On the Performance of Cryptocurrency Funds

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Tuesday, 29th 2021
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

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**Fidelity Bitcoin Fund Attracts $102M in First 9 Months**

New SEC filings show the investment giant's Wise Origin Bitcoin Index Fund is one of the largest of its kind.
Why should we care?

Hedge funds expect to hold 7% of assets in crypto within five years

Forecast could equate to about $312bn in digital currencies across the industry, survey finds

The Intertrust survey signals a major vote of confidence in digital assets © Edgar Su/Reuters

Laurence Fletcher in London JUNE 15 2021
Why should we care?

Within five years the number of funds specialized in cryptocurrency investments increased by roughly 10 times.

The AUM went from few hundred $mln to roughly $50bn (as of end of January 2021)

Active funds (blue bars) vs Assets Under Management (red line).
Our paper:

A comprehensive study on active investment management in cryptocurrency markets.

What we do:

We look at the performance of 250 funds that specialize in cryptocurrency investments from March 2015 to January 2021.

• Benchmark- and risk-adjusted, net-of-fees, returns.

• Bootstrap approach to control for “skill vs luck” + presence of outlying funds (see Kosowski et al. 2006 and Fama and French 2010).

What we find:

• On average, crypto funds generate sizable benchmark- and risk-adjusted alphas.

• This is primarily due to a small fraction of “skilled” outlying funds.

• The large sampling variation, i.e., volatility, makes hard to disentangle managers’ skills once exposures to benchmarks/risk factors are considered.
Cryptocurrency markets and delegated investment management

Cryptocurrency funds provide a peculiar context in which to understand the role of active asset management:

- Cryptocurrency markets are arguably de-coupled from traditional asset classes, i.e., markets are somewhat segmented (see, e.g., Liu and Tsyvinski 2020)
- New and mostly unregulated asset class. Regulation often plays a role with respect to fund managers risk taking behaviors (see, e.g., Novy-Marx and Rauh 2011)
- Low competition compared to traditional funds e.g., scarce competition from cheap and/or passive investment vehicles)
- Outlying performances, within-strategy correlation and non-normality.
Data description
Data description: Fund returns

Monthly net-of-fee returns for 250 funds from March 2015 to January 2021

- Data collected from few sources (Crypto Fund Research + hand collection)
- Managers report returns on a voluntary basis (no legal obligation).
- Funds can be clustered by strategy: Long-term, long-short, market neutral, multi-strategy and opportunistic.

Filters:

- Exclude funds with less than $2mln AUM and less than 12 months returns.
- No revision or survivorship bias, i.e., include “dead” funds in the sample and consider only actual reports returns.
- USD as investment currency and reported performance.

After filtering we are left with 204 active funds as of January 2021
Some of the properties of raw returns
A sketch of the empirical results
Simple regression analysis

\[ y_{t,j} = \alpha_{t,j} + \hat{\beta}_j' \text{Benchmarks}_t + \epsilon_{j,t}, \]

<table>
<thead>
<tr>
<th></th>
<th>Agg</th>
<th>Equal-weight aggregation by investment strategy</th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Long-short</td>
</tr>
<tr>
<td>$\beta_{BTC}$</td>
<td>0.28</td>
<td>0.12</td>
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<tr>
<td></td>
<td>(3.34)</td>
<td>(1.07)</td>
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<tr>
<td>$\beta_{DOL}$</td>
<td>0.09</td>
<td>0.13</td>
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<tr>
<td></td>
<td>(1.27)</td>
<td>(2.24)</td>
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<td>$\beta_{ETF}$</td>
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<td></td>
<td>(3.13)</td>
<td>(1.77)</td>
</tr>
<tr>
<td>$\beta_{ETH}$</td>
<td>0.13</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>(1.74)</td>
<td>(1.21)</td>
</tr>
<tr>
<td>Adj. $R^2$</td>
<td>0.78</td>
<td>0.60</td>
</tr>
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This table reports the betas on the passive benchmark strategies of aggregate funds across all crypto funds and strategy. The top panel reports the betas estimates and robust t-statistics (in parentheses) from the corresponding robustregression. Robust t-statistics are reported in parenthesis. The sample covers the period from March 2015 to January 2021.
Simple regression analysis

\[ y_{t,j} = \alpha_{t,j} + \hat{\beta}_j' \text{Benchmarks}_{t} + \epsilon_{j,t}, \]

