivated by the large differences in the performance of individual funds across 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.

Empirically, 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 survivorship bias, the sample includes not only those funds that are still active, 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, with the only exception of a market drop in the early stage of the Covid-19 pandemic. As a result, our sample not only includes different market phases, i.e., boom, bust and flat market, but also captures major regulatory and institutional changes such as the ban by the Chinese government on crypto exchanges and the introduction of tradable Bitcoin futures contracts on the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE), as well as the first wave of the Covid-19 pandemic. In this respect, it is reasonable to assume that the sample is fairly representative and likely ensure there is sufficient time series variation in the data.

We begin by looking at the aggregate performance of crypto funds in excess of alternative passive investment strategies. That is, we estimate the alpha generated by equal-weight portfolios of all funds as well as funds grouped based on their type and investment strategy. The results show that when aggregating funds there is some evidence of a superior fund performance compared to passive benchmarks such as buy-and-hold investment in Bitcoin (BTC), an equal-weight portfolio invested in the top cryptos by market capitalization, akin to the "dollar risk factor" adapted to cryptocurrencies from Lustig et al. (2011), a value-weight average of the tokens listed on Coinbase and Coinbase Pro, and a buy-and-hold investment in Ethereum (ETH).

By looking at the average fund returns one cannot control for the differences in managers' risk-taking behaviors (see Kosowski et al., 2006 and Fama and French, 2010). Therefore, we focus on the performance of individual funds. Across a wide array of statistical tests, our main results show that, after adjusting for passive benchmarks the right tail of the performance distribution can not be simply due to managers' luck. In other words, we find a positive value of active management that cannot be entirely explained by the sampling variation of the fund returns. However, when controlling for commonalities in the fund returns within a given investment strategy the statistical evidence in favour of skills vs luck becomes substantially weaker, with none of the alphas that is significance at standard significance levels. Overall, our analysis shows that, although the alphas of best performing funds can not be reconciled simply by sampling variation, there is weak evidence that net-of-fees alphas are statistically significant.

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-fees 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.

Intuitively, investors could look at the past fund performances 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 not statistically significant.

In order to make sure our results are not driven by a particular choice of benchmarks and/or statistical procedure we investigate the robustness of the main empirical analysis to both alternative performance measures and different 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 aggregate risk factors such as the market, liquidity, volatility, reversal and momentum, and re-run the main bootstrap analysis. 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. In addition, 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.

These results are interesting in light of the existing debate on the value of active investment management. On the one hand, the conventional wisdom initially articulated by Jensen (1968) and Carhart (1997) states that, on average, active management creates little value to investors. A number of papers support this statement by documenting that (i) the average fund underperforms after fees (Ippolito, 1989; Gruber, 1996; Wermers, 2000; Davis, 2001), (ii) there is no persistence in the performance of the best funds

(Brown et al., 1992; Malkiel, 1995; Elton et al., 1996; Phelps and Detzel, 1997), and (iii) some fund managers have skill, but few are skilled in excess of costs (Fama and French, 2010). The theoretical underpinning of these results is that active management can be considered as zero-sum game before costs: any gain for one manager is offset by a loss for another manager. After subtracting costs, active management becomes a game with a negative sum, and hence the average active manager should necessarily underperform.[6] Another argument in favor of the conventional wisdom is the limited number of investment opportunities, which prevent skilled managers from improving fund performance.[7]

On the other hand, 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 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 persis-

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

[7]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).

tence 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 (see Yermack, 2013, Dyhrberg, 2016, Liu and Tsyvinski, 2018, Bianchi, 2020, Bianchi et al., 2020, and Schwenkler and Zheng, 2020, among others).[8]

Our paper proceeds as follows. Section 2 describes our bootstrap procedure, while Section 3 describes in detail the crypto fund database used in our study. Section 4 shows the empirical results. Section 5 investigates the robustness of the main findings to alternative performance measures and bootstrap procedures. Section 6 concludes.

2 Research Design

We apply a bootstrap procedure to evaluate the performance of cryptocurrency funds over the period from March 2015 to July 2020. There are several reasons why a bootstrap approach is helpful for statistical inference within the context of cryptocurrency markets. For instance, the returns of individual funds exhibit large departures from normality, such as large positive skewness and massive kurtosis, with the cross-section of alphas effectively representing a complex mixture of these non-normal distributions.

We follow Kosowski et al. (2006) and Fama and French (2010) and consider two key

[8] 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. Finally, Schwenkler and Zheng (2020) investigates competition vs contagion effects in idiosyncratic shocks within cryptocurrency markets.

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. Second, with a relatively limited investment opportunity set compared to traditional equity funds, crypto funds operating within a given strategy framework could embark in overlapping investments, which in turn may generate highly correlated returns. By clustering standard errors at the strategy level the resulting t-statistics explicitly takes into account within-strategy returns comovement. For these reasons, we implement a bootstrap both for $\hat{\alpha}$ and $\hat{t}_{\hat{\alpha}}$ and comment the bulk of the empirical results based on the t-statistic rather than the alpha estimates.

To prepare for our bootstrap procedure, we estimate the alphas by comparing the historical net-of-fees fund returns with a set of alternative investment opportunities as represented by low-cost passive funds (see, e.g., Berk and Van Binsbergen, 2015 and Dyakov et al., 2020). 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 more precise estimates of the fund performances despite their short life span.

2.1 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 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 $\left\{\hat{\epsilon}_{it}^b,\ \boldsymbol{x}_t^b;\ t = s_{T_{0i}}^b, \ldots, s_{T_{1i}}^b\right\}$, where $b = 1, \ldots, B$ is the bootstrap index and $s_{T_{0i}}^b, \ldots, s_{T_{1i}}^b$ are drawn randomly from $[T_{0i}, \ldots, T_{1i}]$. Next, we construct a time series of "synthetic" zero-alpha returns for this fund i as

$$y_{it}^b = \hat{\boldsymbol{\beta}}' \boldsymbol{x}_t^b + \hat{\epsilon}_{it}^b, \qquad b = 1, \ldots, B. \tag{2}$$

[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.

