No cryptocurrency experience required: managerial characteristics in cryptocurrency fund performance

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Abstract

This paper investigates the determinants of cryptocurrency fund performance, where we compile a unique dataset of cryptocurrency fund performance and characteristics of the funds and managers. We document substantial differences in cryptocurrency fund manager ability in terms of monthly excess returns as well as risk-adjusted returns. In particular, we find that managers with a PhD and MBA tend to generate significantly higher excess returns and higher risk-adjusted returns while PhD managers are also riskier. Further, our results show that managers with previous hedge fund experience generate significantly higher appraisal ratios indicating their investment-picking ability obtained from their previous experience. However we find that cryptocurrency experience offers no explanatory power indicating that trading cryptocurrencies successfully does not require any specific knowledge in this area. Overall, our findings are consistent with the conventional wisdom that manager qualifications and experience play a significant role in fund performance.

Keywords: Cryptocurrencies; Active Investment Management; Managerial Characteristics; Hedge Funds; Alternative Investments

JEL Codes: G12; G17; E44

1. Introduction

Cryptocurrencies have experienced tremendous growth in the past decade in terms of media exposure and investor attention, mostly due to their innovative features, dramatic price rise and sustained volatility. Bitcoin, the most famous and earliest cryptocurrency, was originally developed in a white paper by Nakamoto (2008) and came into existence in 2009. Since then, the market for cryptocurrencies has skyrocketed with over 6,000 cryptocurrencies being traded with a total market capitalization of over $2 trillion.[1,2] Given the sheer size and growth of the cryptocurrency ecosystem, not only have individual investors traded cryptocurrencies but new types of funds have been created that solely invest in cryptocurrencies. These cryptocurrency funds (crypto funds for short) have emerged enabling investors to gain exposure to active management of cryptocurrencies. The market for crypto funds has grown substantially over the last few years with the 2020 PWC report estimating that the total assets under management (AUM) of crypto funds increased to over $2 billion in 2019 from $1 billion the previous year.[3]

In this paper, we examine the performance of crypto funds and specifically provide a comprehensive analysis of the impact of manager characteristics on crypto fund performance. This is an important and growing area and we perform the first study examining the determinants of the performance of crypto funds. Using monthly crypto fund data, we investigate the performance of crypto funds and provide an analysis of the determinants of their returns, volatility and risk-adjusted returns. To do this, we construct a novel dataset of crypto funds as well as background information on the managers' of the crypto funds over the period January 2017 to December 2020. This time span offers an interesting period to study as it captures the upturn in the Bitcoin market during the second half of 2017 and the subsequent drop in price during 2018 and bull market of 2020. We collect data of fund specific characteristics as well a managerial characteristics to examine the determinants of cryptocurrency fund performance.

[1]Sourced from www.coinmarketcap.com in April 2021.

[2]There is a growing literature on the behaviour of initial coin offerings (ICOs) such as Philippi et al. (2021) and for recent review, Corbet and Cumming (2020) and for a literature survey on fintech in general, see Allen et al. (2021).

[3]The PWC crypto hedge fund report can be found at https://www.pwc.com/gx/en/financial-services/pdf/pwc-elwood-annual-crypto-hedge-fund-report-may-2020.pdf.

We employ Fama and MacBeth (1973) regressions and show that managers with an MBA and PhD education both generate significantly higher monthly excess returns than managers without such qualifications. Further, managers with cryptocurrency experience generate significantly lower excess returns than managers without such experience. However once we study the risk-adjusted returns of the crypto funds, we find that managers with a PhD significantly outperform their peers, while hedge fund experience is also a significant determinant of risk-adjusted returns of the crypto funds. This suggests that previous experience in the investment industry is an important factor in determining the performance of crypto funds while previous cryptocurrency experience offers little explanatory power. We also study the appraisal ratio and find evidence consistent with our previous findings that hedge fund experience is a significant determining factor of crypto fund performance, indicating their investment-picking ability obtained from their previous experiences.

We perform several additional tests to evaluate the robustness of the results. We also consider the ranking of the institution in which the manager received their education from and find that managers that attended highly ranked institutions generate significantly higher appraisal ratios indicating their stock-picking ability. We also consider alternative benchmarks as well as alternative estimation periods and our baseline results are robust to these alternative specifications.

Our paper contributes to the broad literature on upper echelons theory, which states that organization outcomes, such as strategies choices and performance levels, are partially predicted by the background, education and characteristics of the top executives (Hambrick and Mason, 1984). Education has also been described as a reasonable measure of human capital since it reflects not only the information learned, but also the intellectual competence of an individual (Becker, 1994). Many empirical papers have found that the education of managers has a significant impact on future performance. For instance Chevalier and Ellison (1999) show a positive relationship between managers' education and mutual fund performance while Gottesman and Morey (2006) show managers who hold MBAs from schools ranked in the top 30 of the Business Week rankings of MBA programs exhibit performance superior to the performance of both managers without MBA degrees and managers holding MBAs from unranked programs. Li et al. (2011) show that hedge fund managers with higher-SAT undergraduate institutions tend to generate higher raw and risk-adjusted returns while King et al. (2016) show that bank CEOs with MBAs outperform their peers by arguing that management education delivers the skills required to manage large banks and achieve successful performance. Recently, Adams and Jiang (2017) show that CEOs in the UK insurance industry with insurance and financial expertise enhance the financial performance of the firm while Kang et al. (2018) show that hedge fund managers who majored in business or economics outperform other managers. In regards to IQ, a couple of papers find that IQ influences the trading behaviour and performance of investors (Grinblatt et al., 2012, Corgnet et al., 2018, Talpsepp et al., 2020). In our paper, we are the first to study the background and education of managers of crypto funds and find robust evidence that these characteristics have a significant impact on the performance of crypto funds. However importantly, we find that cryptocurrency experience offers no explanatory power which suggests that cryptocurrencies are no different to stocks in terms of trading. This suggests that hedge fund managers with no experience in cryptocurrencies

Our analysis relates to the large literature on the determinants of hedge fund performance. There is evidence that larger hedge funds outperform smaller funds (Amenc and Martellini, 2003, Koh et al., 2003) while there is contrary evidence that smaller funds outperform larger funds (Agarwal et al., 2009, Ammann and Moerth, 2005, Harri and Brorsen, 2004, Scheweis et al., 2002). Research has also found that funds with higher fees also generate higher returns for their investors (Achermann et al., 1999, Amenc and Martellini, 2003, Bae and Yi, 2011, Joenvaara et al., 2012) while Aragon (2007) finds that funds with lockup periods outperform funds without any lockup periods.[4] Sun et al. (2012) study whether skilled hedge fund managers are more likely to pursue unique investment strategies that result in superior performance. They propose a measure of distinctiveness of a fund's investment strategy and show that the higher the distinctiveness of a fund, the better the subsequent performance. DeVault and Sias (2017) show that the political orientation and psychological traits of hedge funds are related to their portfolio decisions while Bussière et al. (2015) find that hedge funds with high commonality exhibit negative returns in the future and therefore offer little diversification benefits to the financial system and to investors. Heuson et al. (2020) show that fund-specific return skewness is associated with managerial skills

[4] For a review on hedge fund performance attribution, see Stafylas et al. (2016).

and future fund performance.

Our work contributes to the ever-growing literature surrounding cryptocurrencies and their impact on financial markets.[5] Early papers studied the inefficiency of cryptocurrencies (Urquhart, 2016, Bariviera, 2017, Duan et al., 2021), their relationship with other assets (Corbet et al., 2018, Urquhart and Zhang, 2019) and the economics of Bitcoin (Dwyer, 2015). Makarov and Schoar (2020) show large arbitrage opportunities across cryptocurrency exchanges while Detzel et al. (2021), Hudson and Urquhart (2021), Li et al. (2021), Shen et al. (2022) all show the trading benefits of cryptocurrency. Cryptocurrencies have also been found to exhibit volatility jumps (Gronwald, 2019, Shen et al., 2020a), be used for illegal transactions (Foley et al., 2019) and as an attractive investment asset (Kajtazi and Moro, 2019, Hu et al., 2019, Platanakis and Urquhart, 2020). However only one paper to our knowledge examines crypto funds. Bianchi and Babiak (2020) examine the risk-return relationship of crypto funds and show that only a small fraction of the funds are able to generate significant and persistent risk-adjusted returns after controlling for sources of systematic risks. They show that active management hardly generates significant value for investors. Therefore we broaden the literature on this new type of fund and provide a thorough study on their determinants of the performance. Our work adds to this literature and provides the first study on the determinants of crypto fund performance.

The remainder of the paper proceeds as follows: Section 2 presents the related literature and hypothesis development while 3 describes the data and methodology. Section 4 reports and discusses the findings while Section 5 provides some robustness analysis. Section 6 summarizes and concludes the paper.

2. Related literature review and hypothesis development

2.1. Manager Education and Performance

Upper echelons theory, proposed by Hambrick and Mason (1984) argues that managers' experience, values and cognitive ability affect their strategies choices and in turn are reflected in firm outcomes and performance. Research in this area has found a host of characteristics that have

[5] For a recent review of the literature of cryptocurrencies, see Corbet et al. (2019).

impacted performance such as career experiences (Custódio and Metzger, 2014, Cumming et al., 2015, Li and Patel, 2019), overconfidence (Hirshleifer et al., 2012, Arena et al., 2018, Chen et al., 2019), masculinity (Jia et al., 2014, Kamiya et al., 2019), emotional traits (Delgado-García et al., 2010) and even the hobbies of managers (Cain and McKeon, 2016, Brown et al., 2018).

One area that has received attention in the literature has been the education of managers where Chevalier and Ellison (1999) shows a positive relationship between managers' education and mutual fund performance where managers with undergraduate degrees from the highly respected Ivy League universities generate higher risk-adjusted returns. Bhagat et al. (2010) show that the market price of stocks increase after the announcement of CEOs with stronger education credentials than the previous CEO, generating significant abnormal returns while King et al. (2016) reports the banks with CEOs with MBAs outperform their peers by arguing that the management education delivers the skills required to manage large banks and achieve successful performance.Adams and Jiang (2017) shows that CEOs in the UK insurance industry with insurance and financial expertise enhance the financial performance of the firm while Fedaseyeu et al. (2018) shows that more qualified directors handle more board functions, resulting in higher pay.

There is also a growing literature on exploratory mindset of individuals and the importance of this behaviour for top executives when the firm is making investment decisions on projects with long-term value. For instance, a recent paper by He and Hirshleifer (2022) argues that CEOs with PhD degrees engage in more innovative projects and tend to be hired by firms that have strong innovative opportunities as these firms might seek out innovative CEOs for there business needs. Recently, Urquhart and Zhang (2021) show that firms with a CEO that holds a PhD significantly outperform firms without such CEOs. The opportunity costs of doctoral education are five years or more in the US that could be spent in a career earning monetary rewards. Research, developing and testing new independent research for a dissertation is an exploratory task that involves novel ideas and problem solving skills. Cryptocurrencies are innovative assets that use blockchain technology to offer individuals the ability to trade without the need of a higher regulatory body. Investors, who are interested in innovation, will be attracted to cryptocurrencies pioneering characteristics such as decentralization, anonymity and transparency. Hence there is a prior that managers who have PhD are more exploratory and innovative and therefore be more attracted and able to understand cryptocurrencies. Therefore, our first hypothesis posits that crypto fund managers with a PhD are able to outperform managers without such an advanced qualification.