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<td></td>
<td>Long-short</td>
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<td>Market neutral</td>
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<td>Opportunistic</td>
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<tr>
<td>( \beta_{\text{BTC}} )</td>
<td>0.28</td>
<td>0.12</td>
<td>0.40</td>
<td>0.05</td>
<td>0.43</td>
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<td>(3.34)</td>
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<td>0.03</td>
<td>0.04</td>
<td>0.03</td>
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<tr>
<td></td>
<td>(1.27)</td>
<td>(2.24)</td>
<td>(1.16)</td>
<td>(0.80)</td>
<td>(0.75)</td>
<td>(0.92)</td>
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<td>( \beta_{\text{ETF}} )</td>
<td>0.19</td>
<td>0.11</td>
<td>0.28</td>
<td>0.11</td>
<td>0.10</td>
<td>-0.08</td>
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<td>(3.13)</td>
<td>(1.77)</td>
<td>(2.85)</td>
<td>(1.58)</td>
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Simple regression analysis

\[
\alpha_{t,j} = y_{t,j} - \hat{\beta}_j'Benchmarks_t, \quad \implies \quad \alpha_{t,j} - \alpha_{t,m} = \gamma + \eta_t,
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<tr>
<td>Alpha</td>
<td>2.50</td>
<td>3.17</td>
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<tr>
<td>t-stat</td>
<td>(2.52)</td>
<td>(3.01)</td>
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<tr>
<td>Difference</td>
<td>0.66</td>
<td>-0.41</td>
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<td></td>
<td>(0.90)</td>
<td>(-0.76)</td>
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This table reports the benchmark-adjusted performance of aggregate funds across all crypto funds and strategy. 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). The bottom panel reports the estimate $\hat{\gamma}$ and robust t-statistics (in parenthesis). The sample covers the period from March 2015 to January 2021.
Simple regression analysis

\[ \alpha_{t,j} = y_{t,j} - \hat{\beta}'_{j} \text{Benchmarks}_t, \quad \implies \quad \alpha_{t,j} - \alpha_{t,m} = \gamma + \eta_t, \]

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Takeaways from the simple regression analysis:

• There is some evidence that fund managers generate value, on average.
• There are differences across investment strategies (within-strategy correlation).
• BTC as a “level” factor
Looking at the average fund performance could be mis-leading (Fama and French 2010)

• Cannot control for the differences in risk-taking behaviors/skills.
• Returns on crypto funds are highly non-normal, i.e., the cross-section of alphas represents a complex mixture of non-normal distributions.

We extend the existing literature and propose a panel semi-parametric bootstrap which accounts for:

• Skill vs luck in performances – simulate zero-alpha returns and estimate the alpha due to sampling variation.
• Strategy-specific exposure to benchmark returns or risk factors.
• Within-strategy correlation.
Bootstrap analysis of individual fund performances

Cross-section of benchmark-adjusted alphas and standardized alphas

Raw benchmark-adjusted alphas

Standardised benchmark-adjusted alphas
Bootstrap analysis of individual fund performances

Cross-section of benchmark-adjusted alphas and standardized alphas

Raw benchmark-adjusted alphas

Standardised benchmark-adjusted alphas (clustered st.err at the strategy level)
On the Performance of Cryptocurrency Funds

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Date Written: March 15, 2021

Abstract

We investigate the performance of funds that specialise in cryptocurrency markets. In doing so, we contribute to a growing literature that aims to understand the value of digital assets as investments. Methodologically, we implement a panel semi-parametric bootstrap approach that samples jointly the cross-sectional distribution of alphas conditional on different benchmark strategies and/or risk factors. Empirically, we show that a small significant fraction of managers are able to generate economically large alphas which are not purely due to sampling variation. However, once we account for the within-strategy correlation of the fund returns, the significance of the alphas substantially decreases below standard threshold confidence levels.

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

JEL Classification: G12, G17, E44, C58

Suggested Citation: