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Performance Measurement of Crypto Funds

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Abstract

Crypto funds (CFs) are a growing intermediary in cryptocurrency markets. We evaluate CF performance using metrics based on alphas, value at risk, lower partial moments, and maximum drawdown. The performance of actively managed CFs is heterogenous: While the average fund in our sample does not outperform the overall cryptocurrency market, there seem to be some few funds with superior skills. Given the non-normal nature of fund returns, the choice of the performance measure affects the rank orders of funds. Compared to the Sharpe ratio, the most commonly applied metric in practice, performance measures based on alphas and maximum drawdown lead to diverging fund rankings. Depending on their ranking of preferences, CF investors should thus consider a bundle of metrics for fund selection and performance measurement.

Keywords: Crypto funds, active investment management, performance measurement, fund selection, blockchain-based digital assets
JEL Codes: G11, G12, G23, G24

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1 Introduction

Crypto funds (CFs) are an arising type of actively managed funds that invest in blockchain-based assets. Their performance has become the focus of attention as the crypto market exhibits extreme levels of volatility. According to CoinMarketCap, the market valuation of all crypto assets reached its all-time high of almost $3,000 billion in November 2021 only to drop to about $800 billion seven months later – a loss of over 70%. Nevertheless, market growth since its early stages and the multi-faceted promises of blockchain technology have attracted many investors, including CFs. Figure 1 illustrates the number of fund foundings over time and reveals the impact of market swings: Growth slowed after the first peak in 2018, but CFs continue to gain in relevance. As of June 2022, more than 800 CFs existed with assets under management (AuM) close to $58 billion (Crypto Fund Research, 2021).

Despite the strong market dynamics and the increasing importance of institutional investors in crypto markets, we still know very little about CFs' value contribution and performance measurement. Our paper aims to fill this gap by addressing the following questions: Do CFs add value for investors? Does the choice of performance measure matter for the evaluation of CFs?

The contribution of our paper is twofold. First, we add to a long debate on the value of active asset management through the lens of a new and growing asset class.[1] To the best of our knowledge, only two studies exist that address the performance of CFs (Bianchi and Babiak, 2022; Cumming et al., 2022).[2] We extend their work by benchmarking CF returns against Liu et al.'s (2022) multi-factor crypto asset pricing model, considering a larger set of funds, and incorporating the crypto market turmoil during the 2021-22 period.

Second, we evaluate CF performance along a broad set of performance measures. The question which measure to use is crucial from a CF investor's perspective given the divergent findings in the investment fund literature whether or not the choice of the performance measure influences the evaluation of funds.[3] Most important, CF returns are highly non-normal, and a frequent concern is that funds with non-normal return distributions cannot be adequately evaluated by using the classic Sharpe ratio. While Eling and Schuhmacher (2007) and Eling (2008) document that various alternative performance measures result in identical rank orderings for hedge funds and mutual funds, other studies (Ornelas et al., 2012; Zakamouline, 2010) find that the choice of the performance measure does

[1]See Agarwal et al. (2015) and Cremers et al. (2019) for a literature reviews on hedge fund and mutual fund performance, respectively.

[2]A related literature examines traditional institutional investors, adding cryptocurrencies to their portfolios (Huang et al., 2022.)

[3]In a more general framework, Platanakis and Urquhart (2019) show that the method for risk estimation matters to assess the performance of cryptocurrency portfolios.

influence the ranking across funds.

Our results confirm that CF returns are heavily right-skewed and fat-tailed. Compared to a value-weighted crypto market index, the average CF outperforms by as much as 1.9% per month. This outperformance vanishes when applying Liu et al.'s (2022) multi-factor crypto asset pricing model based on market, size, and momentum. While CFs outperform the crypto market, they are unable to add value relative to dynamic factors known from the asset pricing literature. Performance measures based on alphas and maximum drawdown lead to diverging rankings compared to the classic Sharpe ratio. Tests of the significance of rank correlations reveal that, in particular, maximum drawdown performance measures are independent from other metrics. We conclude that CF investors, depending on their ranking of preferences, should rely on a bundle of metrics for performance measurement.

