On the Performance of Cryptocurrency Funds

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2nd Crypto Asset Lab conference, Milan

Why should we care?

Cryptocurrencies

Fidelity Says a Third of Big Institutions Own Crypto Assets

By Olga Kharif

9 June 2020, 13:50 CEST *Updated on 9 June 2020, 14:32 CEST*

- Firm surveyed nearly 800 institutions in U.S. and Europe
- More than 25% of the respondents hold Bitcoin, 11% own Ether

Why should we care?

Cryptocurrencies

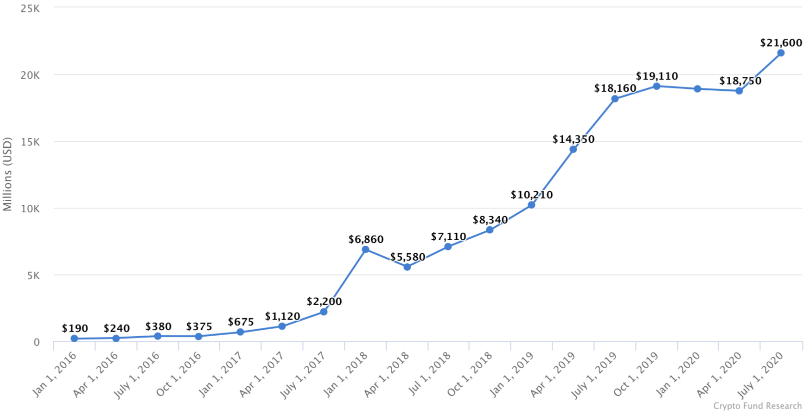
Fidelity Launches Inaugural Bitcoin Fund for Wealthy Investors

By Michael McDonald and Vildana Hajric
26 August 2020, 23:21 CEST

- Money manager to offer Wise Origin Bitcoin Index Fund I
- Qualified clients must make minimum investment of $100,000

Why should we care?

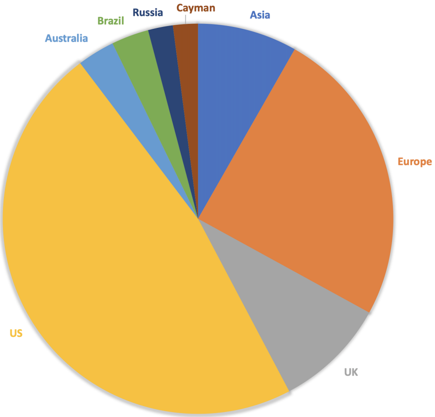
Figure 1. Asset Under Management (mln USD) for crypto funds



This figure reports the Asset Under Management (AUM) for funds that specialise in digital assets. The sample is from January 2016 to July 2020. Source: Crypto Fund Research.

Why should we care?

Figure 2. Geographical distribution of crypto funds



This figure shows the geographical distribution of fund managers that specialise in digital assets. The sample is from March 2015 to July 2020. Source: Bianchi and Babiak 2020.

This paper

What we do:

Empirically: We look at the performance of $+180$ funds that specialise in cryptocurrency investments from March 2015 to July 2020

– Benchmark-adjusted, net-of-fees, returns.

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  - Consider within-strategy returns correlation and heteroschedasticity

What we find:

- The performance of best fund managers can not be explained simply by sampling variation and/or benchmark exposures.
- Weak stat evidence when within-strategy correlation is considered.

The value of active asset management

The ability of fund managers to create value for investors has become a heavily studied question at least since Jensen (1968).

Active management creates little value for investors after fees

(see, e.g., Elton et al 1996, Carhart 1997, Wermers 2000, Davis 2001, Fama and French 2010)

Significant and persistent value of active investment management

(see, e.g., Bollen and Busse 2001, Kothari and Warner 2001, Glode 2011, Kacperczyk et al. 2014, and Berk and Van Binsbergen 2015)

Existing research has long been debating the value of active management in equity markets:

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3. Low competition compared to traditional funds (e.g., no cheap and/or passive investment vehicles).
4. Outlying performances, within-strategy correlation and non-normality.

