

# Appendix

## A Bootstrap methods

In this section we provide details on both the baseline bootstrap procedure as well as the two extensions proposed to investigate the robustness of the main results to alternative assumptions on the data generating process.

### A.1 Baseline bootstrap approach

This appendix provides the details of the baseline procedure with the residual resampling that extends the methodology outlined in [Kosowski et al. \(2006\)](#) and [Fama and French \(2010\)](#). For each fund in our sample, we draw a random sample (with replacement) from the fund residuals conditional on the returns of passive benchmarks (risk factors), creating a pseudo time-series of resampled residuals. Next, an artificial panel of monthly net-of-fees returns is constructed imposing the restriction that a true alpha for each fund is equal to zero. For each pseudo panel, we estimate the benchmark-adjusted (factor-adjusted) fund alphas as the individual fund fixed effects from the panel regression (see, e.g., [Pástor et al., 2015](#)). Thus, we obtain a set of individual fund alphas and their t-statistics based on random samples of months under the null of true fund alphas being zero. We repeat the above steps 10,000 times and save bootstrapped alphas and t-statistics for all simulation runs. We then report the distribution of these cross-sectional alphas and t-statistics.

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#### Procedure

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**Estimate** a benchmark (factor) model using the panel regression. 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 five-factor model includes a value-weight market portfolio (MKT) as well as liquidity (LIQ), momentum (MOM), reversal (REV) and volatility (VOL) long-short portfolios as proxies for systematic sources of risk.

**for** all bootstrap iterations  $b = 1, \dots, B$

**for** all funds  $i = 1, \dots, N$

- Draw a sample of months  $\{s_{T_{0,i}}^b, \dots, s_{T_{1,i}}^b\}$  where  $T_{0,i}$  and  $T_{1,i}$  are, respectively, the dates of the first and last months when returns of fund  $i$  are available

- Construct a time-series of resampled residuals  $\{\varepsilon_{i,t}^b : t = s_{T_0,i}^b, \dots, s_{T_1,i}^b\}$
- Generate a time-series of “synthetic” zero-alpha returns as

$$y_{it}^b = \hat{\beta}' \mathbf{x}_t^b + \varepsilon_{it}^b,$$

in which  $\mathbf{x}_t^b$  are the returns of passive benchmarks (risk factors)

**end**

Estimate the individual fund fixed effects from a panel regression with the benchmark (factor) returns on the right-hand side:

$$y_{it}^b = \hat{\alpha}_i^b + \hat{\beta}^{b'} \mathbf{x}_t^b + \varepsilon_{i,t}^b$$

**end**

**Output:** The bootstrapped individual fixed effects  $\{\hat{\alpha}_i^b : b = 1, \dots, B\}$  and the corresponding t-statistics  $\{\hat{t}_{\hat{\alpha}_i^b}^b : b = 1, \dots, B\}$ .

## A.2 Bootstrap extensions

**A.2.1 Block bootstrap.** The baseline bootstrap procedure assumes the residuals obtained from the panel regression are independently and identically distributed. This is because we resample the residuals in each period independently. The first extension relaxes this assumption by drawing months in blocks. Due to a short sample period, we resample the residuals in blocks of three months. Once the pseudo panel of fund returns is generated by blocks, we apply the remaining steps from the baseline procedure as in Section A.1.

**A.2.2 Independent bootstrap of residuals and explanatory returns.** The second bootstrap extension allows for independent draws of the benchmark returns and residuals. The procedure is constructed as follows:

### Procedure

**Estimate** a benchmark (factor) model using the panel regression. 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 five-factor model includes a value-weight market portfolio (MKT)

as well as liquidity (LIQ), momentum (MOM), reversal (REV) and volatility (VOL) long-short portfolios as proxies for systematic sources of risk.