The remainder of our paper is structured as follows. Section 2 reviews existing literature on CFs and describes our fund performance measures. Section 3 presents the data sample. We show our empirical results in Section 4 and conclude in Section 5.

[Place Figure 1 about here]

2 Crypto Funds and Performance Measurement

While attention on CFs has strongly increased from investors, researchers, and regulators in recent years, the literature on this new asset class is scarce. Most related to our study, Bianchi and Babiak (2022) document that CFs achieve outperformance against the crypto market. Although this outperformance reduces when applying a multi-factor pricing model, they conclude that CF performance is driven by superior skills of active fund managers. Cumming et al. (2022) document similar outperformance relative to the market. They also show that CFs positively influence the financial outcome of token-backed ventures.[4] From a regulatory perspective, Mokhtarian and Lindgren (2018) document that CF regulation still remains at a very early stage even in the U.S., and the same applies for similar efforts at national and supranational levels around the globe.

To estimate CF alphas, we run market model regressions using a value-weighted crypto market index and the U.S. equity market index. In addition, we estimate the three-factor alpha based on Liu et al.'s (2022) crypto market model. They document that three factors, market, size, and momentum, are sufficient to explain the cross-section of returns of a

[4]The positive impact of institutional investors on the financial success of blockchain-based ventures has also been shown by Fisch and Momtaz (2020).

variety of crypto trading strategies.[5] Following Ferson and Qian (2004) and Ferson and Schadt (1996), we assess the distribution of alphas via their t-statistics.

A growing literature shows that the use of different performance measures is important because higher moments of return distribution play a significant role in performance evaluation, but their effect depends on the choice of the performance measure (Ornelas et al., 2012; Zakamouline, 2010). Since CF returns strongly deviate from the normality assumption, this new asset class is an ideal example, where correlations between the Sharpe ratio (the most commonly used benchmark in the industry) and alternative performance measures are expected to be low.

To determine whether the choice of the measure matters in the CF industry, we compare 14 different performance measures. In particular, these encompass classic approaches based on the normality assumption together with a variety of alternative metrics: Sharpe ratio (Sharpe, 1966), single- and multi-factor alphas, information (appraisal) ratio (Treynor and Black, 1973), excess return on value at risk (VaR) (Dowd, 2000), conditional Sharpe ratio (Agarwal and Naik, 2004), modified Sharpe ratio (Gregoriou and Gueyie, 2003), Omega ratio (Keating and Shadwick, 2002), Sortino ratio (Sortino and Van Der Meer, 1991), Kappa 3 ratio (Kaplan and Knowles, 2004), upside potential ratio (Sortino et al., 1999), Calmar ratio (Young, 1991), Sterling ratio (Kestner, 1996), and Burke ratio (Burke, 1994). Table 1 provides detailed definitions of these performance measures. To evaluate whether the choice of a particular measure is critical for CFs' performance evaluation, we compute all measures per CF in our sample, rank funds, and calculate Spearman rank correlations coefficients between the funds' performance measures.

[Place Table 1 about here]

3 Data

Our CF sample comes from Crypto Fund Research (CFR), a U.S.-based data aggregator that provides the most comprehensive database for returns and characteristics of funds focused on blockchain investments. While CFR provides characteristics for over 800 CFs, monthly net-of-fees performance data are available for 352 CFs from January 2017 to June 2022. To avoid suvivorship bias, our sample includes live as well as defunct funds. The difference between the average monthly returns of surviving funds and all CFs in our

[5]For the sake of brevity, we refer to Liu et al. (2022) for a detailed description of factors and strategies. We note that their factor data are only available until December 2021, thus our three-factor model results are based on a shorter sample period.

sample is 0.20%. Figure 2 reports the distribution of all monthly fund returns during our sample period, which strongly deviates from normality.