Data and descriptive statistics

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Fund returns: Monthly net-of-fee returns for $+180$ funds. USD as investment currency. Sample March 2015 - August 2020.

– Managers report returns on a voluntary basis (no legal obligation).
– We include "dead" funds and consider only initially reported returns (no revision and survivorship biases).
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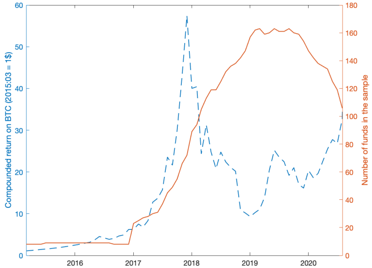
Benchmark strategies: Funds are compared to a set of passive investment strategies (see, e.g., Berk and Van Binsbergen 2015).

- Buy-and-hold investment in BTC/ETH + EW portfolio of top 30 cryptos by size + VW portfolio of cryptos listed on Coinbase.
- Data are from Cryptocompare: volume-weighted average from +250 exchanges + filters on suspicious trading activity (see, e.g., Bianchi and Dickerson 2020).

Data and descriptive statistics

Figure 3. A snapshot of the sample of funds



(a) Number of funds

This figure reports the number of funds in the sample (left panel) and the breakdown of the funds by investment strategy (right panel). Funds are classified in seven categories: "fund of funds", "long-short", "long-term", "market neutral", "multi-strategy", and "opportunistic". The sample is from March 2015 to August 2020.

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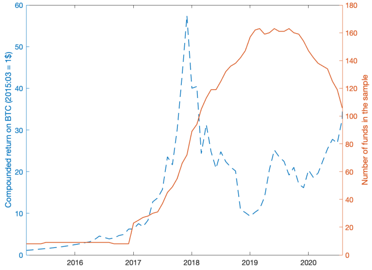
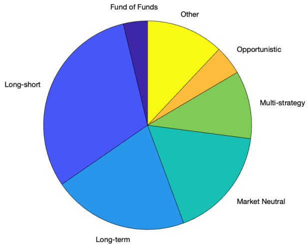


(c) Number of funds



(d) Breakdown by strategy

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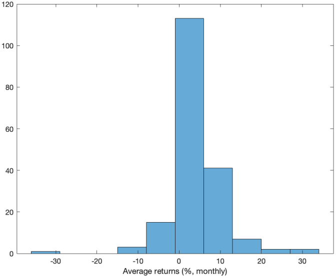
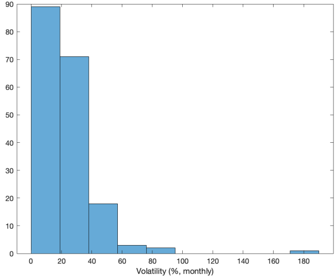
Figure 4. The cross-section of fund returns



(a) Average returns



(b) Volatility

This figure reports the average monthly returns (left panel) and the monthly returns volatility (right panel) for the cross-section of 163 funds in our sample. The sample is from March 2015 to July 2020.

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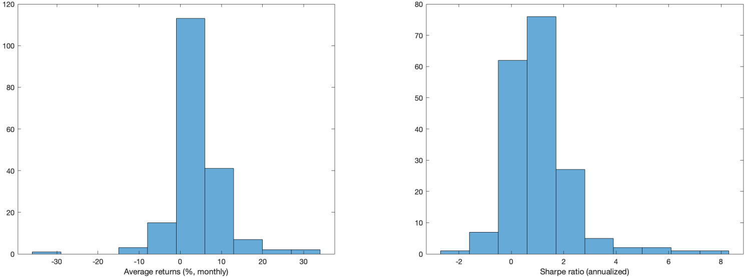

(a) Average returns

(b) Sharpe ratio

This figure reports the average monthly returns (left panel) and the annualised Sharpe ratio (right panel) for the cross-section of 163 funds in our sample. The sample is from March 2015 to July 2020.

