Competition and Speculation in Cryptocurrencies*

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Abstract

We examine how mutual fund managers' performance incentives generated speculative demand during the 2020-2022 cryptocurrency boom and bust. Managers with strong relative performance incentives began investing in crypto after their competitors began investing in it, consistent with a model of competitive performance hedging. In contrast, managers with personal wealth invested in the funds they manage, who had strong direct performance incentives, responded much less to their competitors' investment decisions. Our findings suggest that relative performance incentives can encourage managers to mimic their competitors instead of trading on their beliefs, which can magnify the scope of speculative demand.

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1 Introduction

Cryptocurrencies are speculative assets characterized by high volatility, skewed returns, and uncertainty surrounding their fundamental value.[1] Given these lottery-like features, it is perhaps unsurprising that cryptocurrencies have been popular among unsophisticated retail investors (Benetton and Compiani (2021), Hackethal, Hanspal, Lammer, and Rink (2021), Kogan, Makarov, Niessner, and Schoar (2022)). Yet during the recent crypto boom, a wide range of institutional investors began investing in cryptocurrencies. As the price of Bitcoin rose 1,200% from $5,000 in March 2020 to $65,000 in November 2021, asset management firms, university endowments, and pension funds began adding cryptocurrencies to their portfolios. Many of these investors lost capital as Bitcoin fell 75% to $16,000 by November 2022. What drove these sophisticated institutional investors to invest in such speculative assets?

We present a simple framework in which competition among investment managers amplifies the scope of speculation. We take a standard mean-variance portfolio choice model and introduce relative performance incentives – for example, explicit compensation incentives in which a manager's wage depends on her returns relative to her competitors' returns, or implicit incentives such as career concerns. Initially, optimistic managers who believe that cryptocurrencies have high risk-adjusted returns adopt crypto. Subsequently, other managers are motivated by their relative performance incentives to adopt crypto *in response to* their competitors' crypto holdings, even if they believe that crypto has negative expected returns. Intuitively, managers are exposed to the risk that their competitors will outperform them if future crypto returns are high. Because managers are risk averse, they hedge the risk of underperformance by holding crypto themselves. We refer to this effect as "competition hedging." Competition hedging implies that competition among managers amplifies the initial optimists' beliefs and expands the set of managers who invest in cryptocurrencies.

We test this idea by examining the crypto investment behavior of mutual fund managers from 2015-2022. This context is a useful lab to study competition-driven speculation for two reasons. First, cryptocurrencies are a relatively new asset with significant uncertainty about their returns. If managers are uncertain about the fundamental value of crypto, they may rely relatively more

[1]Liu and Tsyvinski (2020) construct a cryptocurrency return index and estimate a monthly standard deviation of 70.80% from 2011 to 2018. They also find positive skewness – a daily 20% negative return happens with probability 0.48%, while an extreme gain of 20% occurs with probability 0.89%.

on their competitors' investment behavior in their own portfolio choice. Second, we can measure funds' crypto holdings through regulatory filings and we observe features of managers' compensation contracts which generate variation in their competitive incentives. Specifically, we observe whether fund managers have any personal money invested in the fund that they manage, which generates strong direct performance incentives.

We find evidence supporting the following narrative for mutual fund investment in cryptocurrencies during the 2020-2022 boom and bust, described in detail below. Early crypto holders had strong direct performance incentives, suggesting that they believed crypto returns would be positive. Once the crypto price run up began, the early adopters had high returns, which placed pressure on their peer funds to increase returns as well. The managers with no personal wealth invested in their funds and strong flow-performance incentives were most susceptible to this competitive pressure, and they adopted crypto more aggressively in response to their competitors' adoption. We also find evidence the early adopters with skin in the game appear somewhat more successful at exiting their positions before the largest crash, whereas the late adopters with no skin in the game did not. Our results suggest that competition among mutual funds magnified the scope of speculation during the crypto boom.