[Place Figure 2 about here]

4 Empirical Results

Table 2 describes the performance characteristics of our sample of actively managed CFs. Summary statistics in Panel A show that the average fund generates a monthly mean return of 7.8%, with a standard deviation of 5.9%. For the average fund, monthly returns are highly volatile, right-skewed, and fat-tailed. The average fund's Sharpe ratio is 0.248. The alphas benchmarked against the value-weighted crypto market index (α_{cmkt}) indicate that CFs are able to outperform their passive benchmark and generate large and economically relevant excess returns. The mean (median) monthly α_{cmkt} is 1.9% (1.8%), with p-values below 1%. Alphas measured against the U.S. equity market (α_{emkt}) are even higher. In contrast, the average fund's three-factor model alpha (α_{cmft}) turns negative. The mean (median) α_{cmft} is –0.49% (–0.22%), statistically significant at the 5% level. Correcting for dynamic trading strategies captured by the size and momentum factors (Liu et al., 2022), the outperformance of CFs becomes substantially weaker and even seems to disappear.

Panel B illustrates the distribution of t-statistics for fund alphas. Column (1) reports the number of CFs that fall within critical ranges of a standard normal distribution if the estimated alphas followed a normal distribution. The t-statistics of these alphas benchmarked against the aggregate crypto market (α_{cmkt}) in column (2) describe a distribution that is centered to the right of zero, right-skewed, and fat-tailed. Most important, there is substantial heterogeneity in individual CF performance. While 205 of 352 CFs show positive but statistically insignificant alphas, 51 funds exhibit positive alphas that are statistically significant at least at the 10%-level (with t-values exceeding 1.645). This compares to only 16 funds in total that exhibit significantly negative alphas.

A Bonferroni multiple comparison test rejects the null hypothesis that all estimated alphas are jointly equal to zero against the alternative that at least one fund alpha is positive. Column (3) reiterates these findings using the U.S. equity market as benchmark. As expected, in column (4), the multi-factor alpha (α_{cmft}) t-statistics are shifted and centered to the left of zero. Nevertheless, the Bonferroni test still rejects the null hypothesis that no fund alpha is positive. The minimum t-statistics are never statistically significant. Overall, while the mean (median) CF cannot beat the multi-factor benchmark, there is large heterogeneity in fund performance and at least some evidence of skill even when applying this conservative benchmark (Bianchi and Babiak, 2022).

[Place Table 2 about here]

Table 3 shows Spearman rank correlation coefficients between performance measures. The performance measures based on the concept of VaR and partial moments display high rank correlations with the Sharpe ratio. For these groups, although the measures are built on downside rather than symmetric risk concepts, the rank correlations with the Sharpe ratio do not fall below 0.948. Comparing the traditional Sharpe ratio with alphas as well as the information ratio, rank correlations drop notably to a range between 0.601 to 0.826. The relatively low rank correlation between α_{cmkt} and α_{cmft} of 0.503 indicates that rank orders of the two alphas are far from perfectly aligned and highlights the importance to correct CF performance for tradeable factor strategies.

Considering measures based on maximum drawdown, correlations with other performance measures drop substantially to low values in a range between 0.043 and 0.224. The Calmar, Sterling, and Burke ratios define risk based on the largest losses investors could potentially suffer. While the chronological sequence of returns does not change the standard deviation of fund returns, it substantially affects a fund's maximum drawdown. Given extreme crypto market swings, these three measures lead to notably different rankings than all other performance measures.

Following Eling and Schuhmacher (2007), we check the statistical significance of rank correlations using two different tests (not reported). First, we use a standardized version of the Hotelling-Pabst statistic, testing the null hypothesis that two rankings are independent, i.e., the corresponding rank correlation is zero (Hotelling and Pabst, 1936). For rank correlations between performance measures 1-11 (including traditional performance measures and those based on VaR and partial moments) in Table 3, there is no case in which the hypothesis of independence between two related rankings can be confirmed (based on a 5% significance level). In contrast, when comparing the measures building on maximum drawdowns to all other performance measures, the null hypothesis cannot be rejected. Therefore, the Calmar, Sterling, and Burke ratios generate fund rankings that are independent from the other performance measures that ignore risk related to a fund's maximum drawdown.