H1: Managers with a PhD outperform those managers without such an experience

2.2. Manager Hedge Fund Experience and Performance

Also related to the upper echelons theory is the past work experience of managers where it is argued that managers with a relevant experience are more likely to succeed than managers without such an experience. The literature is abound with studies finding that CEOs and managers with certain backgrounds outperform such as Custódio and Metzger (2014) who find that CEOs with past financial experience have more financial expertise while Kang et al. (2020) show that appointing directors with CEO same industry experience enhances the value of the firm. There is also evidence that the foreign experience of managers and CEOs improve their performance as Lee and Kroll (2017) find that time abroad had a positive effect on strategic change and firm performance, while number of countries and cultural distance positively moderated these relationships while Conyon et al. (2018) show that CEOs with foreign experience earn higher compensation than their peers which is attributable to the specialized foreign expertise and foreign networks of CEOs, which stem from foreign experience rather than broader general managerial skills.

Therefore it is expected that managers with past experience in a relevant field may be beneficial to firms. This may be especially beneficial in terms of trading cryptocurrencies. There is a growing literature examining cryptocurrencies and lots of the evidence suggests that cryptocurrencies behave very similarly to traditional assets. There is strong evidence of that traditional technical trading rules, which have been found to very successful in traditional markets such as equity and foreign exchange markets, are successful at predicting cryptocurrency returns (Hudson and Urquhart, 2021, Ahmed et al., 2020). Further, cryptocurrencies have been found to have similar characteristics as traditional assets, such as momentum (Tzouvanas et al., 2020), trading volume driven by investor sentiment (Bianchi and Babiak, 2020), jumps (Chaim and Laurini, 2018, Shen et al., 2020a, Scaillet et al., 2020) and price clustering (Urquhart, 2017, Baig et al., 2019). Therefore, we suggest that trading cryptocurrencies may not be that different to trading traditional assets and that managers who have a previous experience in hedge funds are better equipped to trade cryptocurrencies than managers without such experiences. Therefore, our second hypothesis posits that crypto fund managers with previous experience in hedge fund trading are able to outperform managers without such a background.

H2: Managers with hedge fund experience outperform managers without such an experience

2.3. Manager Education and Risk

Related to our first hypothesis, we also postulate that managers with a PhD may be more inclined to incur more risk. Given the exploratory mindset of individuals who undertake a PhD, as suggested by He and Hirshleifer (2022), managers with a PhD may be willing to undertake more risks. Beber and Fabbri (2012) find that overconfident directors with an MBA degree may be willing to take more risk while Lin et al. (2011) find a positive relationship between a CEO's educational background and private companies' innovation in China. Farag and Mallin (2018) find that CEOs of Chinese IPOs with postgraduate qualifications are more likely to consider risky decisions. This is supported by the study by Orens and Reheul (2013), who find that highly educated CEOs are likely to be less risk-averse, open-minded to new innovative business ideas and better informed about their external environment. Therefore our third hypothesis posits that crypto fund managers with a PhD take on more risk than managers without such an experience.

H3: Managers with a PhD take on more risk than those managers without such an experience

3. Data and Methodology

3.1. Fund Data

We obtain monthly return data on a variety of cryptocurrency funds from Crypto Fund Research, a data provider that provides cryptocurrency fund data and research. Our sample period is from January 2017 to December 2020 thereby capturing 48 months of fund data.[6] Our selection of funds covers cryptocurrency hedge funds (HF), Tokenised Funds (TK), funds of funds (FoF), managed accounts (MA), mutual funds (MF) and index funds (IF). Similar to Bianchi and Babiak (2020), we remove venture capital (VC) and private equity (PE) funds since data is quite sparse throughout the sample and these types of funds focus on long-term investments in ICOs, whereas the other funds focus on more active firms of delegated investments.[7]

We implement a number of filters to our data to ensure it is sufficiently representative of management of cryptocurrency funds. First, we include only those funds with at least 6 months of consecutive returns data. Second, the sample includes both those funds that are actively quoted but also funds that disappeared before the end of the sample, thereby avoiding survivorship bias. Third, we only consider funds in which we can collect all variables for since some funds in the sample fail to report some important variables in our study. In the end, we have data on 119 crypto funds. Figure 1 presents are final funds included in our sample.

We collect data from Crypto Fund Research on the monthly returns, age, management fees, performance fees, high water mark hurdle, minimum investment, lockup period, whether investors need to be accredited of the cryptocurrency funds and the number of employees of the funds. We also collect information on the age of the crypto funds (in months) where we use the 31st December 2020 as the cut-off point. We also collect data on the managerial characteristics from Crunchbase, Linkedin, and the website of the cryptocurrency funds.[8] Specifically, we collect data on the gender of the manager as well as the age. To calculate age, we follow Ewens and Townsend (2020) by using the year of graduation from their undergraduate studies as a fairly accurate proxy for age (assuming individuals are 22 at graduation). We collect information of their subject of their university education and create dummy variables to denote whether the individual studied

[6]Our data sample start date is restricted due to data before this date not being available from Crypto Fund Research.

[7]The hedge fund literature, for example Cremers et al. (2019), often removes funds with a longer-term investment focus and restricts the analysis to active forms of investment.

[8]While we do have information for some funds AUM, we do not have data for over half the sample even after looking through fund prospectuses. A PWC report (https://www.pwc.com/gx/en/financial-services/fintech/assets/pwc-elwood-2019-annual-crypto-hedge-fund-report.pdf) does report information of AUM but we are unable to retrieve their data.

an Economics, Finance or Banking degree, a law degree, a computer science degree or an other degree. We also collect information on whether the manager has an MBA or a PhD.[9] Finally, we collect data on whether the has previous experience of trading in a hedge fund where this is a dummy variable equal to one if the manager has previous worked in a trading capacity. Finally, we collect information on whether the manager has previous blockchain or cryptocurrency experience as specified in their website profile, Linkedin profile or Crunchbase profile where we create a dummy variable equal to 1 if the manager has specified blockchain or cryptocurrency experience.[10] Table 1 presents our variables of interest, their definitions and their sources.

Table 2 reports the descriptive statistics of our variables of interest where Panel A presents the fund characteristics while the CEO characteristics are shown in Panel B. The monthly average return is 6.07% although there is a large variation in monthly average returns with the highest monthly return 465% and a lowest return of -75% indicating the large volatility in returns of cryptocurrency funds. Management fees are on average 1.49% while the average performance fee is 15.50% which range from 0% to 50%. Just over a quarter of our funds have a high water mark hurdle, while the average minimum investment in these funds is just below $200,000. The average lockup period is 4.07 months but some funds require no lockup period whatsoever. The average age of our funds is 32.70 months indicating that these funds are generally quite new companies in their infancy. The number of employees varies from 1 to 34 employed staff while the average is only 6.5, again indicating the relative size of these funds. We find that 98% of our managers are male while the average age is nearly 41 years old and 58% have an undergraduate degree in Economics, Finance or Business while only 9% report no undergraduate degree. Only 5% of the managers have a PhD while 22% have an MBA. Interestingly, 67% of our managers have previous experience in hedge funds and trading, while only 40% have cryptocurrency of blockchain experience. Figure 3 shows the monthly cross-sectional performance of the crypto funds where we document clear evidence that most funds exhibit positive Sharpe ratios and only a few funds have negative skewness.

[9] We did collect data on the subject of their PhD but all managers had a PhD in Mathematics.

[10] We did attempt to find social media data from twitter and reddit (in a way similar to Corbet et al. (2022) for stocks) on these funds but the data was very limited and therefore not included in our analysis.

To begin with, we conduct a simple univariate analysis, where we split our managers into two groups based on each variable of interest. Specifically, we place each manager either into a group with or without a certain characteristic or above or below the medium value and compare their differences. Table 3 reports the findings where we find that managers with PhDs significantly outperform managers without such as education level. This suggests that managers who have some research background and more innovative, as argued in He and Hirshleifer (2022), offer significantly higher returns than funds with managers without such high level degrees. We also find weak statistical evidence (at the 10% level) that managers without an Economics, Finance or Business undergraduate perform better than managers with such an education, while younger managers with MBAs generally outperform. Also, funds that do not have a high water mark hurdle perform better than firms with a hurdle. However this analysis is univariate and therefore does not control for other factors but provides a flavour of the relationship between crypto fund performance and their characteristics.

3.2. Methodology

The data we previously presented will be used to examine the relationship between cryptocurrency fund performance and manager characteristics. One challenge we face is adjusting cryptocurrency fund returns for risk since many studies have shown that standard linear asset pricing models fail to adequately capture the risk and return properties of most hedge funds and therefore we follow Li et al. (2011) and consider two broad classes of models to obtain risk-adjusted cryptocurrency fund returns.

In the first class of models, we use various cryptocurrency indices as benchmarks to adjust for risk in the cryptocurrency ecosystem. These indices may be able to capture the risk exposures of average cryptocurrency funds and automatically adjust for the nonlinearity in hedge fund returns. A main advantage of this approach is that we do not need to explicitly model the risk-taking behavior of hedge funds and that it is easy to implement in that investors can quickly compare the returns of individual funds with those of broad cryptocurrency fund indices. To obtain the risk-adjusted returns, we use the intercept term of regressions of individual cryptocurrency hedge fund returns on the returns on the indices, and the risk exposures as the regression coefficients or the loadings of the indices. We first construct a broad hedge fund index (CFRINDEX) which is the value-weighted average of returns of all cryptocurrency funds in our CFR where the weight is determined by the AUM of the previous month. Therefore this benchmark compares the fund in question to the other crypto funds in our sample.

We also construct a cryptocurrency index (CRYPTOINDEX) which is the value-weighted index of cryptocurrencies according to their market capitalization. Since there is an ever increasing number of cryptocurrencies available we create five different cryptocurrency indices consisting of the top 5 (CRYPTOINDEX5), top 10 (CRYPTOINDEX10), top 15 (CRYPTOINDEX15), top 25 (CRYPTOINDEX25) and top 50 (CRYPTOINDEX50) cryptocurrencies to mimic the return of a simple buy-and-hold strategy on a number of cryptocurrencies. To ensure that our findings are not drive just by the largest cryptocurrencies, we ensure that no single cryptocurrency can constitute a weighting of greater than 40% of the index.[11] We do not extend the benchmarks to any higher than 50 cryptocurrencies since beyond this, many cryptocurrencies are very small, illiquid and unlikely that crypto funds will invest in such coins.

The second class of benchmarks we consider includes the three factor model for cryptocurrencies of Shen et al. (2020b) as well as the common risk factors documented in Liu et al. (2019). Shen et al. (2020b) propose a three factor model consisting of market, size and reversal factors which strongly outperform the cryptocurrency-CAPM model and its performance is robust to different factor constructions. However Liu et al. (2019) find that three factors, namely the cryptocurrency market, size, and momentum, capture the cross-sectional expected cryptocurrency returns. Although they find that nine cryptocurrency factors form successful long-short strategies that generate significant returns, all of these strategies are captured by the cryptocurrency three-factor model. To get an overview of the performance of crypto funds compared to Bitcoin, Figure 2 provides a time-series plot where we can clearly see high correlation between the average return per month of crypto funds and Bitcoin.