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

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

As far as the bootstrap methodology is concerned, the two closest papers to ours are Kosowski et al. (2006) and Fama and French (2010). They both use bootstrap simulations to draw inferences about performance in the cross-section of fund returns. The key 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 individual clustered standard errors (see Cheng et al., 2005; Petersen, 2009). As a result, our approach explicitly takes into account autocorrelation and heteroskedasticity in the alpha standard errors, 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 (CFR henceforth), a website-based data provider that collects in-depth crypto fund data. We manually cross-check and complement the data from CFR by looking at the public prospectus and websites of each fund. Notice that managers report fund returns on a voluntary basis since there is no legal obligation to disclose their performance to the public. The data is not usually revised after reporting for the first time, though a small subset of managers provide estimates first before fully reporting. To avoid any revision bias, we consider only 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 registered employees. That is, we exclude micro funds which escape any kind of investment oversight. The threshold seems low in absolute value, but in relative terms it is not considering the average AUM for crypto hedge funds is slightly more than $40mln, with a distribution that is highly skewed to the left. Indeed, only about a third of the funds in the sample have more than $20mln of AUM. Second, we focus only on those funds that accept US dollars as the investment currency and likewise report their performances in US dollars, so that FX risk is 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.[10] 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. 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

[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.

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 tend to drop towards the end of the sample; virtually no funds after filtering could have been used before March 2015. Although the number of funds considered seems low compared to a typical study in more equity 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 three macro categories of crypto funds: Crypto Hedge Funds (CHF), Tokenised Funds (TF) and Managed Accounts (MA). These are the most common forms of active investment management in the cryptocurrency space.

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

[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.

sometimes even 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 MA.

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

3.1.2 Investment strategies. The investment strategies of crypto funds are somewhat comparable to traditional equity markets. 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.

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.

[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.

3.2 Benchmark strategies

Our main results are 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 for a retail investor. 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

[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. Schwenkler and Zheng (2020) also uses CryptoCompare data to construct weekly returns for a moderate cross-section of cryptocurrencies. 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.

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.[16] 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).[17] 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.[18] The time series of the hypothetical fund returns can be found on the Fred database held by the St.Louis Fed.[19]

[15]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.

[16]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.

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

[18]Taken together, Coinbase and Coinbase Pro exchanges represent one of the largest market place to trade cryptocurrencies.

[19]Although the Coinbase Index 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.

4 Empirical analysis

4.1 A first look at the fund 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 monthly returns (7.85%) and even larger monthly volatility (15.66%), which nevertheless translate into a remarkable 1.74 Sharpe ratio in annualised terms. Interestingly, there is no evidence of crash risk, at least unconditionally, since the skewness of the returns is large and positive. Also, there is a rather 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.

A much more heterogeneous picture emerges when looking at the strategy-specific average returns in the last seven columns of Table 1. There is a substantial difference in monthly returns and volatilities, with the annualised Sharpe ratios that go 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; first, returns on crypto funds, unlike typical hedge funds, are not highly persistent, with the highest AR(1) coefficient being equal to 0.55 for market neutral funds while being almost negligible for the other strategies. This suggests that our bootstrap approach may be less exposed to the 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 as "DOL" the equal-weight investment in the top 30 cryptocurrencies by market capitalisation and "ETF" the returns on the Coinbase Index constructed as a value-weighted passive investment on the digital assets available for trading on Coinbase and Coinbase Pro.

[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.[20] Also, with the only exception of BTC, all benchmark strategies show a positive skewness and exhibit weak persistence in the realised returns.

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

[20] 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).

returns outlined in Section 3.1.[21] In addition, we also look at a more granular classification based on the fund type and 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.[22] This translates into a set of robust standard errors (and in turn t-statistics), which account for heteroskedasticity in the model residuals. In addition to the alphas for the average type- or strategy-specific fund returns, we also report a test of the difference in the performance between the average fund performance and the performance of portfolios clustered by type or strategy.[23] Again, to account for outlying returns, we estimate a robust regression with a bi-square weighting function.

On average, crypto fund returns show a positive and significant benchmark adjusted return of 3.59% on a monthly basis (robust t-stat: 3.81). The aggregate performance is

[21]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, $\hat{\alpha}$ is the estimated performance, and $\hat{\boldsymbol{\beta}}'$ is the exposure to the benchmark returns $\boldsymbol{x}_t = (\mathrm{BTC}_t, \mathrm{ETH}_t, \mathrm{ETF}_t, \mathrm{DOL}_t)'$.

[22]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 $6m$.

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

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).

When we look 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 performances

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 expected returns and volatility as well as the annualised SRs, skewness, and autocorrelation.

[Insert Figure 4 here]

Four facts emerge: first, there is a significant heterogeneity in the cross-section of expected returns and volatility, 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, the right tail of the distribution shows there is a considerable mass of managers which generate SRs upto twice as large as passive investments. Third, although the overwhelming majority of funds have positively skewed returns, there is a non-trivial fraction of funds for which the probability of a large loss is actually higher than the probability of a large gain, at least unconditionally, as indicated 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, by simply looking at the average performance may give a misleading picture (see, e.g., Kosowski et al., 2006). 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 performances is much more pronounced on the right tail, that is, the economic value of the actual alphas is larger than the one that could have been generated by sampling variation, i.e., by luck.

[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 $\hat{t}_{\hat{\alpha}}$. More precisely, only 18 of the total 123 funds in our sample show an alpha that is significant at the conventional 5% confidence level. Second, similar to the alpha estimates, the probability mass of actual t-statistics is shifted to the right side compared to the distribution generated by the bootstrap. However, if we explicitly acknowledge that the performance of funds can be correlated within a given strategy, the statistical significance of manager skills disappears. The right panel shows that, with the exception of two funds with alpha being significant at the conventional 10% confidence level, none of the individual performances is statistical significant.