The second test is based on the Fisher z-transformation. Instead of testing the independence of ranking, we check the hypothesis that a rank correlation is smaller than a certain given rank correlation x. Assuming a 5% level of significance, and considering our performance measures 1-11 in Table 3, the hypothesis that the rank correlation is smaller than x

can only be rejected for all x values smaller than 0.435. In contrast, for the performance measures based on maximum drawdown, this test confirms that the rank correlations with the other performance measures are zero and thus independent. In conclusion, it does matter which measure is used to evaluate CF performance. There can be significant changes in the evaluation of CFs as compared to that found using the Sharpe ratio, most importantly, when applying performance measures considering maximum drawdown risk.

[Place Table 3 about here]

5 Conclusion

This paper assesses the performance of actively managed CFs. We find that CFs outperform a value-weighted crypto market index, but outperformance disappears when considering a three-factor pricing model. However, fund performance is very heterogeneous, and some few funds may still achieve superior returns, improving the efficiency of the cryptocurrency market (Urquhart, 2016). Our results further indicate that the choice of the performance measure does matter. Fund rankings diverge greatly when using alphas and performance measures based on maximum drawdown compared to the Sharpe ratio and other performance metrics. Depending on their ranking of preferences, CF investors should use a bundle of metrics for fund performance measurement.

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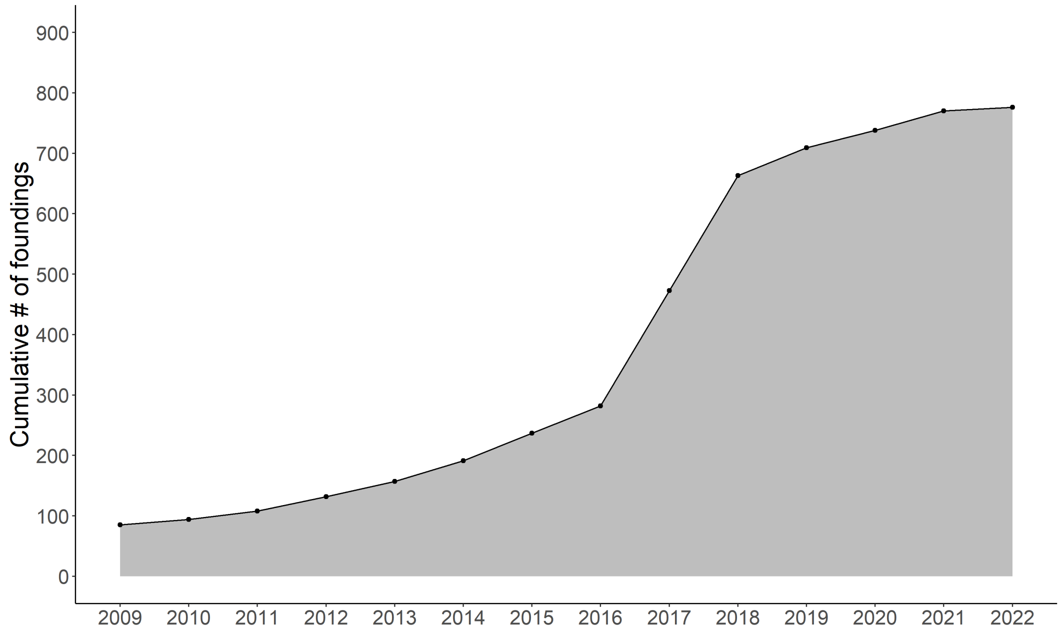
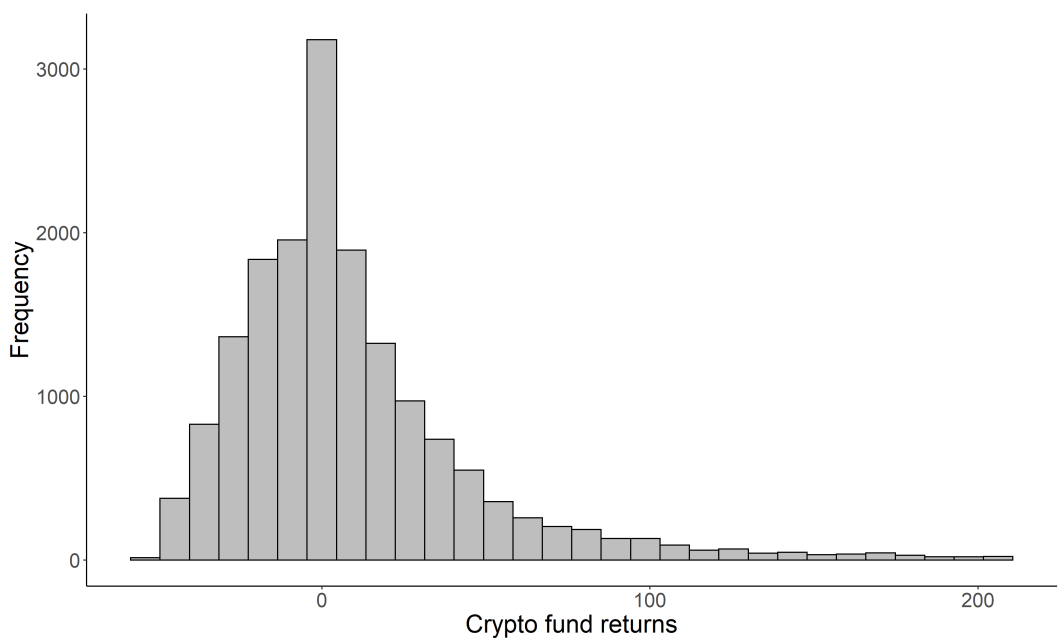
Exhibits