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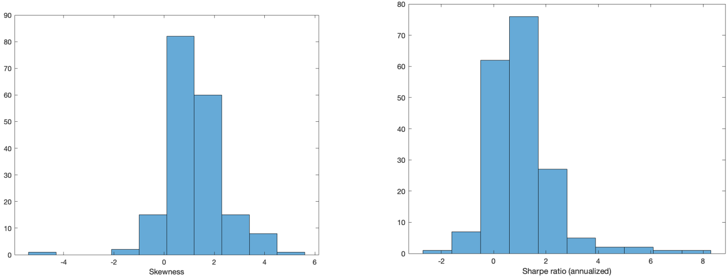

(a) Skewness (b) Sharpe ratio

This figure reports the returns skewness (left panel) and the annualised Sharpe ratio (right panel) for the cross-section of 163 funds in our sample. The sample is from March 2015 to July 2020.

Empirical analysis

Aggregate regression results

$$\alpha_{t,j} = y_{t,j} - \hat{\boldsymbol{\beta}}_j' \boldsymbol{x}_t,$$

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Table 2. The benchmark-adjusted performance of aggregate funds

		Investment strategy					
	Agg	Fund of funds	Long-short	Long-term	Market neutral	Multi-strategy	Opport
Alpha	2.80	4.69	2.97	2.23	1.51	1.55	1.76
t-stat	(2.88)	(3.00)	(2.81)	(1.71)	(2.94)	(1.20)	(1.79)

This table reports the benchmark-adjusted performance of aggregate funds across all crypto funds 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) 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 above. When computing equal-weight fund monthly return in each period, we calculate the sample equal-weight average of active funds in the corresponding time period. The top panel reports the alpha estimates and robust t-statistics (in parentheses) from the corresponding OLS regression. In order to test for the difference in the alphas, we use an approach á la Diebold and Mariano (2002). In particular, we regress the difference in the benchmark-adjusted returns for a given fund type/strategy j, $\alpha_{t,j}$, and the aggregate crypto fund market, $\alpha_{t,m}$, onto a constant;

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

where $\alpha_{t,k} = y_{t,k} - \hat{\boldsymbol{\beta}}_k' \boldsymbol{x}_t$. Testing for the difference in the performance boils down to a test for the significance in $\hat{\gamma}$. The bottom panel reports the estimate $\hat{\gamma}$ and robust t-statistics (in parenthesis). The sample covers the period from March 2015 to July 2020.

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Difference		1.89	0.17	-0.57	-1.28	-1.25	-1.04
t-stat		(2.41)	(0.24)	(-1.11)	(-1.93)	(-1.33)	(-1.83)

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Aggregate regression results

Takeaways from the aggregate regression analysis:

- There is some evidence that fund managers cover their costs and generate value, on average.
- There are differences across investment strategies (within-strategy correlations)

Individual fund performances via bootstrap

Looking at the average fund returns could be misleading (see Kosowski et al., 2006 and Fama and French, 2010).

- Cannot control for the differences in managers' risk-taking behaviors/skills
- The returns of individual funds exhibit non-normality, e.g., large positive skewness.
- That is, the cross-section of alphas represents a complex mixture of non-normal distributions.

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3. Non-normal fund returns + within-strategy returns correlation.

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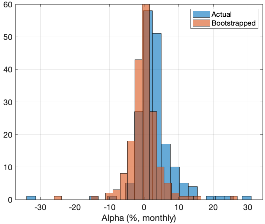
Figure 5. Cross-section of benchmark-adjusted alphas $\hat{\alpha}$ and t-stats $\hat{t}_{\hat{\alpha}}$



(a) Alpha

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. The panels report actual (blue bars) and bootstrapped (red bars) cross-sectional distributions of the alpha and 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 August 2020.

