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.
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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- **Methodologically:** Provide a novel panel bootstrap approach that allows to:

  - Control for “skills vs luck” + presence of outlying funds (see Kosowski et al., 2006 and Fama and French 2010)

  - Consider within-strategy returns correlation and heteroscedasticity
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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).


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

- No study has tested the existence of such value for funds that specialise in digital assets.
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Active management creates little value for investors after fees

Significant and persistent value of active investment management

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This paper
Key features of cryptocurrency markets

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1. Cryptocurrency markets are de-coupled from traditional, centralised, asset classes, i.e., segmented markets (see Liu and Tsyvinski, 2020)
Key features of cryptocurrency markets

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4. Outlying performances, within-strategy correlation and non-normality.
Data and descriptive statistics
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- 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).
- We exclude funds with less than $5mln AUM and with less than 12 months returns (163 funds after filtering).
**Data and descriptive statistics**

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

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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

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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Figure 4. The cross-section of fund returns

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.
Data and descriptive statistics

Figure 4. The cross-section of fund returns

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

\[ \alpha_{t,j} = y_{t,j} - \hat{\beta}_j x_t, \]
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Table 2. The benchmark-adjusted performance of aggregate funds

<table>
<thead>
<tr>
<th>Investment strategy</th>
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<td>Alpha</td>
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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 à 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 \( \alpha_{t,k} = y_{t,k} - \hat{\beta}_k'x_t \). 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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<td>Difference</td>
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<td>-0.57</td>
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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)
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.
Individual fund performances via bootstrap

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We extend existing literature and propose a panel bootstrap approach which accounts for:

1. Skill vs luck in managers’ track records – simulate zero-alpha returns and estimate the alpha due to sampling variation.
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2. Strategy-specific exposure to benchmark returns or risk factors.
3. Non-normal fund returns $+$ within-strategy returns correlation.
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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Individual fund performances via bootstrap

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

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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

This figure plots the histograms of the benchmark-adjusted fund alphas (left panel) and the t-statistics obtained with (right panel) and without (mid panel) clustering the standard errors by investment strategy. The data is split before and after the peak of the market prices in December 2017 where the monthly price of BTC reached its highest point. The top panels report the results for the period until December 2017, whereas the bottom panel reports the results for the period after January 2018. The four passive benchmarks — buy-and-hold investments in Bitcoin (BTC) and Ethereum (ETH), an equal-weight market portfolio (DOL), and a value-weight average of the coins traded on Coinbase (ETF) — represent an investor’s alternative investment opportunity set. The individual alphas are calculated as the individual fund fixed effects from a panel regression. 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 July 2020.
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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.


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.