As a whole, Figure 5 suggests that although there is some evidence of economic performance which may not due simply to sampling variation, such performance may not be statistically significant. 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 in search of yields. It is fair to conjecture that the burst of the ICO bubble could mark a significant change in the profitability of cryptocurrency investments and hence the performance of crypto funds.

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

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 an order of magnitude higher, which is consistent with the idea that investment opportunities were much more favourable during the ICO-bubble.

[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. Finally, Sharpe ratios are substantially lower during the second sub-sample with the only exception of market neutral funds; that is, average returns decrease more than proportionally to realised volatility.

We now turn our focus on the 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 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 3 out of 125 now do 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 of 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 some evidence of managers' skills across subsamples. As a matter of fact, the right tail of the actual distribution of alphas is more skewed to the right than the bootstrapped performances. That is, the fund alphas cannot be simply explained by pure sampling variation. However, when within-strategy correlation in the returns is considered, there is little statistical significance of the alphas across both samples, with a slight stronger evidence during the massive price run up until the end of 2017.

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 July 2019 and January 2020 to check for a persistence in the 12-month and 6-month alpha-sorted fund portfolios, respectively.

[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 as shown in the right panels of Figure 7.

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

In this section we relax these assumptions to assess the marginal contribution of each of the testing ingredients. First, we 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 right and middle panel report the t-statistics with and without clustered standard errors, respectively.

[Insert Figure 8 here]

Except for few nuances, the main results of Section 4 hold. Specifically, although most successful managers generate net-of-fees performances which cannot be reconciled with pure sampling variation, such economic value is not statistically significant when within-strategy return correlation is explicitly considered.

Next, we relax both (1) and (3) above and estimate alphas 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 results.

[Insert Figure 9 here]

Two interesting facts emerge; first, the estimated alphas are significantly larger than the fixed-effects obtained from a panel regression (see Figure 5). This suggests that the short time series available for some of the funds may generate a small-sample bias in univariate OLS estimates. Second, the cross-sectional distribution of the t-statistics shows some evidence of skill vs. luck, that is, the distribution of actual t-statistics is shifted above a standard 5% significance threshold. Interestingly, this result is similar to the one obtained from a panel regression without clustered standard errors. This suggest that taking into account the cross-correlation of the fund returns turn out to be crucial to assess the managers' performance. Indeed, by coupling together the mid panel of Figure 5 and the right panel of Figure 9, one can assume that the overlapping investment opportunity sets within a given strategy make returns correlations particularly relevant for the statistical significance of managers' skills.

5.2 Using factor portfolios

The vast majority of the literature on mutual funds uses factor portfolios to disentangle the alpha from simple exposures to sources of systematic risk. Within the context of cryptocurrency markets, factor portfolios do not necessarily represent feasible investment strategies given the large investment frictions and costs retailers should face to implement typical long-short investment strategies based on momentum, liquidity, volatility, etc.

However, one may argue that there is ambiguous evidence on which asset models investors may use to assess individual fund performances. Therefore, it can still be useful to benchmark fund returns against factor portfolios (see, e.g., Barber et al., 2016; Berk and Van Binsbergen, 2016). In other words, by using risk factors, we can nevertheless compare our main results to a more common approach, which employs hypothetical risk factor portfolios.

To address this issue, we implement our bootstrap approach replacing the set of benchmark returns with a set of risk factor portfolios. 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 returns on a value-weighted portfolio of the 300 cryptos. We then consider both the returns on a cross-sectional momentum strategy (MOM) as outlined by Jegadeesh and Titman (2001) and a simple reversal strategy that goes long on past losers and short on past winners (see De Bondt and Thaler, 1985).[24]

[24] As far as the momentum strategy is concerned, the look-back period l is set to 6 months and maximum leverage equal to 125%. For each cryptocurrency pair i at time t, if the cumulative log return over the previous 180-days is positive, it signals a long position and vice versa. The skipping period for the returns calculation is one month after the portfolio is constructed.

In addition, we consider two additional sources of risk that are relevant in cryptocurrency markets: liquidity and volatility (see Bianchi and Dickerson, 2019). A relatively convenient way to proxy for liquidity risk would be to use high frequency information on bid-ask spreads. In the cryptocurrency space, such information is not easily available at the aggregate level. Bid-ask spreads on a single currency, at a given point in time, could substantially change across exchanges generating fictitious arbitrage opportunities that are difficult to exploit in practice (see, e.g., Makarov and Schoar, 2020). For this reason, we follow Abdi and Ranaldo (2017) and Corwin and Schultz (2012) and proxy bid-ask spreads by using the aggregate Open-High-Low-Close historical pricing data. In particular, for each day and for each of the 300 cryptocurrency pairs, we calculate both the Abdi and Ranaldo (2017) and the Corwin and Schultz (2012) synthetic bid-ask spreads and take the average of the two measures for a given digital asset. Next, we single sort each pair into quintiles based on the average measure. A risk factor is then constructed by going long an equal-weight portfolio of illiquid pairs (fifth quintile) and going short into the liquid pairs (first quintile), again with equal weights. This zero-cost long-short portfolio represents our liquidity factor portfolio.

As far as the volatility 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. 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 persistence of benchmark and factor returns is virtually zero, adding to the conjecture that our main bootstrap approach may not require a block-based resampling of returns and benchmarks/factors.

Figure 10 reports the actual values (light-blue bars) as well as the bootstrap values (light-red bars) of both $\hat{\alpha}$ (left panel) and $\hat{t}_{\hat{\alpha}}$ with (right panel) and without (mid panel) standard errors clustered by investment strategy. The economic magnitude of $\hat{\alpha}$ is rather similar to that obtained using the benchmark strategies. The bulk of alphas are concentrated around an average value of 3.5% on a monthly basis; however, there is a sizable amount of outlying funds with performance well above 10% on a monthly basis.