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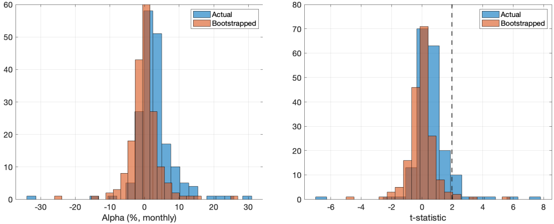

(d) Alpha

(e) Standard t-stat

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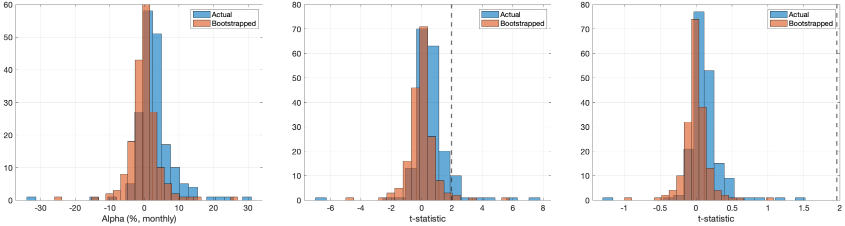

(g) Alpha (h) Standard t-stat (i) Clustered std err

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Individual fund performances across sub-samples

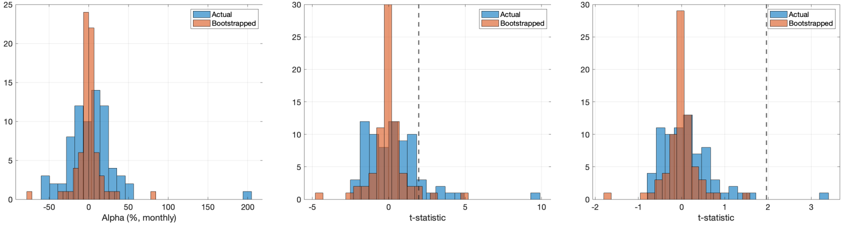
Although the sample size is limited, it is fairly representative of all market phases, e.g., price run-up, crashes, sideways market.

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 August 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.

Individual fund performances across sub-samples

Figure 6. The cross-section of benchmark-adjusted performances

Sample until Dec 2017



(a) Alpha (b) Standard t-stat (c) Clustered std err

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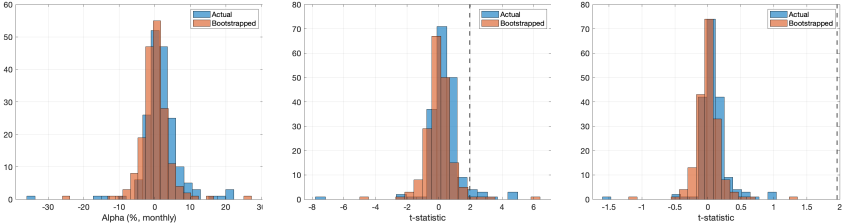
Figure 6. The cross-section of benchmark-adjusted alphas

Sample from Jan 2018



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Further results and robustness checks

We relax some of the assumptions of our bootstrap approach:

1. Time-series dependence (3-month block bootstrap).
2. Independent resampling of fund returns and benchmark strategies.
3. Risk factor portfolios instead of benchmark strategies: VW Market, Momentum, Liquidity and Volatility risk.

The main empirical results are confirmed.

Conclusion

- We use a novel panel bootstrap approach to investigate the net-of-fee performance of funds that specialise in digital assets.
- The results show that:
  - A small fraction of managers seems to generate an economically large performance which cannot be reconciled by "luck".
  - Such performance is somewhat confirmed in the pre- and post-ICO bubble period.
  - However, when within strategy returns correlation is considered the standardised returns are only weakly significant.