Based on the previous benchmark models, we run time-series regressions for each fund to

[11] This is consistent with the indices created by CMC Markets. See https://www.cmcmarkets.com/en/cryptocurrencies/crypto-index for more details.

estimate its risk exposures to the various factors and the risk-adjusted returns. Then we take the estimated risk loadings and risk-adjusted returns as independent variables and run Fama and MacBeth (1973) regressions on various manager characteristics. More specifically, each month we use the past 6 monthly returns to run the following regression:

$$r_{i,t} = \alpha i + \beta_{i,q}^{'} f_t + \epsilon_{i,t} \tag{1}$$

where $r_{i,t}$ is the excess return of fund i over month t, $\beta_{i,q}^{'}$ represents the risk exposure of fund i at month q to the various factors and f_t is the monthly value of the different factors. In the same regression, we also calculate the residual volatility at month m, $\hat{\sigma}_{i,m}$ as:

$$\begin{aligned} \hat{\sigma}_{i,m} &= [var(\hat{\epsilon}_{i,t})]^{1/2} \\ \hat{\epsilon}_{i,t} &= .r_{i,t} - \hat{\alpha}_i - \hat{\beta}_{i,m}^{'} f_t \end{aligned} \tag{2}$$

where both $\hat{\alpha}_i$ and $\hat{\beta}_{i,m}^{'}$ are estimated in equation 1. In addition, we compute the $\alpha(\hat{\alpha}_{i,t}$ and appraisal ratio $(\hat{AR}_{i,t})$ of fund i at month t, respectively as,

$$\hat{\alpha}_{i,t} = r_{i,t} - \hat{\beta}_{i,t}^{'} f_q \tag{3}$$

$$\hat{AR}_{i,t} = \frac{\hat{\alpha}_{i,t}}{\hat{\sigma}_{i,t}} \tag{4}$$

where r_i, q is the excess return of fund i for month t, and f_t is the value of the various factors in month t.

Since the regression is done every month, we implicitly allow $\hat{\alpha}_{i,t}$, $\hat{\beta}_{i,t}$, $\hat{\sigma}_{i,t}$ and $\hat{AR}_{i,t}$ to be time varying. This allows us to capture potential variations over time in trading strategies of crypto funds under study. While $\hat{\beta}_{i,t}$ measures a fund's exposures to various systematic risk factors, $\hat{\sigma}_{i,t}$ measures the amount of idiosyncratic risk a fund takes. While $\hat{\alpha}_{i,t}$ measures a fund's abnormal return, $\hat{AR}_{i,t}$ measures the abnormal return per unit of idiosyncratic risk taken.

To explore the relationship between hedge fund performance and manager characteristics, the empirical analysis in this paper is mainly based on the Fama and MacBeth (1973) regression. As an alternative specification, we also conduct estimation using panel data regression with clustering.

Let $y_{i,t}$ represent one particular measure of hedge fund performance, which would be overall return volatility, factor loadings, raw excess returns, α, residual volatility or appraisal ratio at month t. Let Age_i be the age of the manager, $EFBUG_i$ is whether the managers has a undergraduate degree in economics, finance or business, PhD_i is managers who have a PhD, MBA_i refers to managers with an MBA, $HedgeExp$ and $CryptoExp_i$ refer to managers who have a working experience in the hedge fund or cryptocurrency fund industry, $FundAge_i$ refers to the age of the fund, $Employees_i$ is the number of employees in the firm while $Lockup_i$ and $Hurdle_i$ both refer to the lockup period and hurdle dummy respectively. We then estimate the following Fama and MacBeth (1973) regression for each month t:

$$\begin{aligned} y_{i,q} = b_0 + b_1 Age_i + b_2 EFB.UG_i + b_3 PhD_i + b_4 MBA_i + b_5 HedgeExp_i + \\ b_6 CryptoExp_i + b_7 FundAge_i + b_8 Employees_i + b_9 Lockup_i + b_{10} Hurdle_i + \mu_{i,t} \end{aligned} \tag{5}$$

4. Empirical Results

In this section, we explore the relationship between hedge fund performance and manager characteristics.

4.1. Results Based on Raw Returns

Table 4 reports the Fama and MacBeth (1973) regressions of raw excess returns and total return volatility as dependent variables in equation 5. The regression results reveal a strong positive relationship between managers with higher education qualifications and excess returns. Specifically, managers with PhDs generate significantly higher excess returns than managers without such an education of magnitude 12.9%. We also find weak statistical evidence (at the 10% level) that managers with a MBA outperform managers without such a qualification. Interestingly, we find little evidence that cryptocurrency experience or hedge fund experience offer any explanatory power.

We also examine the risk-taking behaviors of fund managers by using fund total return volatility as the dependent variable. Fund total return volatility is calculated as the volatility of monthly returns over the past 12 months and is updated every quarter. Given that certain hedge fund investors care only about absolute performance, total return volatility is a reasonable measure of fund risk and has the advantage of being model free. We find that funds run by younger managers are significantly more volatile than funds run by older managers while managers with cryptocurrency experience also run statistically more volatile funds than funds run with managers without such experience. Further, funds with a high water mark hurdle are significantly less volatile than funds without such a hurdle, indicating that funds without such a fee mechanism are more risky than funds with a hurdle. Therefore these results suggest that better educated managers can achieve higher returns and that the cryptocurrency experience of managers is a determining factor of the risk of the fund while younger managers also take more risks.

4.2. Results Based on Risk-Adjusted Returns

Although the results in Table 4 are interesting, raw hedge fund returns could be compensated by risk taking. For investors who are interested in selecting managers with positive abnormal performance, it is more interesting to study the relation between risk-adjusted returns and manager characteristics. In this section, we relate hedge fund risk-taking behaviors and risk-adjusted returns to manager education and other characteristics. While we use α to control for factor risks, we use residual volatility and appraisal ratio to control for non-factor risks.

Before we examine the cross-sectional differences in abnormal returns of Crypto funds, we first provide some distributional statistics on the αs under different benchmark models in Table 5. At the end of each month, we calculate the α of each hedge fund as in equation 4 using the 9 risk-adjustment models we consider. Then for each quarter, we calculate the mean, standard deviation, and 5th, 25th, 50th, 75th, and 95th percentiles of the αs under each model of all funds. The time-series averages of all the previous quantities are reported for each model and we find that for most models the average αs are positive and the highest average αs are for the three factor model suggested by Shen et al. (2020b) and the risk factors by Liu et al. (2019). The only models that generate a negative average are the models based on a crypto index of all cryptocurrencies and a crypto index based on the top 50 cryptocurrencies according to market capitalization, indicating the extreme returns found in smaller cryptocurrencies.

Panel A of Table 6 reports the results of the Fama and MacBeth (1973) regressions of the Crypto funds α on the managerial characteristics and fund characteristics. We find a significant positive relationship between α and PhD, which is robust to all benchmarks we study. This indicates that managers with a PhD generate significantly higher αs up to 11% higher than managers without a PhD. We also find a significant relationship between hedge fund experience and risk-adjusted returns from the crypto fund index and crypto index, indicating that firms run by managers with hedge fund experience generate significant risk-adjusted returns compared to other funds and the CRYPTOINDEX, but this finding is not significant relationship when we use other market-based benchmarks. This suggests that managers who have hedge fund experience will increase risk-adjusted returns by 4.4% and 4.5% respectively but the importance of hedge fund experience for managers is only significant when using other funds and the universe of cryptocurrencies as benchmarks. We find that no other manager characteristics offer consistent significant power in explaining the risk-adjusted returns of the crypto funds.

Panels B and C of Table 6 report the Fama and MacBeth (1973) regressions of residual volatility and appraisal ratio where we find that funds run by younger managers, managers with a PhD degree and managers with cryptocurrency experience significantly higher residual volatility than funds without such managerial characteristics. We also find that funds with more employees and no high water mark hurdle experience higher residual volatility. Panel C examines the appraisal ratio which enables us to examine the alpha of a fund and its risk of the selection of cryptocurrencies. Interestingly, we find a significant relationship between the appraisal ratio and crypto funds with a manager who has hedge fund experience indicating that managers with hedge fund experience have superior investment picking ability. This is consistent against all of our benchmarks thereby indicating the robustness of this finding and the value of this experience. We also find across most benchmarks, that there is a significant negative relationship between the appraisal ratio and the number of employees of a fund indicating that smaller funds have performed better than larger funds and have superior investment picking ability.

Our findings in Table 6 indicate that firms with managers with PhDs generate significantly higher risk-adjusted returns but also higher residual volatility while funds with managers with hedge fund experience generate significant appraisal ratios. Consequently, our analysis suggests that the background of managers of crypto funds does have a significant effect on the performance of crypto funds. Therefore our findings support our three hypotheses laid out in Section 2. Interestingly, we find that cryptocurrency experience of the managers offers no explanatory power in explaining the performance of crypto funds. This suggests that crypto funds are no different to regular finds and a manager does not require a specific background in the cryptocurrency area to be a successful manager of a crypto fund but hedge fund experience is vitally important for managers picking stocks.

5. Robustness

In this section, we offer a number of robustness measures to ensure the validity of our baseline results.

5.1. Institution Ranking

Gottesman and Morey (2006) find evidence that fund managers with MBAs from school ranked in the top 30 of the Business Week rankings of MBA programs exhibit performance superior to the performance of both managers with MBA degrees and managers holding MBAs from unranked programs. However only 22% of our managers received MBAs and therefore using a subsample of managers with top MBAs would leave us with a very small sample. Therefore we study our full dataset of managers and capture the ranking of the institution in which they attended for their undergraduate studies. We use the 2020 world QS rankings as well as the 2020 Times Higher Education World rankings and include a dummy variable equal to one if the university they studied at is in the top 100 of the two different rankings in a similar way to King et al. (2016). We find that 31 and 33 funds respectively have managers with a top 100 education and therefore represents a good proportion of our dataset.[12] Table 7 reports the main results but with the inclusion of

[12] We acknowledge that the rankings of institutions may differ over time from the time the manager received the qualification and became manager of a crypto fund. However, the rankings of the top 100 institutions does not

the QS rankings dummy variable and we find that managers with a degree from the QS top-100 ranked university do not generate any significantly higher risk-adjusted return but they do take on significantly less risk than their counterparts. However, managers from a QS top-100 ranked institution do generate significant appraisal ratios indicating their stock-picking ability. All of our other findings remain consistent with the inclusion of the QS top-100 ranking.

5.2. Alternative Benchmarks

In our analysis so far, we have used various benchmarks based on an index of crypto fund returns, cryptocurrency indices and factor models that have been published in the literature. However we also implement various other benchmarks such as the CRIX index, a market-weighted cryptocurrency index Trimborn and Hardle (2018) as well as crescent cryptocurrency index and the cryptocurrency 30 index.[13] Table 8 reports the results and we find consistent findings to our previous analysis.

5.3. Alternative Estimation Period

In our previous analysis, we used the past 6 months of crypto fund returns in our Fama and MacBeth (1973) regressions. This is due to the fact that our sample period is not very long and we required enough observations to estimate the performance of funds with certain manager characteristics. However we also re-estimate our results and use 12 months as the estimation period rather than 6 months in case our sample period is too short and to include a full calendar year. Table 9 reports the results and we find consistent findings to our previous analysis.

5.4. Non-Cryptocurrency Factors

So far in our analysis, we have examined the factors that determine cryptocurrency fund performance but have limited our analysis to cryptocurrency variables. However it could be the case that non-cryptocurrency factors could be determinants of cryptocurrency fund performance since

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change that much by studying a correlation matrix over the previous ten years' of rankings and given the average age of our managers is relatively young at 40 years old, the rankings today should be a good proxy for the level of education received.

[13]Both alternative cryptocurrency indices can be found at `https://www.crescentcrypto.com/cryptocurrency-market-index/` and `https://cci30.com` respectively.

there is evidence that cryptocurrency performance is linked to traditional financial assets (for instance see Corbet et al. (2018), Platanakis and Urquhart (2020), Conlon and McGee (2020).[14] Therefore we regress our cryptocurrency fund returns on a set of global benchmarks to determine whether the alpha from this regression provides similar results. Specifically, we collect data on the S&P500, TED spread, Treasury rate, VIX, US dollar and Bloomberg commodity index and regression our fund returns on each of these in turn. We then regression the alpha from this regression on our determinants where we report our findings in Table 10 documents the findings and we reveal that our PhD variable is still statistically significant at the 1% in all the specifications. This suggests that our findings are robust to non-cryptocurrency factors and that our cryptocurrency fund performance is not determined by traditional financial market forces.