[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 left panel in Figure 10 shows that the fraction of funds with significant alphas is slightly higher when using factor portfolios rather than benchmark strategies. As show in the middle and right panels, sampling variation, or luck, cannot explain the performance of the few outlying funds. However, there is still overall weak statistical significance of the individual fund performances.

5.3 Time-series dependence in fund returns

Our main bootstrap procedure assumes that the residuals are only weakly autocorrelated. Tables 1-4 and a bottom panel of Figure 4 show that the persistence of fund returns is low compared to traditional equity mutual funds. The persistence of fund returns is also explored in more detail in Appendix B where we look at the autocorrelation function up to 20 lags for different types of funds and investment strategies.

For the sake of completeness, in this section we further explore the sensitivity of our results to the possibility of some conditional dependence in fund returns. Specifically, we compare the results of the main bootstrap procedure to its modification where we re-sample returns in blocks of a fixed size. More details on the procedure can be found in

Appendix A.2. Due to the short history of data, we set the length of the blocks equal to three months (if the length of the historical data for a specific fund is not a divisor of 3, one of the blocks will contain one or two observations only). With the only exception of market neutral funds, this is largely consistent with the small auto-correlation of returns shown in Figure B.1.

[Insert Figure 11 here]

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

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. This approach breaks any possible time correlation between explanatory returns and model residuals. As outlined in Kosowski et al. (2006), such a correlation could possibly arise if the performance model specified does not fully capture the set of possible explanatory factors.

The extended bootstrap approach works as follows; let T_{0i} and T_{1i} represent the dates of the first and the last available returns for the fund i, respectively. For each fund i, we draw one sample with replacement from the fund residuals $\left\{\hat{\epsilon}^b_{it};\ t_\epsilon = s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}\right\}$, and one *separate* sample with replacement from the benchmark returns $\left\{\boldsymbol{x}^b_t;\ t_x = \tau^b_{T_{0i}}, \ldots, \tau^b_{T_{1i}}\right\}$. Note that the indicators $s^b_{T_{0i}}, \ldots, s^b_{T_{1i}}$ and $\tau^b_{T_{0i}}, \ldots, \tau^b_{T_{1i}}$ 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 $\hat{t}_{\hat{\alpha}}$ with and without clustered standard errors (right and mid panel, respectively). The results are virtually the same as in the main empirical analysis, that is there is some evidence of economic value for the best performing funds, but such evidence is not statistically significant when within-strategy returns correlation is explicitly acknowledged.

6 Conclusion

This paper provides the first examination of the value of active asset management in a new and unregulated asset class such as cryptocurrencies. 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 which takes into account specific features of cryptocurrency funds such as outlying returns and within-strategy correlations. In our empirical investigation, we measure the value of fund managers through their ability to generate positive and significant alphas.

We consider a set of benchmark strategies to extract the value of the active investment management. Our results show that a sizable minority of managers can generate the performance covering their cost and possibly could create a positive value for investors. However, once within-strategy correlations among fund returns is taken into account, there is weak statistical significance in favour of managers' performance, that is there is weak evidence of significant and positive alphas even for the best performing funds.

While existing research has long been debating the value of active management in traditional asset classes, no study has tested the existence of such a value in the new and fast-growing industry of cryptocurrency funds. This paper fills this gap and conducts the first comprehensive statistical analysis of active investment management in crypto funds by extending the bootstrap approach outlined by Kosowski et al. (2006) and Fama and French (2010).

References

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

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

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

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

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

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

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

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

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

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

Bernstein, P. L. (1998). Where, oh where are the. 400 hitters of yesteryear? *Financial Analysts Journal*, 54(6):6–14.

Bianchi, D. (2020). Cryptocurrencies as an asset class: An empirical assessment. *Journal of Alternative Investments*, forthcoming.

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

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

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

Bollen, N. P. and Busse, J. A. (2001). On the timing ability of mutual fund managers. *The Journal of Finance*, 56(3):1075–1094.

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

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

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

Cheng, S., Nagar, V., and Rajan, M. V. (2005). Identifying control motives in managerial ownership: Evidence from antitakeover legislation. *The Review of Financial Studies*, 18(2):637–672.

Chordia, T., Roll, R., and Subrahmanyam, A. (2008). Liquidity and market efficiency. *Journal of Financial Economics*, 87(2):249–268.

Chordia, T., Roll, R., and Subrahmanyam, A. (2011). Recent trends in trading activity and market quality. *Journal of Financial Economics*, 101(2):243–263.

Conrad, J., Wahal, S., and Xiang, J. (2015). High-frequency quoting, trading, and the efficiency of prices. *Journal of Financial Economics*, 116(2):271–291.

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

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

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

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

DeMiguel, V., Garlappi, L., and Uppal, R. (2009). Optimal versus naive diversification: How inefficient is the 1/n portfolio strategy? *The review of Financial studies*, 22(5):1915–1953.

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

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

Dyck, A., Lins, K. V., and Pomorski, L. (2013). Does active management pay? new international evidence. *The Review of Asset Pricing Studies*, 3(2):200–228.

Dyhrberg, A. H. (2016). Bitcoin, gold and the dollar - a garch volatility analysis. *Finance Research Letters*, 16:85–92.

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

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

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

Getmansky, M., Lo, A. W., and Makarov, I. (2004). An econometric model of serial correlation and illiquidity in hedge fund returns. *Journal of Financial Economics*, 74(3):529–609.

Glode, V. (2011). Why mutual funds "underperform". *Journal of Financial Economics*, 99(3):546–559.

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

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

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

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

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

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

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

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

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

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

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

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

Kothari, S. and Warner, J. B. (2001). Evaluating mutual fund performance. *The Journal of Finance*, 56(5):1985–2010.

Linnainmaa, J. T. (2013). Reverse survivorship bias. *The Journal of Finance*, 68(3):789–813.

Liu, Y. and Tsyvinski, A. (2018). Risks and returns of cryptocurrency. Technical report, National Bureau of Economic Research.