**for** all bootstrap iterations  $b = 1, \dots, B$

**for** all funds  $i = 1, \dots, N$

- Draw a sample of months for the residuals  $\{s_{T_{0,i}}^b, \dots, s_{T_{1,i}}^b\}$ , and a sample of month for the benchmark returns  $\{\tau_{T_{0,i}}^b, \dots, \tau_{T_{1,i}}^b\}$ , where  $T_{0,i}$  and  $T_{1,i}$  are the dates of the first and last months when returns of fund  $i$  are available
- Construct a time-series of resampled residuals  $\{\varepsilon_{i,t_\varepsilon}^b : t_\varepsilon = s_{T_{0,i}}^b, \dots, s_{T_{1,i}}^b\}$
- Construct a time-series of resampled benchmark returns  $\{\mathbf{x}_{i,t_x}^b : t_x = \tau_{T_{0,i}}^b, \dots, \tau_{T_{1,i}}^b\}$
- Generate a time-series of “synthetic” zero-alpha returns as

$$y_{it}^b = \hat{\boldsymbol{\beta}}' \mathbf{x}_{t_x}^b + \varepsilon_{i,t_\varepsilon}^b,$$

in which  $\mathbf{x}_{t_x}^b$  are resampled returns of passive benchmarks (risk factors)

**end**

Estimate the individual fund fixed effects from a panel regression with the benchmark (factor) returns on the right-hand side:

$$y_{it}^b = \hat{\alpha}_i^b + \hat{\boldsymbol{\beta}}^{b'} \mathbf{x}_{t_x}^b + \varepsilon_{i,t_\varepsilon}^b$$

**end**

**Output:** The bootstrapped individual fixed effects  $\{\hat{\alpha}_i^b : b = 1, \dots, B\}$  and the corresponding t-statistics  $\{\hat{t}_{\hat{\alpha}_i}^b : b = 1, \dots, B\}$ .

## B Additional results

### B.1 Persistence of fund returns

The returns of hedge funds and other alternative investments are often highly serially correlated. Such strong autocorrelation could be due to illiquidity exposure and smoothed returns (see, e.g., [Getmansky et al., 2004](#)). Figure B.1 shows that this may not be the case for cryptocurrency funds. The figure shows the autocorrelation function up to 20 lags of the average returns across different types of funds (first row) and different investment strategies (second and third row). With the only mild exception of market neutral strategy, there is no strong evidence of a long-lasting persistence in the return

dynamics, which may require to “clean” the raw net-of-fees returns from autocorrelation.

[Insert Figure B.1 here]

Figure B.2 further confirms that there is not actually momentum, i.e., persistence, in the dynamics of raw returns, that is, a high return today does not necessarily predict a high return next month. In particular, the figure shows the post-formation returns from January 2020 (left panel) and from July 2019 (right panel) to the end of the sample.

[Insert Figure B.2 here]

The lines in the graph depict the average returns of funds in each of the three portfolios in the month of initial ranking (the “formation” month) and in each of the next months after formation. The first portfolio consists of funds in the top decile with the highest six-month returns, the second portfolio – funds in the bottom decile with the lowest six-month returns, and the third portfolio – remaining funds with the six-month returns in the second to ninth deciles. Clearly, there is not much evidence of momentum in raw returns, especially in the long term.

## B.2 Cumulative returns

For the sake of completeness, in this section we look at the dynamics of the cumulative returns of cryptocurrency funds vs. passive benchmark returns, as well as the dynamics of the cumulative returns across different fund types and investment strategies.