Figure 1: **Evolution of crypto funds**



Note: This figure displays the cumulative number of crypto fund foundings from 2009 until September 2022. In total, our sample includes about 800 CFs with a reported founding year.

Figure 2: **Return distribution of crypto funds**



Note: This figure shows the distribution of monthly (discrete) crypto fund returns in % during our sample period from January 2017 to June 2022. The sample contains returns for 352 crypto funds with a total of 16,808 fund-month observations.

Table 1: **Definitions of performance measures**

Performance measure	Formula	Variable definition
	Panel A: Traditional performance measures	
Sharpe Ratio	$(r_i - r_f)/\sigma_i$	r_i is the average monthly return of CF i, r_f the monthly risk-free rate, and σ_i the standard deviation of the monthly excess return
$\alpha_{i,cmkt},\ \ \alpha_{i,emkt}$	$r_i - (r_f + \beta_{i,m} \times (r_m - r_f)),\ \ m = \{cmkt, emkt\}$	$\beta_{i,m}$ is the sensitivity of CF i's returns to the returns of the index m and r_m the monthly index return; $beta_{i,m}$ can be expressed as $\frac{Cov(r_i,r_m)}{Var(r_m)}$; the index m can be the value-weighted crypto market index $cmkt$ or the U.S. equity market index $emkt$
Information Ratio	$\alpha_{i,cmkt}/\sigma(\epsilon_{i,cmkt})$	$\alpha_{i,cmkt}$ is CF_i's monthly crypto market alpha and $\sigma(\epsilon_{i,cmkt})$ the tracking error, which is the standard deviation of the difference between the returns of CF_i and the crypto market index
$\alpha_{i,cmft}$	$r_i - (r_f + \beta_{i,cmkt} \times (r_{cmkt} - r_f) + \beta_{i,SMB} \times SMB + \beta_{i,MOM} \times MOM)$	r_{cmkt} is the monthly crypto market return; SMB is the size factor of crypto returns; MOM is the momentum factor of crypto returns; the three factors follow the work of Liu et al. (2022)
	Panel B: Performance measures based on value at risk	
Excess Return on VaR	$(r_i - r_f)/VaR_i$	VaR_i represents $CF_i's$ value at risk computed by $VaR_i = -(r_i - z_\alpha \times \sigma_i)$ where z_α is the standard normal distribution quantile for the significance level α
Conditional Sharpe Ratio	$(r_i - r_f)/CVaR_i$	$CVaR_i$ is the conditional value at risk and defined as $CVaR_i = E[-r_{i,t} \| r_{i,t} \leq -VaR_i]$
Modified Sharpe Ratio	$(r_i - r_f)/MVaR_i$	$MVaR_i$ is the modified value at risk based on the Cornish-Fisher expansion (Favre and Galeano, 2002) and computed as $MVaR_i = -(r_i + \sigma_i \times (z_\alpha + 1/6 \times (z_\alpha^2 - 1) \times S_i + 1/24 \times (z_\alpha^3 - 3 \times z_\alpha) \times E_i - 1/36 \times (2 \times z_\alpha^3 - 5 \times z_\alpha) \times S_i^2))$ where S_i and E_i denote the skewness and excess kurtosis of CF_i, respectively
	Panel C: Performance measures based on lower partial moments	
Omega Ratio	$(r_i - \tau)/LPM_{1,i}(\tau)\ + 1$	Lower partial moments (LPMs) measure negative return deviations relative to a minimal acceptable return τ as $LPM_{n,i}(\tau) = \frac{1}{T}\sum_{t=1}^{T} max[\tau - r_{i,t}, 0]^n$; LPMs are of order $n = 1$ for the Omega Ratio
Sortino Ratio	$(r_i - \tau)/\sqrt[2]{LPM_{2,i}(\tau)}$	LPMs are of order $n = 2$
Kappa 3 Ratio	$(r_i - \tau)/\sqrt[3]{LPM_{3,i}(\tau)}$	LPMs are of order $n = 3$
Upside Potential Ratio	$HPM_{1,i}(\tau)/\sqrt[2]{LPM_{2,i}(\tau)}$	Following the logic of LPMs, HPMs measure positive return deviations relative to a minimal acceptable return; HPMs are of order $n = 1$, LPMs of order $n = 2$
	Panel D: Performance measures based on maximum drawdowns	
Calmar Ratio	$(r_i - r_f)/ - MDD_{i,l}$	Max. drawdowns (MDDs) measure risk as the largest return losses of CF_i during the sample period; $MDD_{i,l}$ is CF_i's largest decline
Sterling Ratio	$(r_i - r_f)/(\frac{1}{N}\sum_{j=1}^{N} - MDD_{i,j})$	Evaluates risk as the average of the N largest drawdowns
Burke Ratio	$(r_i - r_f)/\sqrt[2]{\sum_{j=1}^{N} MDD_{i,j}^2}$	Measures risk as the square root of the sum of the N largest squared drawdowns