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

Lynch, A. W. and Musto, D. K. (2003). How investors interpret past fund returns. *The Journal of Finance*, 58(5):2033–2058.

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

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

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

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

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

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

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

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

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

Pedersen, L. H. (2018). Sharpening the arithmetic of active management. *Financial Analysts Journal*, 74(1):21–36.

Petersen, M. A. (2009). Estimating standard errors in finance panel data sets: Comparing approaches. *The Review of Financial Studies*, 22(1):435–480.

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

Politis, D. N. and Romano, J. P. (1994). The stationary bootstrap. *Journal of the American Statistical association*, 89(428):1303–1313.

Schwenkler, G. and Zheng, H. (2020). Competition or contagion? evidence from cryptocurrency peers. *Evidence from Cryptocurrency Peers (April 10, 2020).*

Sharpe, W. F. (1991). The arithmetic of active management. *Financial Analysts Journal*, 47(1):7–9.

Sharpe, W. F. (2013). The arithmetic of investment expenses. *Financial Analysts Journal*, 69(2):34–41.

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

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

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

Table 1: **A first look at crypto fund 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 $\alpha_{t,k} = y_{t,k} - \hat{\boldsymbol{\beta}}_k^{\prime} \boldsymbol{x}_t$. 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.

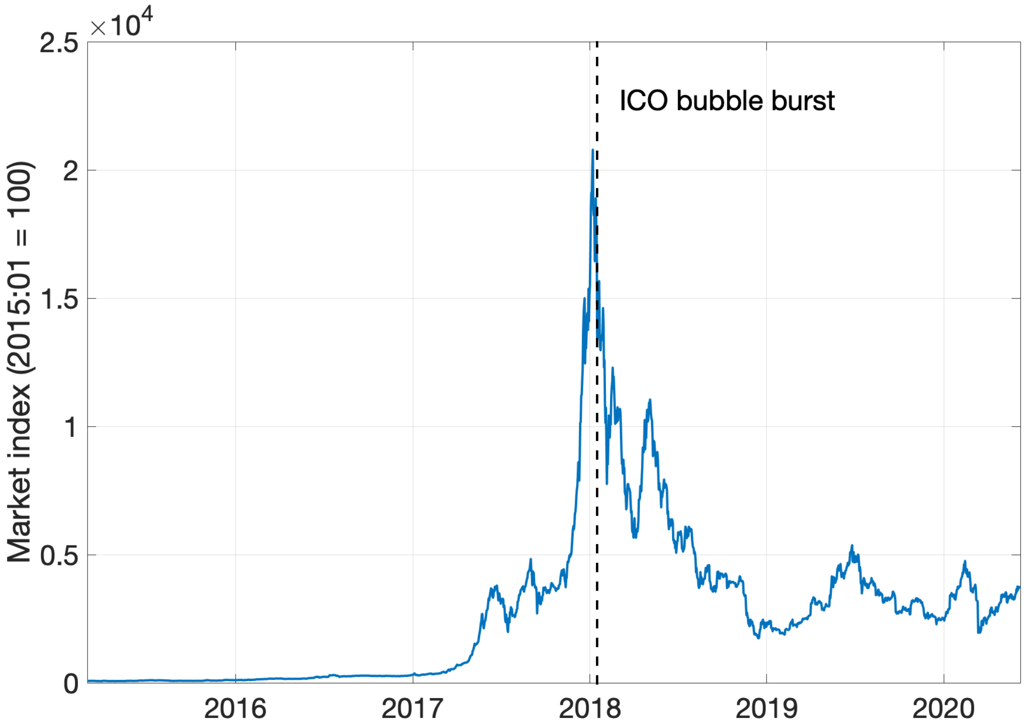
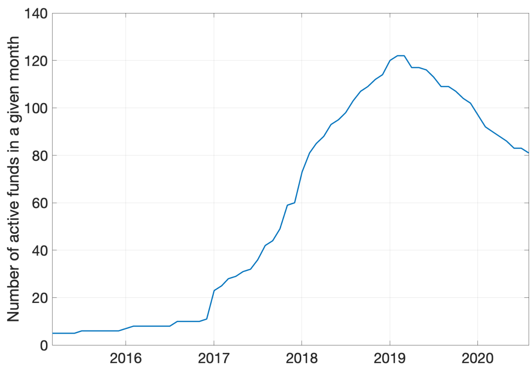
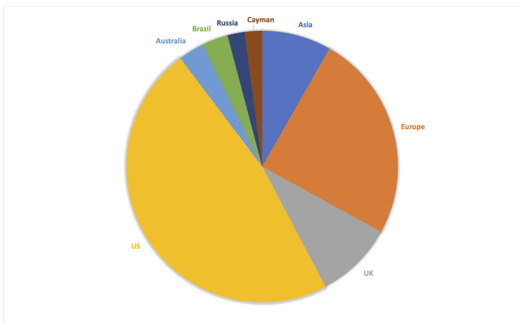


Figure 2: **A snapshot of the sample of funds**

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.



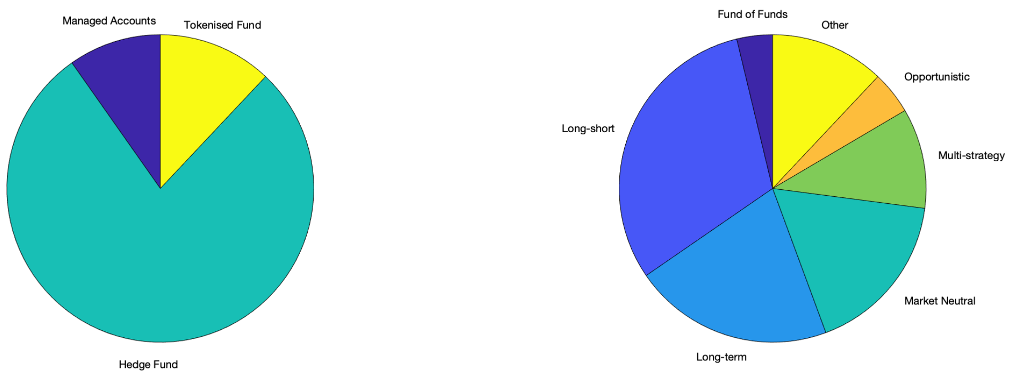
(a) Number of funds



(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.