We begin by analyzing the managers who held crypto before the Bitcoin price run up in 2017. We find two characteristics related to manager incentives which positively predict crypto holdings, conditional on fund size, age, and manager characteristics: i) managers that invest their personal wealth in the fund they manage and ii) funds that are directly-sold rather than broker-sold. Both of these characteristics generate strong incentives to produce high absolute returns and align incentives between managers and their investors (Cremers, Driessen, Maenhout, and Weinbaum (2009), Del Guercio and Reuter (2014)). Furthermore, since the early crypto adopters had very few peers holding crypto, their decisions were unlikely to be driven by a competitive hedging motive.

Next, we examine the large crypto price run-up from 2020-2021, during which the fraction of mutual funds holding crypto tripled from 2% to 6%.[2] This masks substantial heterogeneity

[2]This scale of mutual fund investment in crypto assets is similar to mutual fund investment in non-traditional asset-backed securities (e.g. non-prime RMBS or CDOs) in the run-up to the 2008 financial crisis. For example, Chernenko, Hanson, and Sunderam (2014) finds that among inexperienced mutual fund managers, adoption of non-traditional ABS rose from about 3% in 2003 to 8% by 2007 (see Figure 2, Panel A).

in crypto holdings across investment styles and strategies. For example, in 2020, about 10% of funds in the Small Growth Morningstar category held crypto, while only about 1% of funds in the Large Growth Morningstar category did.

We use this heterogeneity in crypto adoption across Morningstar categories as a proxy for variation in competitive pressure to invest in faced by funds. Indeed, a strong predictor of whether a fund adopted crypto during the run up is the fraction of the fund's competitors within the same Morningstar category that held crypto before the run up. There are both belief and incentive-based explanations for this pattern. An example of a belief-based explanation is that mutual funds try to learn from their competitors, believing that they have valuable information about the prospects of the assets they hold. Another possibility is that managers with similar beliefs sort into the same competitor groups, so a manager's exposure to competitors holding crypto is correlated with the manager's own beliefs. An incentive-based explanation is that managers are hedging the risk of future underperformance in the state of the world where competitors' returns increase due to crypto.

To distinguish between these explanations, we test three predictions from our conceptual framework which leverage variation in manager incentives. First, we find that the effect of competition on a fund's probability of adopting crypto is significantly stronger for managers who *do not* invest personal wealth in the funds they manage. This result is consistent with the prediction that managers with stronger relative performance incentives hedge their relative performance risk more aggressively. It also implies a shift in the composition of cryptocurrency investors during the run up – early adopters are managers who have skin in the game, whereas late adopters are managers without skin in the game.

Second, we find that the effect of competition on a fund's probability of adopting crypto is larger for funds which face a strong flow-performance relationship. We measure each fund's flow-performance incentives using past returns. Chevalier and Ellison (1997) show that the flow-performance relationship is convex, which means that the lowest-performing funds have relatively weak performance incentives since their flows remain similar regardless of future performance, whereas the mid-to-high performing funds have relatively strong performance incentives since their flows change dramatically in response to future performance. Consistent with the model's prediction, we find that funds with poor recent performance are not responsive to their competitors' crypto holdings, whereas funds with moderate to strong recent performance are the most responsive.

Third, to control for unobserved heterogeneity in manager beliefs, we focus on managers who manage multiple funds with the same performance benchmark but different sets of competitors. In our framework, if a manager's investment in cryptocurrencies is driven solely by his beliefs about crypto returns, then he will hold crypto in all of his funds or none of his funds.[3] Conversely, if a manager has competitive incentives to hold cryptocurrencies, then he will be more likely to hold crypto in his funds which compete with other funds that hold crypto. In the data, we find that managers who run multiple funds are significantly more likely to adopt crypto in their funds which have more competitors holding crypto.

These findings suggest that managers' peer groups influence their decisions to adopt crypto during the run up in a way that cannot be fully explained by beliefs. However, an important question that arises from these results is whether the key incentive at play is competitive hedging or whether fund managers in different categories are simply catering to different investors. For example, if investors in tech funds want crypto exposure and tech managers begin holding crypto to cater to the investors, this leads to correlated investment decisions among competing funds that are not driven by any direct interaction between managers. In absence of a natural experiment which generates random variation in cryptocurrency holdings, we cannot definitively identify the causal effect of a competitor's crypto holdings on a fund's decision to adopt crypto. Instead, we conduct two tests to examine whether the patterns we observe are driven by catering rather than competitive hedging.