5.5. Volatility and Cryptocurrency Fund Performance

Cryptocurrency funds have done relatively well in our sample period, but as seen in Figure 2, these funds tend to dampen the volatility with cryptocurrencies, displaying much less downside risk, albeit at the expense of lower upside returns.[15] Therefore the question arises, do the well-educated managers manage the volatility better? To study this, we split our sample into high and low volatility periods based on the median and re-estimate our Fama and MacBeth (1973) regressions. Table 11 provides a summary of the findings which shows that the PhD managers do significantly better during periods of high volatility, but this significance disappears during low volatility periods. This suggests that our managers with PhDs do significantly better during periods where the cryptocurrency market is experiencing high volatility and therefore are better at managing volatility than non-PhD managers which is an important and sought after skill in the cryptocurrency space.[16]

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[14] We thank the referee for this excellent suggestion.

[15] We thank the referee for pointing this out.

[16] We do not report the full table to conserve space but they are available upon request from the corresponding author.

6. Summary and Conclusion

Interest in cryptocurrencies has increased substantially since the introduction of Bitcoin in 2008 with many active investors attracted by the high volatility of cryptocurrencies compared to traditional financial assets. In recent years, cryptocurrency funds have emerged, which enables individuals to invest in funds specifically aimed at generating returns from the cryptocurrency sphere. These crypto assets are significantly different to traditional financial assets and therefore the managers of these funds may be quite different to traditional hedge and mutual funds. In this paper, we examine the impact of cryptocurrency fund and manager characteristics on the performance of cryptocurrency funds. Our paper is related to upper echelons theory that the past experience and characteristics of managers impact on their performance. We posit that managers with an exploratory mindset, proxied by a PhD degree, and managers with previous hedge fund experience, generate superior crypto fund performance compared to managers without such backgrounds.

We show substantial differences in cryptocurrency fund performance and managerial characteristics. Specifically, we find that managers with a PhD or MBA generate significantly higher excess returns, while managers with a PhD also generate significantly higher risk-adjusted returns. Further, managers with hedge fund experience also perform significantly better than managers without such experience in terms of appraisal ratios, indicating their investment-picking ability. Also, managers with a PhD do undertake more risk-taking than managers without such a qualification, consistent with our hypotheses. Interestingly, we find that cryptocurrency experience offers no benefit to cryptocurrency managers suggesting that successful managers in these funds need not have previous work experience in cryptocurrencies to perform well. This suggests that cryptocurrency trading is not that different or specialized compared to traditional trading in hedge funds and that previous experience in hedge fund trading is especially important for crypto fund managers.

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Table 1: Variable definitions. This table provides definitions of the variables employed in this study, along with the source of that data.

Variable	Definition	Source
Panel A: Fund Characteristics		
Monthly Returns	The return, in percentage, of the hedge fund during that month	Crypto Fund Research
Monthly Excess Returns	The difference, in percentage, between monthly returns and monthly risk-free interest rate	Crypto Fund Research
Fund Age	The number of months the fund has been active and reports returns	Crypto Fund Research
Management Fee	The fee the fund charge to their clients for management of the fund	Crypto Fund Research
Performance Fee	The fee the fund charge to their clients for performance	Crypto Fund Research
High Water Mark Hurdle	A dummy variable equal to one if the fund has a high water mark hurdle, zero otherwise	Crypto Fund Research
Minimum Investment	The minimum investment, in dollars, the fund accepts from clients	Crypto Fund Research
Accredited Investors Only	A dummy variable equal to one if the fund only accepts accredited investors only	Crypto Fund Research
Lockup Period	The amount of months before the client can take their capital out of the fund	Crypto Fund Research
Panel B: Manager Characteristics		
Gender	A dummy variable equal to one if the manager is male, zero otherwise	Linkedin and Crunchbase
Age	The age of the manager	Linkedin and Crunchbase
EFB UG	A dummy variable equal to one if the manager has an undergraduate degree in Economics, Finance or Banking, zero otherwise	Linkedin and Crunchbase
Other UG	A dummy variable equal to one if the manager has an undergraduate degree in a subject other than Economics, Finance, Banking, Law or Computer Science, zero otherwise	Linkedin and Crunchbase
No UG	A dummy variable equal to one if the manager has no undergraduate degree, zero otherwise	Linkedin and Crunchbase
MBA	A dummy variable equal to one if the manager has a MBA, zero otherwise	Linkedin and Crunchbase
PhD	A dummy variable equal to one if the manager has a PhD, zero otherwise	Linkedin and Crunchbase
Hedge Fund Experience	A dummy variable equal to one if the manager has previous experience in a hedge fund	Linkedin and Crunchbase
Cryptocurrency/Blockchain Experience	A dummy variable equal to one if the manager has previous experience in cryptocurrencies or blockchain	Linkedin and Crunchbase

Table 2: Descriptive statistics of fund characteristics and manager/CEO characteristics. This table provides the mean, standard deviation, median, maximum, minimum, skewness and kurtosis of our fund characteristics and manager/CEO characteristics whose definitions can be found in Table 1.

	Mean	Std. Dev.	Median	Max	Min	Skew	Kurt
Panel A: Fund Characteristics							
Monthly Returns	6.07%	0.30	1.22%	465.00%	-75.00%	4.77	51.44
Management Fee	1.49%	0.01	2.00%	12.50%	0.00%	4.32	36.95
Performance Fee	15.50%	0.11	20.00%	50.00%	0.00%	-0.16	2.77
High Water Mark Hurdle	0.30	0.46	0.00	1.00	0.00	0.90	1.80
Minimum Investment	$182,160.87	343467.64	$100,000.00	$2,500,000.00	$0.00	3.66	20.72
Lockup period	4.07	7.13	0.00	36.00	0.00	2.18	8.65
Age (months)	32.70	10.50	35.00	48.00	8.00	-0.41	2.62
Employees	6.48	4.85	6.00	34.00	1.00	3.22	16.58
Accredited Investors Only	0.32	0.47	0.00	1.00	0.00	0.76	1.58
Panel B: manager/CEO Characteristics							
Gender	0.98	0.13	1.00	1.00	0.00	-7.38	55.52
Age	40.95	8.71	41.00	67.00	24.00	0.61	3.30
EFB UG	0.58	0.50	1.00	1.00	0.00	-0.34	1.11
No UG	0.09	0.28	0.00	1.00	0.00	2.93	9.60
MBA	0.22	0.41	0.00	1.00	0.00	1.37	2.88
PhD	0.05	0.22	0.00	1.00	0.00	4.03	17.22
QSTop100	0.32	0.47	0.00	1.00	0.00	0.76	1.58
Hedge Fund Experience	0.67	0.47	1.00	1.00	0.00	-0.72	1.52
Cryptocurrency/Blockchain Experience	0.40	0.93	0.00	9.00	0.00	6.90	63.49

Table 3: Univariate results. This table provides the simple differences between managers with and without certain characteristics. We split variables such as age by the medium value of all managers. Our fund characteristics and found/CEO characteristics whose definitions can be found in Table 1. ***, ** and * indicates significance at the 1%, 5% and 10% levels respectively.

	Yes/High	No/Low	Difference	t-statistics
PhD	16.161	4.560	11.601***	3.998
Cryptocurrency/Blockchain Experience	5.510	5.430	0.080	0.054
EFB UG	4.316	7.063	-2.747*	-1.913
Eligible Dummy	5.330	5.512	-0.182	-0.131
Hedge Fund Experience	5.392	5.604	-0.212	-0.142
High Water Mark Hurdle	3.847	6.112	-2.265*	-1.936
MBA	5.684	4.448	1.236*	1.871
Manager Age	4.219	6.679	-2.459*	-1.689
Fund Age	4.935	5.929	-0.993	-0.781
Employees	6.183	4.894	1.289	0.897
Lockup period	6.127	5.184	0.943	0.691

Table 4: Raw Return, Total Volatility and Manager Characteristics. This table presents the results of the Fama and MacBeth (1973) regressions of crypto fund excess returns and total returns, volatility and manager/CEO characteristics whose definitions can be found in Table 1.

	Monthly Excess Return	Total Return Volatility
PhD	12.930***	5.099
	(3.052)	(1.603)
Hedge Fund Experience	-5.146	1.627
	(-1.458)	(1.150)
MBA	1.033*	1.813*
	(1.909)	(1.767)
Manager Age	-0.066	-0.220***
	(-1.247)	(-4.163)
EFB UG	2.101	4.296
	(0.921)	(1.448)
Cryptocurrency/Blockchain Experience	5.929	12.121***
	(1.245)	(3.053)
Fund Age	-1.712	0.222
	(-1.097)	(0.789)
Employees	0.254	0.078
	(0.816)	(0.430)
Lockup period	-0.415	-0.036
	(-0.875)	(-0.491)
High Water Mark Hurdle	-6.456	-6.010***
	(-1.532)	(-4.069)
Intercept	18.485**	16.359***
	(2.427)	(4.182)
$Adj R^2$	14.06%	9.32%

Table 5: Cross-Sectional Distributions of Risk-Adjusted Returns under Different Models. At each quarter, we calculate the *alpha* of each crypto fund as in equation 4 using the 9 risk-adjustment models and the mean, standard deviation, and 5th, 25th, 50th, 75th, and 95th percentiles of the *alpha* under each model of all crypto funds.

	CFRINDEX	CRYPTOINDEX	CRYTOINDEX5	CRYTOINDEX10	CRYTOINDEX15	CRYTOINDEX25	CRYTOINDEX50	SUW3	LTW3
Mean	0.033	-0.276	2.292	3.938	2.182	1.597	1.536	4.919	6.677
Std. Dev	12.079	11.876	26.095	101.728	14.752	12.999	10.361	20.975	17.791
5%	-12.198	-12.900	-8.730	-8.816	-8.847	-8.996	-9.360	-11.360	-10.427
25%	-3.318	-5.011	-1.719	-1.764	-1.760	-2.017	-2.201	-1.567	-0.676
50%	0.105	-0.505	0.864	0.829	0.827	0.709	0.654	2.064	2.395
75%	2.249	2.162	3.621	3.506	3.505	3.341	3.173	8.930	10.152
95%	12.996	15.354	17.858	17.538	17.644	16.854	16.386	30.749	36.076

Table 6: Risk-Adjusted Returns and Manager Characteristics using 6 months estimation period. This table reports the results of Fama and MacBeth (1973) regressions of hedge fund *alpha*, factor loadings, residual volatility, and appraisal ratio under different benchmark models on manager characteristics, with firm control variables. We use 9 different models as described in section 3.2 and the manager characteristics are defined in Table 1. To eliminate outliers, we delete the top and bottom 1% observations for each quarter. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively. The time-series averages of quarterly adjusted R^2 are also reported.