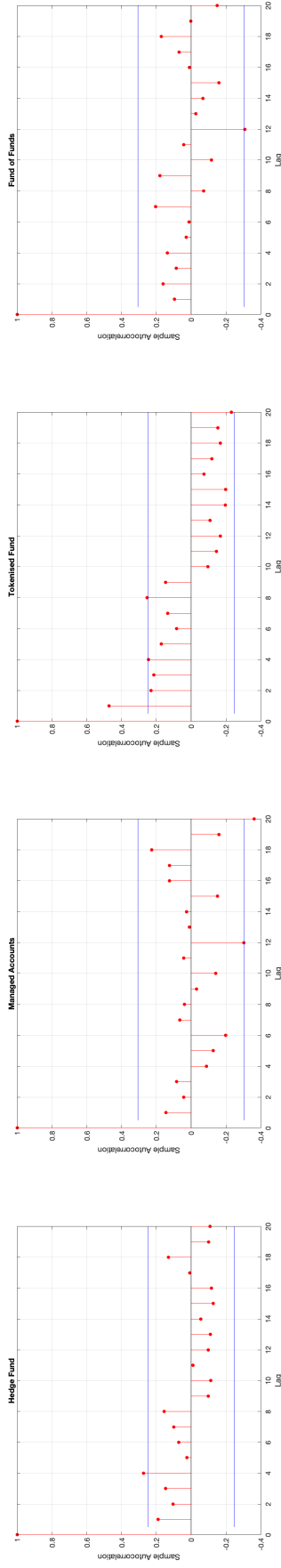
**B.2.1 Crypto funds vs. benchmark returns.** Figure C.1 illustrates the cumulative sum of log returns of an equal-weight average of the fund returns and compares it against a buy-and-hold investment in Bitcoin, an equal-weight (DOL) and a value-weight (Market) portfolio of top 300 cryptocurrencies in terms of market capitalisation, as well as a value-weighted portfolio of the digital assets available on Coinbase (ETF). The data covers the period from March 2015 to July 2020. Two observations are noteworthy. First, there is strong comovement around the dynamics of BTC across all passive investment strategies. That is, there is evidence of a “level” effect of BTC on cryptocurrency markets. Second, despite the dramatic decline in Bitcoin in later periods considered, the cumulative return of all funds only slightly declined during 2018 and in fact manages to recover by the end of 2019.

### **B.3 Returns across fund type and investment strategies**

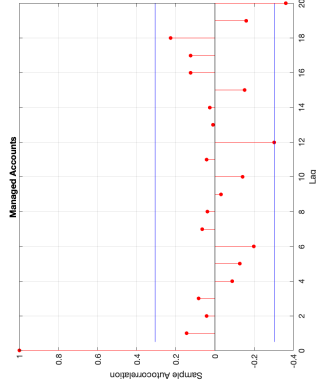
Figure C.2 shows that the compounded returns across different fund groups share a similar time variation during the considered period. An equal-weight average return for each fund type and strategy dramatically increases in the first half of the sample before starting to decline in 2018. The compounded returns then stabilise and start to recover towards the end of 2019. In relative terms, the market neutral funds are the best among other investment strategy funds.

Figure B.1: Autocorrelation function per fund type or investment strategy

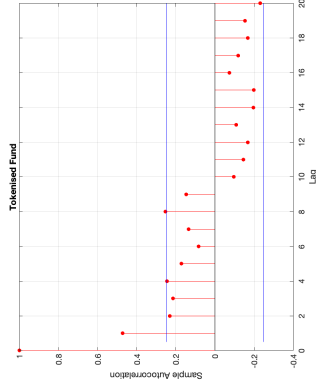
This figure shows the autocorrelation function up to 20 lags of equal weight portfolio returns aggregated across each type of funds and the investment strategy. The sample period is from March 2015 to July 2020.