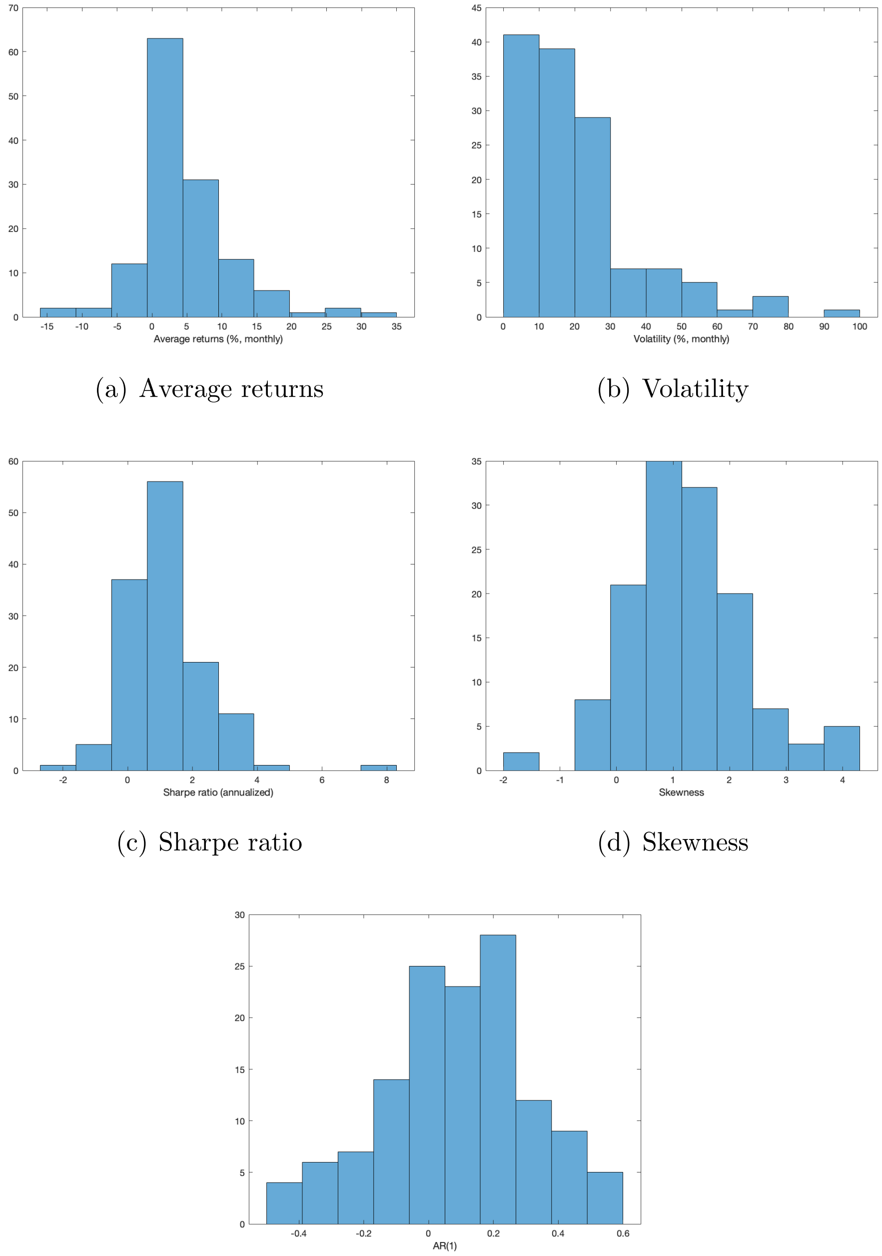


(a) Funds by type

(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

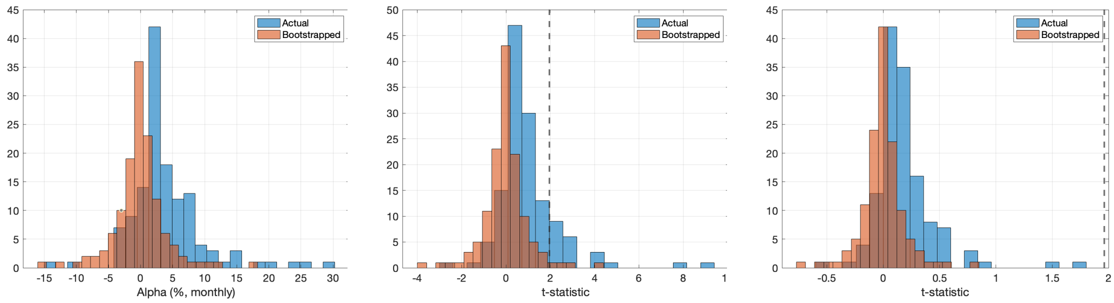
(c) Sharpe ratio

(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.

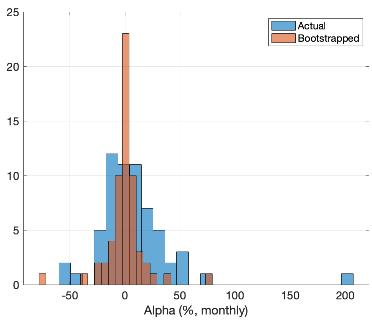


(a) Alpha (b) Standard t-statistics (c) Clustered standard errors

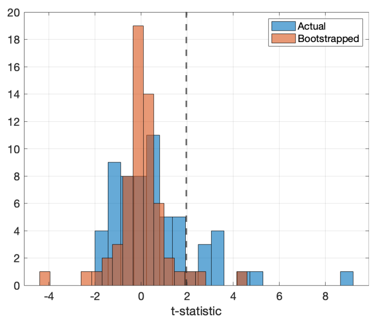
Figure 6: **The cross-section of benchmark-adjusted alphas across sub-samples**

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.

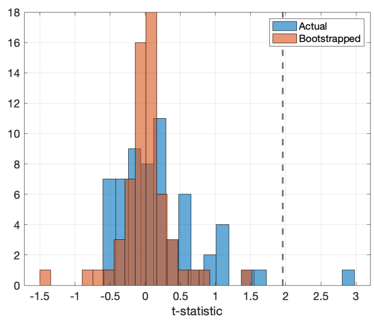
Sample until Dec 2017



(a) Alpha

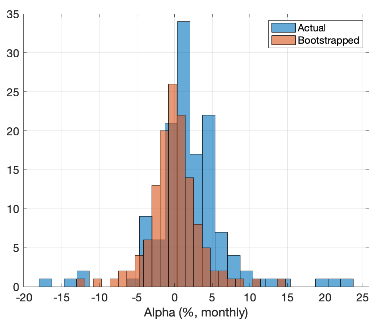


(b) Standard t-statistics

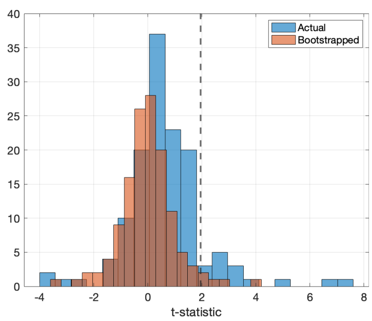


(c) Clustered standard errors

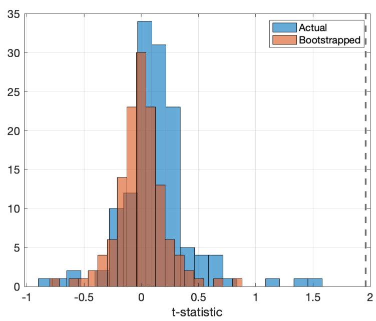
Sample from Jan 2018



(d) Alpha



(e) Standard t-statistics

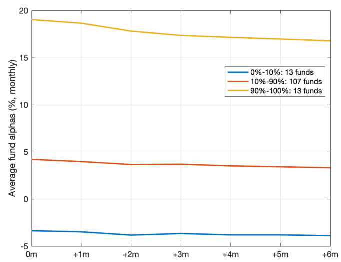


(f) Clustered standard errors

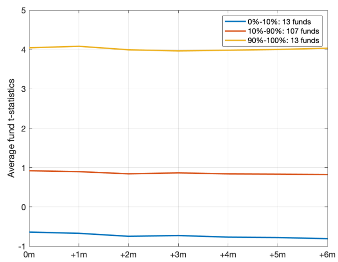
Figure 7: **Persistence of benchmark-adjusted alphas**

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.

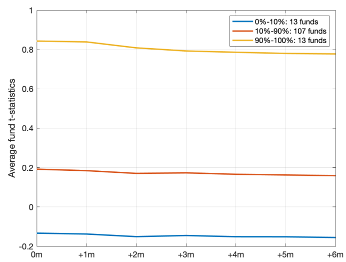
Panel A: Short-term persistence



(a) Alpha

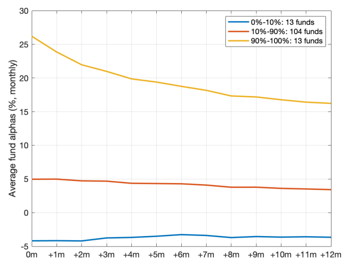


(b) Standard t-statistics

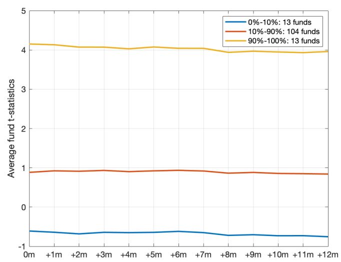


(c) Clustered standard errors

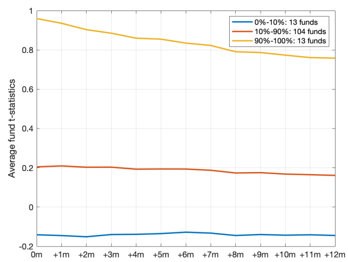
Panel B: Long-term persistence



(d) Alpha



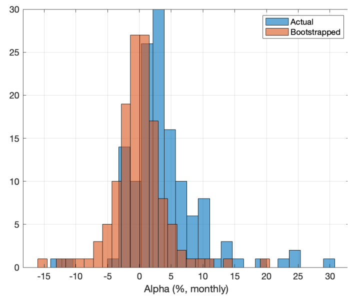
(e) Standard t-statistics



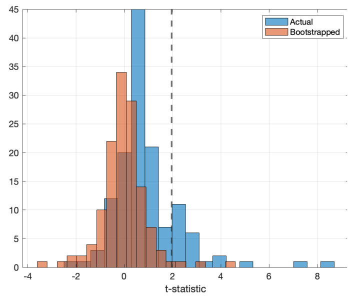
(f) Clustered standard errors

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

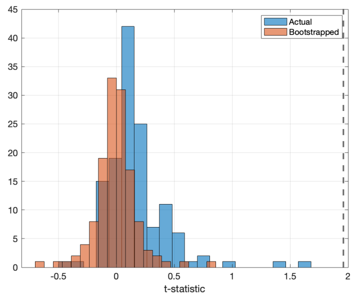
This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. Unlike the main empirical analysis the betas on the benchmark portfolios are restricted to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