	CFRINDEX	CRYPTOINDEX	CRYPTOINDEX5	CRYPTOINDEX10	CRYPTOINDEX15	CRYPTOINDEX25	CRYPTOINDEX50	SUW3	LTW3
Panel A: Fama-MacBeth Regression of Risk-Adjusted Returns on Manager Characteristics									
	CFRINDEX	CRYPTOINDEX	CRYPTOINDEX5	CRYPTOINDEX10	CRYPTOINDEX15	CRYPTOINDEX25	CRYPTOINDEX50	SUW3	LTW3
PhD	8.097***	8.063***	9.547***	13.765**	9.170***	7.830***	8.177***	11.314***	9.847***
	(4.779)	(4.799)	(4.188)	(2.430)	(5.076)	(5.008)	(5.385)	(4.934)	(3.987)
Hedge Fund Experience	5.487***	4.533***	2.054*	-8.489	1.407	2.975***	2.904***	-2.378	-3.466
	(4.591)	(5.233)	(1.812)	(-0.783)	(1.207)	(3.465)	(3.661)	(-1.232)	(-1.670)
Manager Age	-0.023	-0.027	-0.038	-0.325	-0.063**	-0.029	-0.028	-0.105**	-0.148***
	(-0.712)	(-0.972)	(-1.507)	(-1.149)	(-2.285)	(-1.369)	(-1.362)	(-2.259)	(-3.292)
EFB UG	-1.817**	-2.169***	0.385	5.051	-0.169	-1.937**	-1.590**	1.763	2.452
	(-2.454)	(-3.413)	(0.216)	(0.896)	(-0.210)	(-2.117)	(-2.579)	(1.098)	(1.415)
MBA	5.251**	5.460***	7.183**	5.172**	5.264**	3.308*	3.975**	0.687	3.117
	(2.185)	(2.880)	(2.080)	(2.365)	(2.529)	(1.698)	(2.193)	(0.272)	(1.207)
Cryptocurrency/Blockchain Experience	-0.642	-0.765	-2.251	-9.265	-2.025*	-0.229	-0.641	1.602	3.646**
	(-0.579)	(-0.814)	(-1.195)	(-1.200)	(-1.885)	(-0.229)	(-0.727)	(0.891)	(2.116)
Fund Age	0.413**	0.469***	0.436***	0.245	0.429***	0.453***	0.451***	0.283	0.295
	(2.448)	(3.024)	(3.168)	(1.008)	(3.049)	(3.247)	(3.180)	(1.552)	(0.889)
Employees	-0.282***	-0.279***	-0.191**	-0.356**	-0.234***	-0.244***	-0.240***	-0.021	-0.057
	(-2.823)	(-3.353)	(-2.344)	(-2.437)	(-3.220)	(-3.537)	(-3.352)	(-0.181)	(-0.515)
Lockup period	-0.136	0.124***	0.118**	0.700	0.189***	0.157***	0.145***	0.474**	0.243
	(-1.025)	(2.720)	(2.091)	(1.248)	(3.101)	(3.199)	(3.046)	(2.638)	(1.054)
High Water Mark Hurdle	1.052	1.421*	3.100*	1.088	1.823**	0.636	1.086	-1.435	-4.590***
	(1.081)	(1.857)	(1.716)	(0.876)	(2.064)	(0.701)	(1.477)	(-0.941)	(-3.058)
Intercept	-4.348**	-3.728**	-1.153	20.430	1.296	-0.470	-0.879	8.083**	12.820***
	(-2.186)	(-2.078)	(-0.679)	(0.987)	(0.663)	(-0.359)	(-0.670)	(2.695)	(3.808)
Adj R^2	17.49%	15.41%	13.29%	13.32%	12.97%	14.67%	14.33%	14.53%	11.94%
Panel B: Fama-MacBeth Regression of Residual Volatility on Manager Characteristics									
	CFRINDEX	CRYPTOINDEX	CRYPTOINDEX5	CRYPTOINDEX10	CRYPTOINDEX15	CRYPTOINDEX25	CRYPTOINDEX50	SUW3	LTW3
PhD	8.676***	7.880***	8.091***	8.234***	8.269***	8.338***	8.370***	5.140*	5.514**
	(4.213)	(3.452)	(3.720)	(3.815)	(3.795)	(3.825)	(3.810)	(2.007)	(2.116)
Hedge Fund Experience	-1.735	-3.355*	-2.936	-2.928	-2.979	-2.969	-2.996	-7.120***	-7.619***
	(-1.022)	(-1.713)	(-1.542)	(-1.556)	(-1.560)	(-1.562)	(-1.575)	(-3.115)	(-3.312)
Manager Age	-0.073***	-0.122***	-0.113***	-0.103***	-0.107***	-0.109***	-0.108***	-0.140***	-0.133***
	(-3.014)	(-4.374)	(-5.081)	(-4.631)	(-4.830)	(-4.933)	(-4.882)	(-5.204)	(-4.772)
EFB UG	-1.782	-1.529	-2.203**	-2.188**	-2.155**	-2.179**	-2.144**	-0.031	0.540
	(-1.408)	(-1.356)	(-2.200)	(-2.178)	(-2.182)	(-2.231)	(-2.168)	(-0.020)	(0.350)
MBA	2.863**	3.112**	3.221**	3.245**	3.243**	3.326**	3.351**	-1.604	-0.833
	(2.132)	(2.249)	(2.405)	(2.355)	(2.377)	(2.426)	(2.447)	(-1.075)	(-0.515)
Cryptocurrency/Blockchain Experience	5.706***	5.129***	3.801***	4.120***	3.925***	3.749***	3.763***	10.689***	11.167***
	(4.002)	(4.141)	(4.166)	(4.188)	(4.143)	(4.054)	(4.069)	(3.725)	(3.639)
Fund Age	-2.131*	-1.578*	-1.208	-1.271	-1.191	-1.141	-1.146	-3.488**	-3.660**
	(-1.710)	(-1.732)	(-1.606)	(-1.634)	(-1.642)	(-1.609)	(-1.628)	(-2.063)	(-2.051)
Employees	0.386***	0.384***	0.356***	0.351***	0.350***	0.343***	0.348***	0.657***	0.712***
	(3.329)	(3.530)	(3.516)	(3.490)	(3.488)	(3.417)	(3.470)	(3.657)	(3.626)
Lockup period	-0.229	0.025	0.375	0.308	0.374	0.464*	0.460*	-1.577*	-1.692*
	(-0.803)	(0.098)	(1.460)	(1.260)	(1.516)	(1.816)	(1.785)	(-1.853)	(-1.887)
High Water Mark Hurdle	-5.747***	-5.876***	-4.484***	-4.679***	-4.526***	-4.357***	-4.412***	-9.439***	-9.693***
	(-5.513)	(-6.319)	(-5.931)	(-6.158)	(-6.113)	(-6.244)	(-6.324)	(-3.870)	(-3.808)
Intercept	30.528***	29.652***	25.959***	26.056***	25.599***	25.285***	25.266***	52.349***	52.241***
	(3.164)	(3.993)	(4.115)	(4.026)	(4.177)	(4.197)	(4.223)	(4.244)	(4.082)
Adj R^2	13.32%	13.63%	12.39%	12.16%	12.27%	12.06%	12.18%	11.74%	13.91%
Panel C: Fama-MacBeth Regression of Appraisal Ratio on Manager Characteristics									
	CFRINDEX	CRYPTOINDEX	CRYPTOINDEX5	CRYPTOINDEX10	CRYPTOINDEX15	CRYPTOINDEX25	CRYPTOINDEX50	SUW3	LTW3
PhD	0.262	0.457**	0.183	0.190	0.189	0.215	0.220	0.324*	0.141
	(1.574)	(2.670)	(1.005)	(1.044)	(1.041)	(1.183)	(1.221)	(1.714)	(0.785)
Hedge Fund Experience	0.721***	0.618***	0.566***	0.569***	0.572***	0.581***	0.580***	0.353***	0.389***
	(6.026)	(7.156)	(6.740)	(6.769)	(6.781)	(6.801)	(6.795)	(5.149)	(6.364)
Manager Age	0.001	-0.000	0.000	0.000	0.000	0.001	0.000	-0.003	-0.007**
	(0.128)	(-0.042)	(0.039)	(0.067)	(0.060)	(0.184)	(0.106)	(-0.906)	(-2.271)
EFB UG	0.183*	0.269**	0.247*	0.247*	0.248*	0.246*	0.234*	0.347**	0.260**
	(1.731)	(2.347)	(1.956)	(1.974)	(1.985)	(1.922)	(1.823)	(2.549)	(2.227)
MBA	0.028	0.161*	-0.013	0.001	-0.007	-0.009	0.001	0.044	0.089
	(0.312)	(1.783)	(-0.139)	(0.007)	(-0.082)	(-0.102)	(0.010)	(0.567)	(1.551)
Cryptocurrency/Blockchain Experience	0.180	0.152	0.175	0.168	0.167	0.175	0.174	0.075	-0.001
	(1.430)	(1.320)	(1.462)	(1.428)	(1.422)	(1.464)	(1.456)	(1.035)	(-0.019)
Fund Age	0.109**	0.113**	0.102*	0.101*	0.103*	0.105*	0.106*	0.077*	0.099**
	(2.052)	(2.155)	(1.945)	(1.943)	(1.942)	(1.923)	(1.931)	(1.993)	(2.114)
Employees	-0.029***	-0.028***	-0.025***	-0.025***	-0.025***	-0.025***	-0.024**	-0.015**	-0.026***
	(-2.853)	(-3.256)	(-2.812)	(-2.883)	(-2.864)	(-2.788)	(-2.666)	(-2.229)	(-3.363)
Lockup period	0.067	0.072**	0.058**	0.059**	0.061**	0.060**	0.061**	0.091*	0.093**
	(1.499)	(2.058)	(2.103)	(2.082)	(2.170)	(2.162)	(2.117)	(1.882)	(2.185)
High Water Mark Hurdle	0.134	0.138	0.113	0.115	0.114	0.120	0.118	0.177	0.137
	(1.264)	(1.216)	(1.040)	(1.055)	(1.028)	(1.096)	(1.068)	(1.460)	(1.313)
Intercept	-1.416**	-1.606***	-1.119**	-1.121**	-1.140**	-1.207**	-1.211**	-0.525	-0.344
	(-2.682)	(-3.137)	(-2.127)	(-2.142)	(-2.155)	(-2.228)	(-2.227)	(-1.414)	(-0.843)
Adj R^2	18.31%	17.13%	17.10%	17.09%	17.16%	17.19%	16.96%	16.03%	15.57%

Table 7: Risk-Adjusted Returns and Manager Characteristics using 6 months estimation period including the ranking of the institution. This table reports the results of Fama and MacBeth (1973) regressions of hedge fund *alpha*, factor loadings, residual volatility, and appraisal ratio under different benchmark models on manager characteristics, with firm control variables. We use 9 different models as described in section 3.2 and the manager characteristics are defined in Table 1. To eliminate outliers, we delete the top and bottom 1% observations for each quarter. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively. The time-series averages of quarterly adjusted R^2 are also reported.

	CFRINDEX	CRYPTOINDEX	CRYPTOINDEX5	CRYPTOINDEX10	CRYPTOINDEX15	CRYPTOINDEX25	CRYPTOINDEX50	SUW3	LTW3
Panel A: Fama-MacBeth Regression of Risk-Adjusted Returns on Manager Characteristics									
QS Dummy	-1.317	-0.799	-1.425	-2.247	-1.542	-1.437	-1.362	-1.066	-1.936
	(-1.066)	(-0.559)	(-1.171)	(-1.587)	(-1.254)	(-1.168)	(-1.099)	(-0.888)	(-1.551)
PhD	9.813***	9.511***	11.207***	16.255**	10.958***	9.531***	9.832***	12.495***	11.557***
	(4.859)	(4.212)	(4.082)	(2.481)	(4.519)	(4.202)	(4.396)	(4.358)	(3.873)
Hedge Fund Experience	5.511***	4.704***	2.159*	-9.240	1.384	3.005***	2.964***	-2.481	-4.066*
	(4.996)	(5.604)	(1.947)	(-0.795)	(1.163)	(3.687)	(3.931)	(-1.258)	(-1.970)
Manager Age	-0.027	-0.033	-0.044*	-0.305	-0.064**	-0.032	-0.032	-0.109**	-0.126***
	(-0.782)	(-1.179)	(-1.760)	(-1.177)	(-2.437)	(-1.472)	(-1.522)	(-2.260)	(-2.871)
EFB UG	-0.205	-0.636	1.953	7.133	1.484	-0.331	-0.007	2.963	3.898*
	(-0.320)	(-0.709)	(1.027)	(1.167)	(1.356)	(-0.271)	(-0.008)	(1.442)	(1.727)
MBA	5.697**	5.871***	7.558**	5.043**	5.546**	3.599*	4.273**	0.992	2.955
	(2.374)	(3.105)	(2.182)	(2.188)	(2.657)	(1.828)	(2.345)	(0.395)	(1.110)
Cryptocurrency/Blockchain Experience	-1.434	-1.601	-2.984	-10.477	-2.836**	-1.015	-1.427	0.967	2.932*
	(-1.013)	(-1.256)	(-1.483)	(-1.282)	(-2.147)	(-0.801)	(-1.198)	(0.620)	(1.945)
Fund Age	0.499*	0.563**	0.537**	0.364	0.533**	0.554**	0.553**	0.346**	0.364
	(1.994)	(2.243)	(2.351)	(1.228)	(2.300)	(2.417)	(2.364)	(2.197)	(1.123)
Employees	-0.221***	-0.247***	-0.127*	-0.283**	-0.169***	-0.181***	-0.179***	0.045	0.023
	(-2.752)	(-3.441)	(-1.945)	(-2.159)	(-3.072)	(-3.538)	(-3.384)	(0.337)	(0.178)
Lockup period	-0.066	0.205**	0.200**	0.758	0.266***	0.235***	0.224***	0.530**	0.274
	(-0.689)	(2.586)	(2.261)	(1.397)	(2.970)	(2.902)	(2.865)	(2.576)	(1.175)
High Water Mark Hurdle	2.309*	2.907**	4.297**	2.221	3.017**	1.836	2.311**	-0.646	-4.116***
	(1.711)	(2.430)	(2.215)	(1.476)	(2.590)	(1.523)	(2.125)	(-0.464)	(-3.117)
Intercept	-5.160**	-4.369**	-2.040	19.025	0.319	-1.398	-1.771	7.483**	11.551***
	(-2.262)	(-2.254)	(-1.159)	(0.939)	(0.157)	(-0.983)	(-1.227)	(2.599)	(3.632)
$Adj R^2$	19.39%	18.92%	17.70%	17.26%	17.41%	19.17%	18.62%	15.10%	13.44%
Panel B: Fama-MacBeth Regression of Residual Volatility on Manager Characteristics									
QS Dummy	-9.777***	-10.917***	-10.094***	-10.239***	-10.107***	-10.142***	-10.183***	-11.644***	-11.730***
	(-5.205)	(-6.011)	(-5.555)	(-5.531)	(-5.569)	(-5.610)	(-5.642)	(-5.539)	(-5.507)
PhD	18.170***	18.350***	17.907***	18.188***	18.102***	18.186***	18.243***	16.225***	16.633***
	(6.305)	(6.029)	(6.186)	(6.232)	(6.202)	(6.259)	(6.251)	(5.626)	(5.682)
Hedge Fund Experience	-3.487**	-5.367***	-4.796***	-4.808***	-4.840***	-4.843***	-4.879***	-9.547***	-10.104***
	(-2.558)	(-3.228)	(-2.980)	(-3.044)	(-2.991)	(-3.009)	(-3.029)	(-4.684)	(-4.877)
Manager Age	-0.030	-0.065**	-0.066***	-0.056**	-0.060**	-0.061**	-0.060**	-0.083***	-0.078**
	(-1.106)	(-2.224)	(-2.784)	(-2.316)	(-2.511)	(-2.611)	(-2.554)	(-2.822)	(-2.607)
EFB UG	4.713**	5.522***	4.504**	4.618**	4.566**	4.539**	4.588**	7.253***	7.779***
	(2.361)	(2.998)	(2.607)	(2.616)	(2.632)	(2.630)	(2.647)	(3.524)	(3.635)
MBA	5.610***	5.978***	5.959***	6.030***	5.979***	6.069***	6.095***	1.872	2.779
	(3.548)	(3.870)	(3.896)	(3.888)	(3.897)	(3.948)	(3.953)	(1.095)	(1.427)
Cryptocurrency/Blockchain Experience	3.319***	2.679***	1.327*	1.617**	1.442**	1.273*	1.293*	8.323***	8.858***
	(3.289)	(3.168)	(1.961)	(2.333)	(2.069)	(1.749)	(1.783)	(3.413)	(3.292)
Fund Age	-1.928	-1.391	-1.031	-1.089	-1.014	-0.963	-0.967	-3.301*	-3.472*
	(-1.526)	(-1.498)	(-1.328)	(-1.358)	(-1.355)	(-1.313)	(-1.330)	(-1.939)	(-1.935)
Employees	0.678***	0.706***	0.656***	0.656***	0.650***	0.644***	0.650***	1.008***	1.067***
	(3.864)	(4.189)	(4.049)	(4.027)	(4.029)	(3.998)	(4.041)	(4.676)	(4.631)
Lockup period	0.071	0.371	0.729**	0.663**	0.733**	0.820**	0.815**	-1.246	-1.381*
	(0.265)	(1.358)	(2.352)	(2.262)	(2.382)	(2.468)	(2.426)	(-1.654)	(-1.705)
High Water Mark Hurdle	-2.987***	-3.153***	-1.620*	-1.782**	-1.650*	-1.504	-1.573*	-7.016***	-7.387***
	(-3.947)	(-3.735)	(-1.790)	(-2.078)	(-1.874)	(-1.649)	(-1.723)	(-3.375)	(-3.313)
Intercept	25.038**	23.597***	20.409***	20.418***	20.032***	19.706***	19.663***	46.233***	46.233***
	(2.629)	(3.256)	(3.311)	(3.224)	(3.351)	(3.346)	(3.365)	(3.824)	(3.665)
$Adj R^2$	18.50%	19.24%	16.46%	16.99%	16.86%	16.78%	16.93%	12.12%	13.23%
Panel C: Fama-MacBeth Regression of Appraisal Ratio on Manager Characteristics									
QSDummy	0.647***	0.656***	0.624***	0.626***	0.625***	0.635***	0.641***	0.479***	0.435***
	(7.698)	(6.879)	(7.064)	(7.151)	(7.135)	(7.177)	(6.956)	(4.731)	(3.800)
PhD	-0.240	-0.045	-0.304	-0.298	-0.298	-0.279	-0.278	0.003	-0.117
	(-1.495)	(-0.251)	(-1.641)	(-1.604)	(-1.610)	(-1.494)	(-1.501)	(0.013)	(-0.427)
Hedge Fund Experience	0.843***	0.741***	0.678***	0.683***	0.685***	0.697***	0.697***	0.422***	0.452***
	(7.384)	(8.222)	(7.893)	(7.934)	(7.945)	(7.955)	(7.955)	(4.919)	(6.140)
Manager Age	-0.003	-0.003	-0.003	-0.003	-0.003	-0.002	-0.003	-0.004	-0.007***
	(-0.636)	(-0.897)	(-0.793)	(-0.749)	(-0.756)	(-0.633)	(-0.743)	(-1.388)	(-2.702)
EFB UG	-0.073	0.018	-0.010	-0.010	-0.007	-0.013	-0.024	0.202	0.170
	(-0.669)	(0.137)	(-0.069)	(-0.074)	(-0.054)	(-0.089)	(-0.169)	(0.949)	(0.777)
MBA	-0.116	0.013	-0.137	-0.128	-0.135	-0.140	-0.131	-0.071	-0.041
	(-1.305)	(0.155)	(-1.636)	(-1.564)	(-1.614)	(-1.671)	(-1.554)	(-1.005)	(-0.702)
Cryptocurrency/Blockchain Experience	0.251	0.227	0.250*	0.242*	0.242*	0.250*	0.248*	0.115	0.000
	(1.651)	(1.598)	(1.723)	(1.701)	(1.695)	(1.735)	(1.716)	(0.975)	(0.001)
Fund Age	0.086	0.089	0.078	0.078	0.079	0.081	0.082	0.044	0.066*
	(1.591)	(1.622)	(1.416)	(1.420)	(1.426)	(1.414)	(1.423)	(1.276)	(1.748)
Employees	-0.045***	-0.044***	-0.041***	-0.041***	-0.041***	-0.040***	-0.040***	-0.026***	-0.037***
	(-4.462)	(-5.111)	(-4.473)	(-4.548)	(-4.547)	(-4.473)	(-4.378)	(-3.646)	(-4.281)
Lockup period	0.068	0.075	0.060	0.061	0.063	0.062	0.063	0.114	0.131*
	(1.204)	(1.567)	(1.464)	(1.469)	(1.532)	(1.517)	(1.502)	(1.651)	(1.853)
High Water Mark Hurdle	0.137	0.146	0.108	0.110	0.109	0.117	0.118	0.216	0.233
	(0.979)	(0.991)	(0.779)	(0.793)	(0.782)	(0.847)	(0.843)	(1.107)	(1.152)
Intercept	-1.066**	-1.249**	-0.755	-0.760	-0.779	-0.842	-0.843	-0.222	-0.098
	(-2.024)	(-2.426)	(-1.428)	(-1.447)	(-1.467)	(-1.548)	(-1.543)	(-0.578)	(-0.232)
$Adj R^2$	18.31%	17.13%	17.10%	17.09%	17.16%	17.19%	16.96%	16.03%	15.57%

Table 8: Risk-Adjusted Returns and Manager Characteristics using 12 months estimation period with alternative benchmarks. This table reports the results of Fama and MacBeth (1973) regressions of hedge fund *alpha*, factor loadings, residual volatility, and appraisal ratio under different benchmark models on manager characteristics, with firm control variables. We use 9 different models as described in section 3.2 and the manager characteristics are defined in Table 1. To eliminate outliers, we delete the top and bottom 1% observations for each quarter. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively. The time-series averages of quarterly adjusted R^2 are also reported.

	CRIX	CCMIX	CCI30
Panel A: Fama-MacBeth Regression of Risk-Adjusted Returns on Manager Characteristics			
PhD	9.435***	9.307***	7.149***
	(4.739)	(4.520)	(4.185)
Hedge Fund Experience	1.548	2.200	2.097**
	(1.374)	(1.601)	(2.416)
Manager Age	-0.024	-0.018	-0.020
	(-0.892)	(-0.539)	(-0.733)
EFB UG	-0.950*	-0.955	-1.753*
	(-1.757)	(-1.376)	(-1.870)
MBA	3.507**	3.695**	2.330
	(2.199)	(2.452)	(1.082)
Cryptocurrency/Blockchain Experience	0.230	0.751	-0.414
	(0.433)	(0.828)	(-0.395)
Fund Age	0.451***	0.505***	0.480***
	(3.710)	(3.975)	(3.275)
Employees	-0.157***	-0.124***	-0.314***
	(-3.682)	(-3.224)	(-3.414)
Lockup period	0.078	0.067	0.158***
	(1.475)	(0.859)	(3.110)
High Water Mark Hurdle	-0.275	-0.381	0.277
	(-0.762)	(-0.802)	(0.292)
Intercept	-0.521	-2.164	0.691
	(-0.278)	(-0.884)	(0.535)
Panel B: Fama-MacBeth Regression of Residual Volatility on Manager Characteristics			
PhD	10.147***	10.998***	9.282***
	(3.596)	(3.613)	(3.983)
Hedge Fund Experience	-5.498**	-5.737**	-2.627
	(-2.418)	(-2.257)	(-1.350)
Manager Age	-0.090***	-0.088***	-0.095***
	(-3.364)	(-3.663)	(-4.112)
EFB UG	-0.850	-0.122	-1.386
	(-0.654)	(-0.077)	(-1.236)
MBA	2.965**	2.554*	3.182**
	(2.203)	(1.942)	(2.423)
Cryptocurrency/Blockchain Experience	5.581***	6.965***	4.472***
	(4.137)	(3.741)	(3.655)
Fund Age	-1.012**	-1.636**	-1.501*
	(-2.158)	(-2.215)	(-1.903)
Employees	0.435***	0.590***	0.383***
	(4.014)	(3.866)	(3.476)
Lockup period	0.218	-0.214	0.281
	(0.819)	(-0.582)	(1.024)
High Water Mark Hurdle	-5.509***	-6.873***	-5.150***
	(-5.877)	(-4.714)	(-6.303)
Intercept	25.140***	28.237***	26.783***
	(5.751)	(4.506)	(4.122)
$AdjR^2$	15.37%	17.20%	12.90%
Panel C: Fama-MacBeth Regression of Appraisal Ratio on Manager Characteristics			
PhD	0.319*	0.218	0.210
	(1.811)	(1.210)	(1.131)
Hedge Fund Experience	0.562***	0.552***	0.544***
	(7.091)	(7.174)	(6.712)
Manager Age	-0.002	-0.002	-0.000
	(-0.473)	(-0.549)	(-0.108)
EFB UG	0.182	0.214*	0.291**
	(1.417)	(1.797)	(2.180)
MBA	0.075	0.043	0.001
	(0.890)	(0.452)	(0.012)
Cryptocurrency/Blockchain Experience	0.112	0.130	0.171
	(0.959)	(1.179)	(1.446)
Fund Age	0.124*	0.129**	0.094*
	(2.002)	(2.142)	(1.828)
Employees	-0.024**	-0.023**	-0.023**
	(-2.453)	(-2.642)	(-2.455)
Lockup period	0.080**	0.095**	0.061*
	(2.190)	(2.301)	(2.015)
High Water Mark Hurdle	0.164	0.133	0.121
	(1.351)	(1.137)	(1.095)
Intercept	-1.222**	-1.246**	-0.957*
	(-2.106)	(-2.226)	(-1.824)
$AdjR^2$	15.24%	15.62%	17.32%

Table 9: Risk-Adjusted Returns and Manager Characteristics using 12 months estimation period. This table reports the results of Fama and MacBeth (1973) regressions of hedge fund *alpha*, factor loadings, residual volatility, and appraisal ratio under different benchmark models on manager characteristics, with firm control variables. We use 9 different models as described in section 3.2 and the manager characteristics are defined in Table 1. To eliminate outliers, we delete the top and bottom 1% observations for each quarter. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively. The time-series averages of quarterly adjusted R^2 are also reported.

	CFRINDEX	CRYPTOINDEX	CRYTOINDEX5	CRYTOINDEX10	CRYTOINDEX15	CRYTOINDEX25	CRYTOINDEX50	SUW3	LTW3
Panel A: Fama-MacBeth Regression of Risk-Adjusted Returns on Manager Characteristics									
PhD	10.098***	9.077***	10.703***	15.669**	10.255***	8.616***	9.031***	8.919***	9.267***
	(6.291)	(5.605)	(4.506)	(2.460)	(6.129)	(6.654)	(7.293)	(7.829)	(7.244)
Hedge Fund Experience	3.256***	3.280***	1.607	-10.699	0.848	2.611***	2.417***	0.437	-0.329
	(4.100)	(4.857)	(1.347)	(-0.860)	(0.812)	(3.624)	(3.956)	(1.016)	(-0.681)
Manager Age	-0.026	-0.043	-0.047*	-0.380	-0.075***	-0.035**	-0.035**	-0.115***	-0.093***
	(-1.074)	(-1.604)	(-1.890)	(-1.162)	(-3.085)	(-2.233)	(-2.397)	(-2.800)	(-3.916)
EFB UG	-0.456	-1.539***	1.057	6.513	0.441	-1.615	-1.173**	-0.584	0.240
	(-1.048)	(-3.317)	(0.515)	(1.004)	(0.539)	(-1.687)	(-2.082)	(-1.101)	(0.660)
MBA	2.124***	2.958***	5.274	2.872*	2.995*	0.684	1.393**	1.602	0.406
	(2.858)	(6.656)	(1.478)	(1.757)	(2.020)	(0.592)	(2.101)	(0.968)	(0.449)
Cryptocurrency/Blockchain Experience	0.419	-0.075	-1.870	-10.027	-1.625	0.441	0.036	-0.584	2.924**
	(0.905)	(-0.156)	(-0.922)	(-1.113)	(-1.601)	(0.502)	(0.056)	(-0.507)	(2.703)
Fund Age	0.161**	0.210***	0.198***	-0.028	0.182**	0.215***	0.210***	0.489***	0.181**
	(2.254)	(3.002)	(2.948)	(-0.120)	(2.596)	(2.841)	(2.870)	(2.771)	(2.045)
Employees	-0.107**	-0.130***	-0.059	-0.248	-0.106**	-0.122***	-0.112***	-0.177**	-0.177***
	(-2.434)	(-3.297)	(-1.045)	(-1.575)	(-2.588)	(-3.244)	(-3.039)	(-2.469)	(-4.730)
Lockup period	0.083***	0.166***	0.126**	0.808	0.212***	0.180***	0.173***	0.261***	0.069***
	(2.948)	(6.464)	(2.438)	(1.238)	(3.485)	(4.502)	(4.633)	(3.332)	(3.206)
High Water Mark Hurdle	-0.598	-0.421	2.367	0.033	0.887	-0.474	-0.043	0.031	-2.088***
	(-1.554)	(-0.910)	(1.152)	(0.026)	(1.016)	(-0.546)	(-0.071)	(0.046)	(-4.384)
Intercept	-3.215*	-1.971	-0.825	24.300	2.070	0.018	-0.320	5.740**	9.493***
	(-2.026)	(-1.142)	(-0.498)	(1.017)	(1.143)	(0.019)	(-0.329)	(2.466)	(4.423)
Adj R^2	17.76%	17.16%	14.27%	14.31%	14.66%	16.25%	16.32%	16.40%	12.91%
Panel B: Fama-MacBeth Regression of Residual Volatility on Manager Characteristics									
PhD	10.151***	7.957***	9.094***	9.277***	9.295***	9.314***	9.385***	6.158**	6.384**
	(5.746)	(3.777)	(5.325)	(5.483)	(5.493)	(5.532)	(5.551)	(2.636)	(2.689)
Hedge Fund Experience	-3.082**	-4.518***	-3.784**	-3.750**	-3.766**	-3.767**	-3.798**	-10.463***	-10.966***
	(-2.113)	(-2.730)	(-2.291)	(-2.319)	(-2.316)	(-2.321)	(-2.332)	(-3.887)	(-3.990)
Manager Age	-0.104***	-0.151***	-0.139***	-0.131***	-0.134***	-0.135***	-0.134***	-0.163***	-0.157***
	(-4.467)	(-5.228)	(-6.134)	(-5.801)	(-5.985)	(-6.060)	(-6.020)	(-4.937)	(-4.704)
EFB UG	-1.779	-1.947*	-2.672**	-2.703**	-2.623**	-2.688**	-2.647**	-0.459	-0.136
	(-1.477)	(-1.787)	(-2.500)	(-2.503)	(-2.472)	(-2.548)	(-2.512)	(-0.350)	(-0.108)
MBA	4.876**	4.799**	4.692**	4.822**	4.700**	4.746**	4.801**	0.562	0.960
	(2.178)	(2.169)	(2.145)	(2.170)	(2.155)	(2.172)	(2.188)	(0.309)	(0.514)
Cryptocurrency/Blockchain Experience	7.141***	6.620***	5.376***	5.676***	5.608***	5.459***	5.437***	10.242***	10.219***
	(4.147)	(4.369)	(4.619)	(4.647)	(4.622)	(4.676)	(4.670)	(4.132)	(4.204)
Fund Age	-2.150**	-1.798*	-1.798*	-1.757*	-1.801*	-1.762*	-1.752*	-3.000**	-3.047**
	(-2.062)	(-1.997)	(-1.859)	(-1.914)	(-1.900)	(-1.885)	(-1.892)	(-2.172)	(-2.154)
Employees	0.566***	0.574***	0.531***	0.519***	0.528***	0.520***	0.523***	0.770***	0.791***
	(4.203)	(4.508)	(4.285)	(4.274)	(4.244)	(4.228)	(4.266)	(4.273)	(4.344)
Lockup period	0.330	0.663	1.059**	0.959**	1.009**	1.066**	1.063**	-0.203	-0.105
	(0.870)	(1.606)	(2.268)	(2.112)	(2.213)	(2.263)	(2.252)	(-0.583)	(-0.346)
High Water Mark Hurdle	-7.720***	-8.054***	-6.608***	-6.826***	-6.783***	-6.660***	-6.664***	-9.956***	-9.870***
	(-4.683)	(-5.598)	(-5.831)	(-5.758)	(-5.829)	(-5.936)	(-5.909)	(-4.805)	(-4.945)
Intercept	45.714***	45.050***	43.696***	42.853***	43.496***	43.041***	42.803***	71.280***	71.382***
	(3.241)	(3.672)	(3.254)	(3.363)	(3.310)	(3.313)	(3.327)	(3.833)	(3.765)
Adj R^2	22.14%	20.72%	20.09%	20.49%	20.25%	20.23%	20.46%	18.25%	20.33%
Panel C: Fama-MacBeth Regression of Appraisal Ratio on Manager Characteristics									
PhD	0.375***	0.427***	0.312**	0.320**	0.324**	0.334**	0.348**	0.231	0.156
	(2.849)	(3.114)	(2.141)	(2.211)	(2.245)	(2.338)	(2.462)	(1.576)	(1.165)
Hedge Fund Experience	0.492***	0.455***	0.398***	0.393***	0.400***	0.406***	0.405***	0.301***	0.315***
	(4.942)	(5.144)	(4.303)	(4.244)	(4.302)	(4.298)	(4.296)	(3.647)	(4.018)
Manager Age	0.004	0.002	0.004	0.005	0.005	0.005	0.005	0.000	-0.003
	(1.136)	(0.660)	(1.195)	(1.218)	(1.235)	(1.238)	(1.279)	(0.018)	(-0.863)
EFB UG	0.235***	0.261***	0.251***	0.255***	0.254***	0.254***	0.252***	0.309***	0.286***
	(2.912)	(3.115)	(2.762)	(2.761)	(2.758)	(2.773)	(2.772)	(3.631)	(3.885)
MBA	0.055	0.140	0.053	0.055	0.053	0.051	0.056	0.006	-0.017
	(0.551)	(1.411)	(0.511)	(0.540)	(0.514)	(0.498)	(0.547)	(0.066)	(-0.183)
Cryptocurrency/Blockchain Experience	0.132**	0.097*	0.088	0.091	0.088	0.091	0.090	0.132***	0.133**
	(2.287)	(1.828)	(1.583)	(1.654)	(1.592)	(1.632)	(1.628)	(2.810)	(2.714)
Fund Age	0.022	0.028*	0.021	0.021	0.021	0.022	0.021	0.018	0.021
	(1.528)	(1.942)	(1.421)	(1.401)	(1.436)	(1.473)	(1.462)	(1.516)	(1.515)
Employees	-0.033***	-0.035***	-0.032***	-0.032***	-0.033***	-0.033***	-0.032***	-0.023***	-0.026***
	(-3.938)	(-4.483)	(-3.881)	(-3.885)	(-3.903)	(-3.889)	(-3.843)	(-3.758)	(-3.736)
Lockup period	0.073	0.091*	0.087*	0.087*	0.088*	0.089*	0.089*	0.081*	0.077
	(1.687)	(1.781)	(1.743)	(1.743)	(1.757)	(1.765)	(1.766)	(1.700)	(1.616)
High Water Mark Hurdle	0.172**	0.175*	0.189**	0.184*	0.188*	0.186*	0.185*	0.156*	0.111
	(2.065)	(1.866)	(2.033)	(1.991)	(2.019)	(1.987)	(1.962)	(1.927)	(1.668)
Intercept	-0.841***	-0.892***	-0.646**	-0.636**	-0.657**	-0.680**	-0.699**	-0.270	-0.106
	(-3.184)	(-3.335)	(-2.431)	(-2.437)	(-2.515)	(-2.576)	(-2.655)	(-1.141)	(-0.369)
Adj R^2	21.36%	21.24%	21.60%	21.54%	21.54%	21.49%	21.38%	22.91%	23.05%

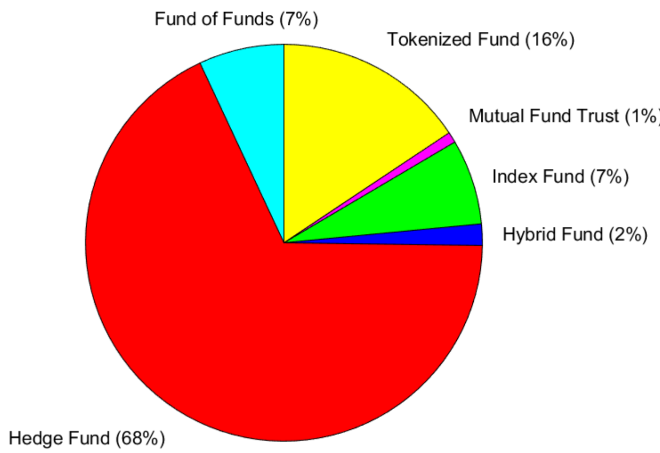
Table 10: Non-Cryptocurrency factors. This table presents the results of the Fama and MacBeth (1973) regressions of cryptocurrency fund excess returns where the raw returns are regressed on a number of non-cryptocurrency fund factors and the alpha is then regressed on manager/CEO characteristics whose definitions can be found in Table 1. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively.