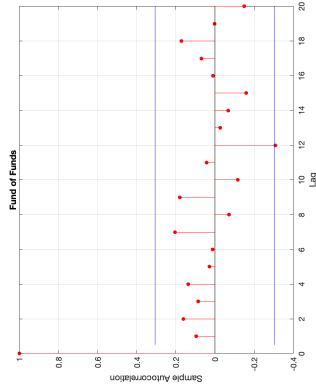
(a) Hedge fund



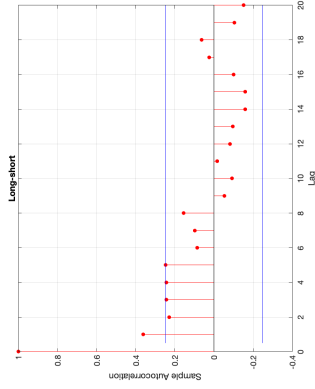
(b) Managed accounts



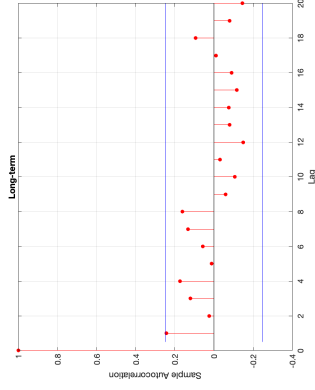
(c) Tokenized fund



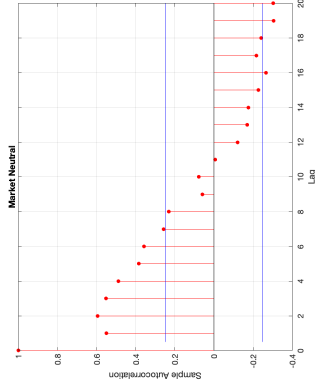
(d) Fund of funds



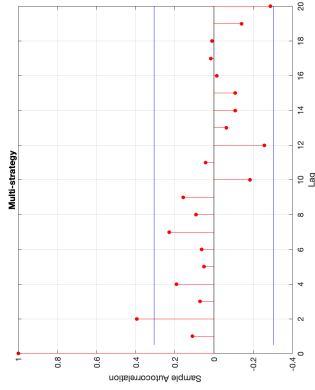
(e) Long-short



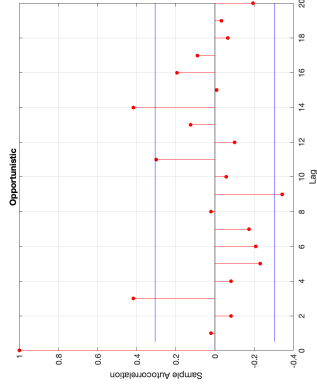
(f) Long-term



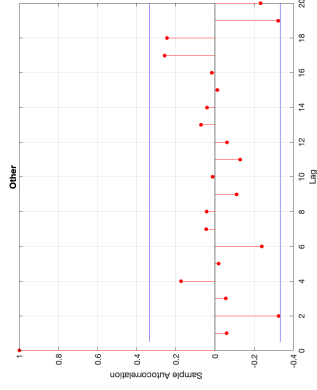
(g) Market neutral



(h) Multi-strategy



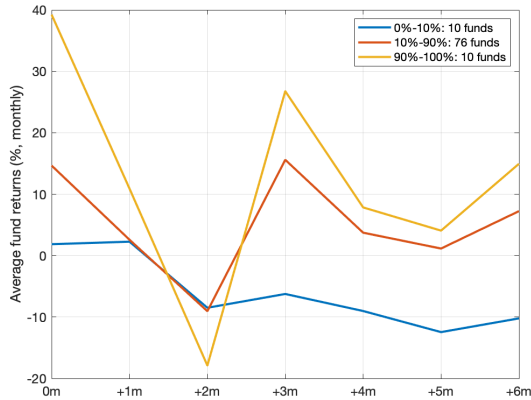
(i) Opportunistic



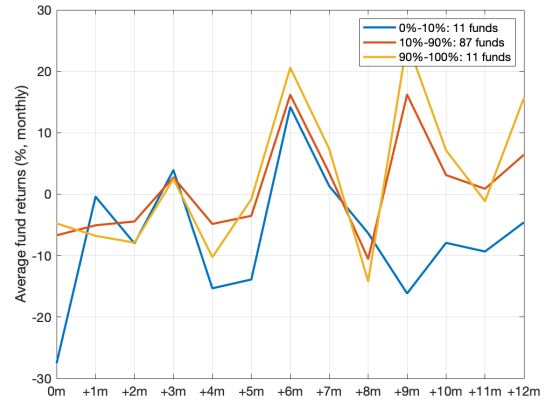
(j) Other

Figure B.2: Persistence of the fund performance

This figure plots the post-formation returns from January 2020 (left panel) and from July 2019 (right panel) to the end of the sample. The lines in the graph depict the average returns of funds in each of the three portfolios in the month of initial ranking (the “formation” month) and in each of the next months after formation. The first portfolio consists of funds in the top decile with the highest six-month returns, the second portfolio – funds in the bottom decile with the lowest six-month returns, and the third portfolio – remaining funds with the six-month returns in the second to ninth deciles. The sample period is from March 2015 to July 2020.



(a) Short-term return persistence



(b) Long-term return persistence

Figure C.1: Fund returns vs. cryptocurrency returns

This figure plots the time series of the fund returns proxied as an equal-weight average of each fund performance. The fund performance is calculated as the cumulative sum of log returns and is compared against a simple buy-and-hold investment in BTC, an investment in both an equal-weight and a value-weight portfolio of the major cryptocurrency pairs in terms of market capitalisation, and an investment in a value-weight average of the coins traded on Coinbase. The sample period is from March 2015 to July 2020.

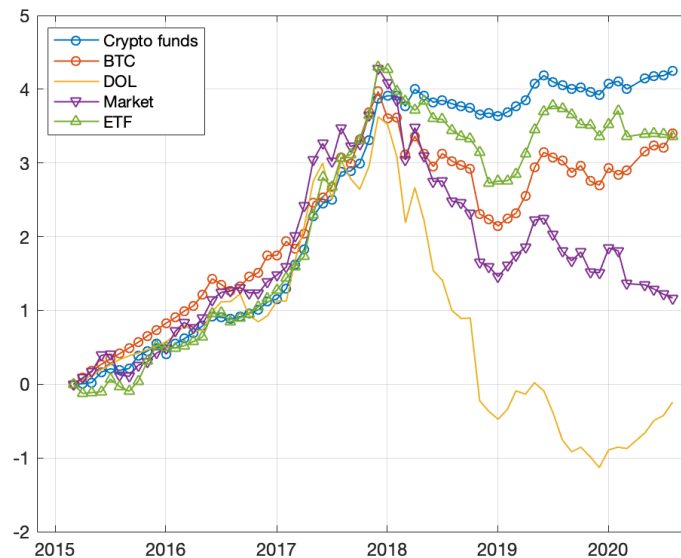
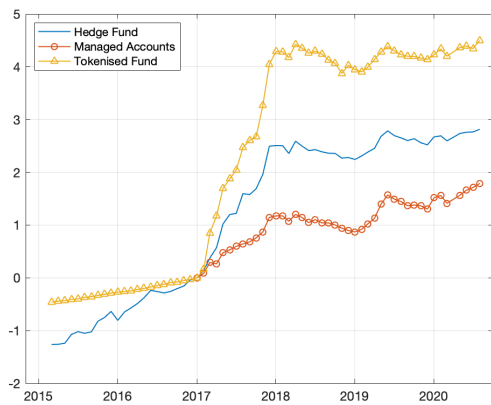
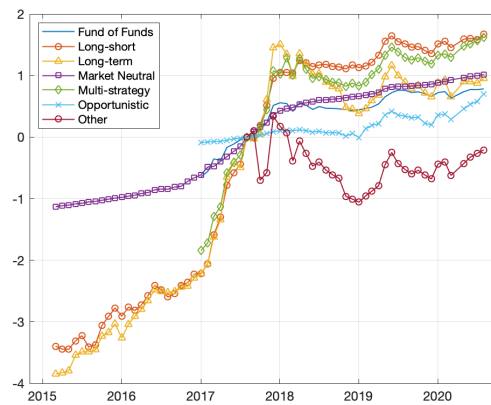


Figure C.2: **Compounded returns per fund type or investment strategy**

This figure plots the time series of fund returns for each type of fund (left panel) and investment strategy (right panel). The returns on each fund are aggregated as an equal-weight average of the returns within a given type/strategy. The fund performance is calculated as the cumulative sum of log returns. The cumulative log returns per fund type are normalised to 0 in January 2017 when the managed accounts were introduced. The cumulative log returns per investment strategy are normalised to 0 in August 2017 when the first fund with the “Other” strategy was introduced. The sample period is from March 2015 to July 2020.



(a) Cumulative log returns per fund's type



(b) Cumulative log returns per strategy