Note: This table defines the measures used to evaluate the performance of crypto funds. The ratios are grouped into categories based on their approach to assess a fund's risk-return profile. Variables are defined at the first occurrence and suppressed thereafter for brevity. All measures, except $\alpha_{i,cmft}$, are based on data for the sample period from January 2017 to June 2022. For $\alpha_{i,cmft}$, we rely on the crypto market factors as provided by Liu et al. (2022), which are available only until December 2021. The size factor (SMB) is constructed using market capitalization, and the momentum factor (MOM) is based on past three-week return windows. Liu et al. (2022) provide detailed descriptions. In addition, the following parameter values are chosen for measures in Panel B, C, and D: The VaR-based ratios are computed with a significance level of α = 5%. For the measures based on lower and higher partial moments, we apply a minimal acceptable return of 0%. For the Sterling and Burke ratios, we use the five largest drawdowns (N = 5).

Table 2: **Performance characteristics of crypto funds**

Panel A: Summary statistics					
Crypto Fund	**Mean**	**SD**	**Q1**	**Median**	**Q3**
Return mean, in %	7.752***	5.861	3.563	8.331***	11.779
Return SD, in %	32.213	14.524	20.130	35.431	43.843
Return skewness	1.166	0.747	0.823	1.259	1.606
Return excess kurtosis	2.109	2.846	0.349	1.557	3.154
Sharpe Ratio	0.248	0.226	0.171	0.260	0.330
α_{cmkt}, in %	1.868***	3.726	–0.089	1.813***	3.331
α_{emkt}, in %	6.308***	5.286	2.636	6.738***	9.832
α_{cmft}, in %	-0.486**	4.576	-2.859	-0.215**	2.058
# of monthly returns	47.750	16.076	37.750	52	61