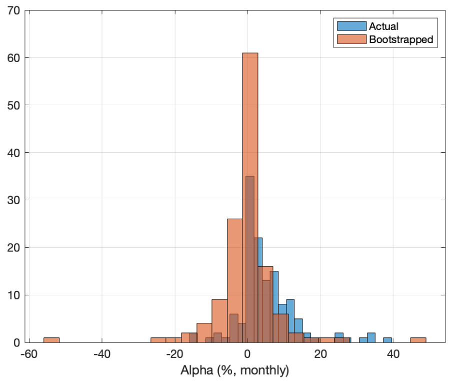
(b) Standard t-stats



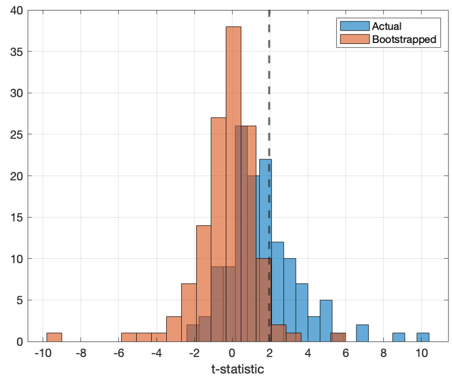
(c) Clustered t-stats

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.



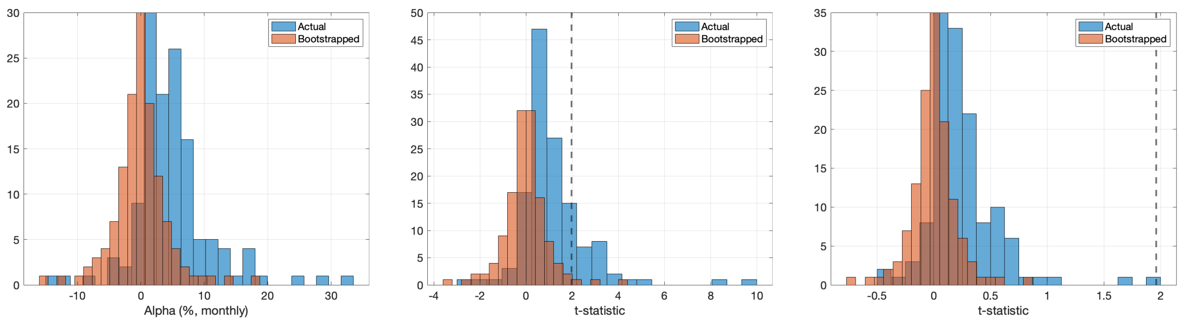
(a) Alpha



(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.

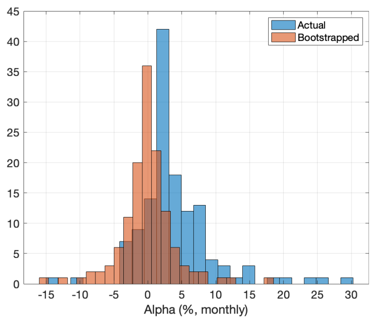


(a) Alpha (b) Standard t-statistics (c) Clustered standard errors

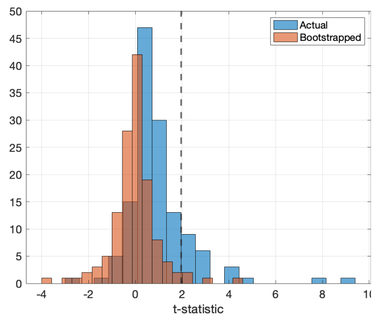
Figure 11: **The cross-section of fund alphas using alternative bootstrap procedures**

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.

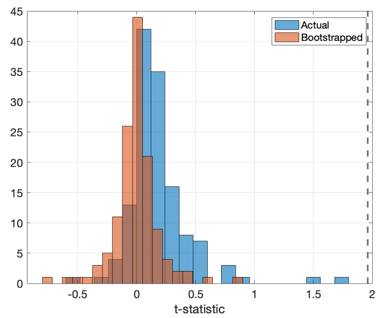
Panel A: Block bootstrap



(a) Alpha

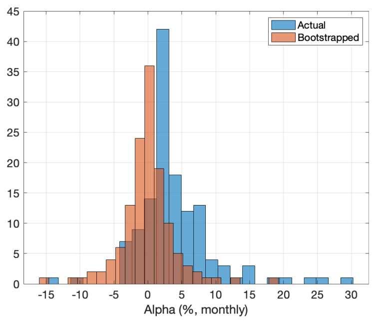


(b) Standard t-statistics

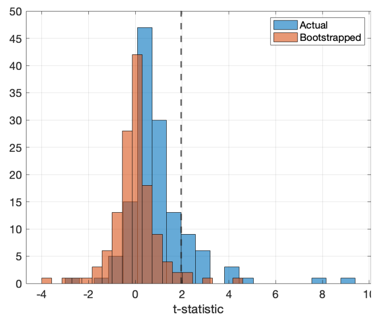


(c) Clustered standard errors

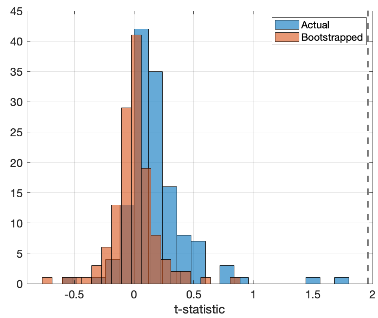
Panel B: Independent resampling of benchmark returns and residuals



(d) Alpha



(e) Standard t-statistics



(f) Clustered standard errors

Abstrakt

Zkoumáme výkonnost fondů, které se zaměřují na trhy s kryptoměnami. Naší prací přispíváme ke stále se rozšiřující literatuře věnované pochopení role digitálních aktiv jakožto investičních instrumentů. Implementujeme novou metodologii založenou na boostrapu, který provádí sdružený výběr průřezových rozdělení alf a bere v potaz nenormální rozdělení výnosů fondů a jejich korelaci v rámci obchodní strategie. Zjišťujeme, že významná menšina správců fondů je schopna pokrýt náklady fondu a generovat vysoké hodnoty alf. Nicméně, nacházíme pouze slabý statistický důkaz o schopnostech manažerů, pokud je brána v potaz společná variace v rámci obchodní strategie.

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