	SP500	TED Spread	Treasury Rate	VIX	US Dollar Index	Bloomberg Commodity
PhD	15.378***	10.008***	13.616***	8.754***	11.102***	9.419***
	(3.970)	(3.240)	(5.268)	(4.323)	(3.888)	(4.383)
Hedge Fund Experience	-4.667	-0.298	3.906**	-1.906	-0.092	-0.874
	(-1.588)	(-0.187)	(2.552)	(-1.123)	(-0.041)	(-0.615)
MBA	2.792	2.155	5.074**	1.715	7.452**	2.830*
	(1.342)	(1.577)	(2.154)	(0.881)	(2.334)	(1.709)
Manager Age	-0.093*	-0.070	-0.076	-0.059*	-0.140**	-0.081**
	(-1.979)	(-1.071)	(-1.029)	(-1.730)	(-2.163)	(-2.449)
EFB UG	4.256	0.875	-0.471	-0.282	0.846	0.881
	(1.347)	(0.318)	(-0.328)	(-0.202)	(0.513)	(0.624)
Cryptocurrency/Blockchain Experience	3.809*	0.512	6.496**	2.359*	-1.593	0.283
	(1.859)	(0.372)	(2.352)	(1.732)	(-0.845)	(0.207)
Fund Age	-0.628	0.056	-0.593*	0.269	0.261	0.077
	(-1.225)	(0.111)	(-1.787)	(1.649)	(1.082)	(0.361)
Employees	0.091	0.068	-0.132	-0.095	-0.073	-0.064
	(0.545)	(0.603)	(-1.585)	(-0.996)	(-0.877)	(-1.045)
Lockup Period	-0.586	0.269	-1.058**	0.368*	-0.153	0.164
	(-1.470)	(1.158)	(-2.021)	(1.987)	(-0.282)	(1.282)
High Water Mark Hurdle	-2.371	-0.594	-3.700	-2.667*	1.448	-0.263
	(-1.189)	(-0.439)	(-1.587)	(-1.995)	(1.086)	(-0.217)
Intercept	15.970***	6.562***	6.304	8.287***	5.615	6.886**
	(3.298)	(3.018)	(1.498)	(3.000)	(1.677)	(2.370)
$Adj R^2$	14.17%	13.62%	12.21%	12.75%	15.38%	12.50%

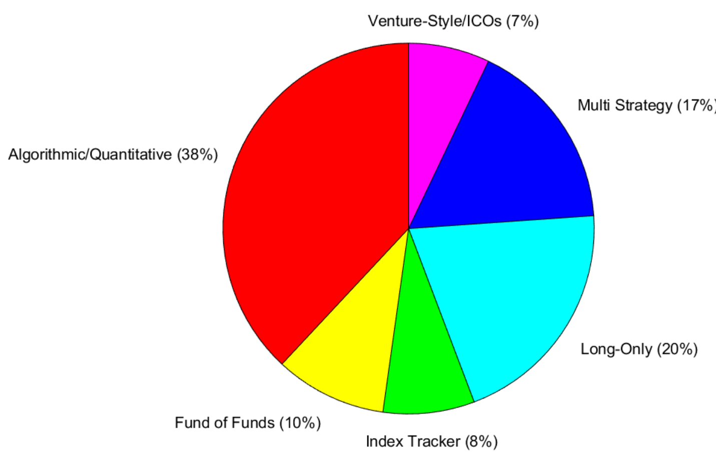
Table 11: High and low volatility. This table presents the results of the Fama and MacBeth (1973) regressions of cryptocurrency fund excess returns where we split our sample in periods of high and low volatility. We include all control variables as in previous tables. We report t-statistics below in parentheses, where ***, **, and * entries represent significance at the 1%, 5%, and 10% levels, respectively.

CFRINDEX		CRYPTOINDEX		CRYPTOINDEX5		CRYPTOINDEX10		CRYPTOINDEX15		CRYPTOINDEX25	
High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
9.188***	1.205	8.237***	1.386	10.411**	1.088*	8.244***	1.116*	7.855***	1.109*	4.805*	1.121*
(4.309)	(1.199)	(4.596)	(1.683)	(2.119)	(1.800)	(3.147)	(1.843)	(2.987)	(1.816)	(1.827)	(1.801)
CRYPTOINDEX50		CRIX		CCMIX		CCI30		SUW3		LTW3	
High	Low	High	Low	High	Low	High	Low	High	Low	High	Low
5.724**	1.143*	9.982***	1.274**	8.139***	1.024*	4.851**	-0.149	4.723*	2.258**	6.213***	1.160**
(2.572)	(1.822)	(3.474)	(2.174)	(4.345)	(1.719)	(2.131)	(-0.141)	(1.776)	(2.249)	(3.243)	(2.422)

Breakdown by fund type and investment style



(a) Fund Type



(b) Investment Strategy Type

Figure 1: This figure plots the distributions of funds per type of fund and investment strategy. Funds are clustered by type and labeled as “hedge fund”, “tokenized fund”, ”index fund”, ”funds of funds”, “hybrid funds” and ”mutual fund trust”. Classification by investment strategy is defined as “Algorithmic/Quantitative”, ”Long-Only”, ”Multi Strategy”, ”Fund of Funds”, ”Index Tracker” and ”Venture-Style/ICOs”, all denoted by Crypto Fund Research. The sample period is from January 2017 to December 2020.

Average Return of Crypto Funds and the Bitstamp Bitcoin price over our sample period

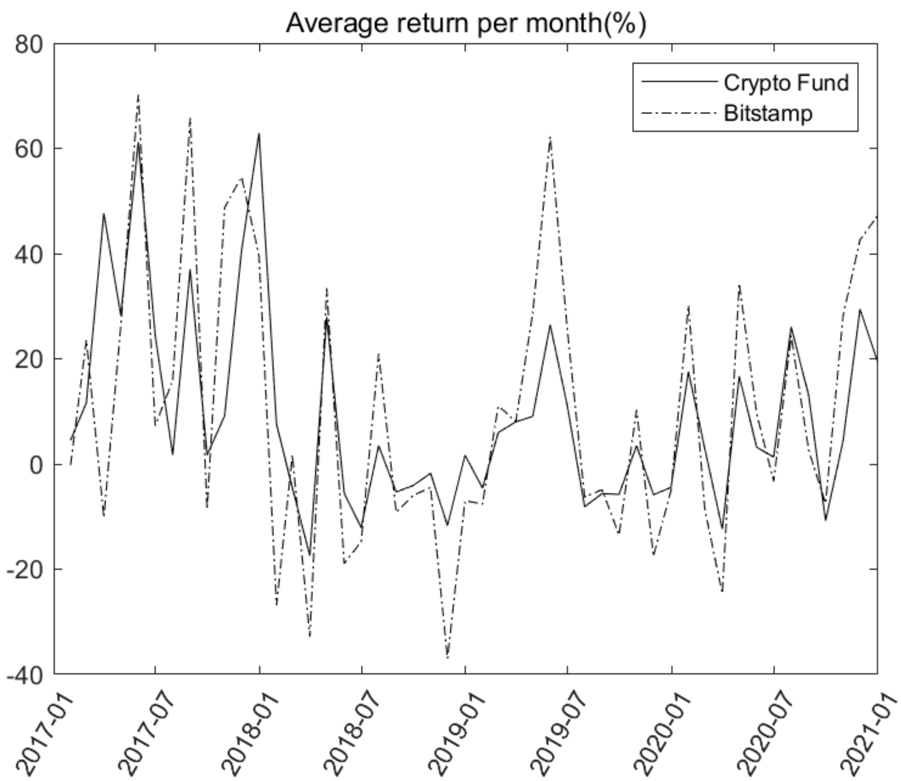


Figure 2: This figure plots the average monthly return (%) of crypto funds in our sample and the Bitstamp Bitcoin price over our full sample period from January 2017 to December 2020.

Cross-sectional performance of crypto funds.

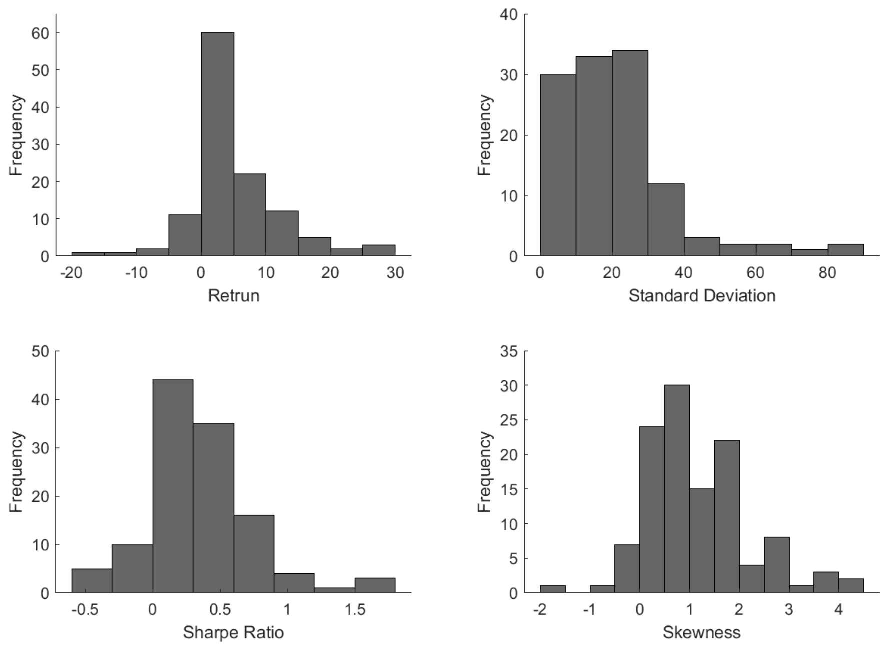


Figure 3: This figure plots the cross-sectional distribution of average returns (%, monthly), volatility standard deviation, monthly), Sharpe ratios (monthly) and skewness (monthly) for the sample of cryptocurrency funds under investigation. The sample period is from January 2017 to December 2020.