Panel B: Distribution of t-statistics for fund alphas				
	Null (1)	**Crypto market model** (2)	**Equity market model** (3)	**Crypto three-factor Model** (4)
Minimum t-statistic		–2.910	–2.551	–3.193
Bonferroni p-value (–)		1.000	1.000	1.000
$t \leq$ –2.326	1.760	4	3	7
–2.326 $< t \leq$ –1.960	7.040	6	1	5
–1.960 $< t \leq$ –1.645	8.800	6	2	11
–1.645 $< t \leq$ 0	158.400	80	30	159
0 $< t \leq$ 1.645	158.400	205	160	128
1.645 $< t \leq$ 1.960	8.800	17	50	14
1.960 $< t \leq$ 2.326	7.040	10	47	9
$t >$ 2.326	1.760	24	59	18
Maximum t-statistic		6.655	7.106	5.662
Bonferroni p-value (+)		0.001	0.0003	0.003

Note: Panel A reports summary statistics for the 16,808 monthly returns of the 352 sample crypto funds. The return statistics are first calculated on the fund-level and then aggregated across CFs. Alphas are based on CAPM regressions relative to the crypto market, the U.S. equity market, and the crypto three-factor model based on Liu et al. (2022). Equity market data are retrieved from the website of Kenneth R. French. *, **, and *** indicate statistical difference from zero at the 0.10, 0.05, and 0.01 level, respectively, and are based on t-tests for means and Wilcoxon-tests for medians. Panel B shows the distribution of robust t-statistics for the estimated alphas of all CFs. The rows contain the number of CFs for which the t-statistic falls within distinctive ranges of a standard normal distribution. As a point of reference, column (1) shows the number of CFs per range for the hypothetical scenario that fund alphas followed a normal distribution. Columns (2)-(4) display the actual distribution of alpha t-statistics for the crypto market model, the U.S. equity market model, and the crypto three-factor model. The Bonferroni p-value is the one-tailed p-value of the minimum and maximum t-statistics multiplied by the number of CFs. It tests the null hypothesis that all alphas are jointly equal to zero against the alternative that at least one fund alpha is negative (Bonferroni p-value (–)) or positive (Bonferroni p-value (+)). The sample period is from January 2017 to June 2022. Results for the crypto three-factor alphas are based on data only until December 2021.

Table 3: **Rank correlations of performance measures**

	1.	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.	14.
Traditional performance measures														
1. Sharpe Ratio														
2. α_{cmkt}	0.645													
3. Information Ratio	0.826	0.863												
4. α_{cmft}	0.601	0.503	0.638											
Performance measures based on value at risk														
5. Excess Return on VaR	1.000	0.645	0.826	0.584										
6. Conditional Sharpe Ratio	0.990	0.668	0.823	0.561	0.990									
7. Modified Sharpe Ratio	0.995	0.615	0.810	0.596	0.995	0.978								
Performance measures based on partial moments														
8. Omega Ratio	0.982	0.668	0.832	0.594	0.982	0.976	0.965							
9. Sortino Ratio	0.972	0.695	0.830	0.570	0.972	0.978	0.949	0.988						
10. Kappa 3 Ratio	0.960	0.704	0.822	0.545	0.960	0.974	0.934	0.975	0.997					
11. Upside Potential Ratio	0.948	0.702	0.814	0.539	0.947	0.964	0.919	0.961	0.991	0.997				
Performance measures based on maximum drawdown														
12. Calmar Ratio	0.136	0.043	0.200	0.066	0.137	0.113	0.153	0.142	0.115	0.106	0.102			
13. Sterling Ratio	0.155	0.067	0.224	0.110	0.156	0.129	0.174	0.158	0.131	0.120	0.116	0.996		
14. Burke Ratio	0.151	0.062	0.218	0.101	0.152	0.126	0.170	0.155	0.128	0.117	0.113	0.997	1.000	
Mean	0.720	0.529	0.671	0.462	0.719	0.713	0.712	0.721	0.717	0.709	0.701	0.254	0.272	0.268

Note: This table presents the Spearman rank correlations between all 14 performance measures used to compare the performance across crypto funds. The performance measures are grouped into categories based on their approach to assess the funds' risk-return profile. The sample period is from January 2017 to June 2022. Since the crypto market factors are only available until December 2021, the rank correlations of α_{cmft} are based on the period January 2017 to December 2021. The row "Mean" indicates the mean rank correlation of one performance measure to all other ratios.