First, we examine whether funds are communicating their crypto holdings to investors. If managers are catering to investors' crypto demand, we would expect them to advertise their crypto holdings, potentially through the fund prospectuses or names. We gather the prospectuses of all the mutual funds which hold crypto from 2020-2022 and we search for key words related to cryptocurrencies in the prospectus text. Importantly, fund prospectuses include a salient section in which the fund details its investment strategy and the potential risks associated with their strategy. Of the 423 prospectuses we examine, only 4% mention crypto when discussing their

[3]This prediction holds up to some constraints across funds such as differences in investment mandates. For example, if a manager holds crypto in their technology fund but not in their value fund, this could be because crypto is outside the mandate of the value fund. We account for this possibility in our empirical analysis below.

investment strategy.[4] If funds were primarily catering to investor demand, we might expect to see many more funds mentioning crypto in a salient part of their prospectuses. In terms of catering through fund names, previous research suggests that mutual funds take advantage of popular investment styles by changing their names to generate significant abnormal inflows (Cooper, Gulen, and Rau (2005)). We examine changes in fund names during the run up and we do not find systematic evidence for this pattern.[5]

Our second test examines crypto holdings by funds' investor clientele. If fund investors do not demand crypto, then there should be no difference in the catering behavior of managers with or without skin in the game. If fund investors have strong demand for crypto, then we should see managers without skin in the game catering aggressively and managers with skin in the game abstaining. We proxy for investor crypto demand using the retail share of a fund's AUM, under the assumption that retail investors have stronger crypto demand than institutional investors on average. We find little evidence that manager skin in the game has a larger effect on cryptocurrency adoption for high retail share funds than low retail share funds, which is inconsistent with a key prediction of the catering channel.

In our final set of analyses, we examine funds' trading behavior during the crypto price crash. While we find little evidence that mutual funds as a whole were able to time the cryptocurrency crash, we find differences in timing ability by manager incentives. We find that managers with skin in the game were more aggressive in timing the aggregate cryptocurrency bubble – they exhibited strong inflows into crypto during the run up in 2021, and they had net outflows in 2022Q1, right before the large crypto crash in 2022Q2. In contrast, managers with no skin in the game invested a smaller fraction of their portfolios in crypto during 2021, and they did not appear to time the bubble.[6]

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[4] 94% of them mention crypto key words at some point in the prospectus, typically as a legal disclaimer about the risks of cryptocurrencies towards the end of the document.

[5] For example, crypto holding funds are not more likely to change their name within the past 3 years than non-crypto holding funds. We do find a few specific examples of funds appearing to cater through name changes, but the practice does not appear widespread.

[6] We document an example of market timing by examining MicroStrategy, a business software vendor which pivoted its business strategy to holding Bitcoin in August 2020 and saw its stock price rise by 750% by February 2021. Given the timing of this switch, we split mutual funds based on whether they held MicroStrategy before 2020 or after 2020. Funds which held MicroStrategy before 2020 reduced their holdings from 10% of shares outstanding to 2.5% two quarters after the firm announced that it held crypto. Funds which held MicroStrategy only after 2020 increased their exposure after the price peak - they went from holding 2.5% in 2021Q1 to holding over 15% by 2022Q1, and they were exposed to significantly negative returns in 2022Q2. Morgan Stanley funds appeared to have timed the bubble well

In sum, our results suggest that competition among mutual funds during the 2020-2022 cryptocurrency boom-bust cycle encouraged managers with strong relative performance incentives to adopt crypto after their competitors began holding crypto.

Our paper relates to a long literature which studies speculation and asset price bubbles. Many papers explore how heterogeneous beliefs and deviations from rational expectations generate booms and busts (see Xiong (2013) for an overview and Bordalo, Gennaioli, Kwon, and Shleifer (2021) for a recent example). A key question that emerges from this literature is why rational investors fail to trade against irrational ones. Some authors have argued that rational arbitrageurs face frictions which prevent them from eliminating mispricings, such as short sales constraints, capital constraints, or noise trader risk (e.g. Bris, Goetzmann, and Zhu (2007), Mitchell, Pedersen, and Pulvino (2007), De Long, Shleifer, Summers, and Waldmann (1990)). Our paper presents a complementary explanation – rational investors have competitive incentives to participate during a bubble to hedge the risk of short-term underperformance.

A related literature analyzes empirically the role of beliefs about the future path of returns and incentives faced by money managers in driving investor behavior during bubbles. Greenwood and Nagel (2009) find that young inexperienced managers were heavily invested in tech stocks during the technology bubble, and they argue that beliefs about returns drove managers' behavior. Chernenko et al. (2014) examine mutual fund and insurance company holdings of collateralized debt obligations and private-label mortgage backed securities during the 2008 financial crisis. They argue that mutual funds were largely motivated by beliefs about returns and insurance companies were motivated by incentives to take risks owing to agency frictions. Kashyap, Kovrijnykh, Li, and Pavlova (2023) propose a model in which manager benchmarking incentives arise endogenously from optimal contracts, and they show that incentive contracts create a pecuniary externality through their effect of asset prices. Their model features managers with homogeneous beliefs about returns and different abilities to add alpha, whereas our model emphasizes how heterogeneous beliefs interact with benchmarking incentives to drive speculation in a novel setting.

Our findings also relate to the literature on portfolio mimicking that is based on relative consumption motives of end investors. Our competition hedging incentive is similar to the mech-

- they quickly took a large stake in MicroStrategy in 2020Q4 after Bitcoin holdings were announced and profited from the run up, then sold their stake during the peak in 2021Q1.

anism proposed by Lauterbach and Reisman (2004), who argue that individuals who care about their consumption relative to that of their neighbors will overweigh domestic stocks to mimic their neighbors. Demarzo, Kaniel, and Kremer (2004) generate a similar effect in a model in which agents compete for local resources through their portfolio choice. While our paper focuses on financial intermediaries rather than end investors, we view it as complementary in the sense that our data allow us to estimate the strength of relative consumption motives emphasized by these papers.

The rest of our paper is organized as follows. Section 2 presents a portfolio choice model which incorporates beliefs and incentives. Section 3 describes our cryptocurrency holdings and manager incentives data and presents summary statistics. In Section 4 we investigate the role of incentives in speculation. Section 5 concludes.

2 Conceptual Framework

We develop a framework to illustrate how beliefs and incentives affect a manager's portfolio choice. The purpose of the framework is to guide our empirical analysis with predictions which allow us to separate the role of beliefs and incentives. We start with a simple two-period model that we use to characterize mutual fund manager portfolio choice as a function of subjective one-period return beliefs, hedging incentives, and incentives to cater to clients.[7] We then extend to three-periods to accommodate manager market timing and explore the dynamics of competition hedging.

2.1 Setup

There are two periods, $t = 0, 1$. There are N risky assets and one risk-free bond. Risky assets are claims to cash flows $\tilde{D}$, realized at $t = 1$, where $\tilde{D} \sim N(\mu, \Sigma)$. The variables $\tilde{D}$ and μ are $N \times 1$ vectors and Σ is an invertible positive definite matrix. The risk-free bond pays an interest rate that is normalized to zero. Managers have CARA utility over their wealth W, $U(W) = -\exp(-\gamma W)$ where γ is the coefficient of absolute risk aversion.

[7] The basic structure of our model comes from Kashyap et al. (2023), though their model incorporates manager alpha and optimal contracts, whereas ours focusing on competition hedging and catering.

The manager's compensation has four parts: the first is a linear payout based on absolute performance of the portfolio x, the second depends on performance relative to a benchmark (e.g. S&P 500, Russell 2000), the third depends on fund flows related to ex-post returns, and the fourth depends on flows related to ex-ante investor demand.[8] The manager's returns (absolute performance) are $r_x = x^\top \tilde{D}$. The benchmark portfolio returns and competitors returns are $r_b = \theta_b^\top \tilde{D}$ and $r_c = \theta_c^\top \tilde{D}$ respectively where θ is a vector of portfolio weights. Fund flows based on returns are a linear function of realized returns relative to competitors. Specifically, flows equal $f \cdot (r_x - r_\mathbf{c})$ where f is a scalar. Lastly, fund flows based on ex-ante investor demand are given by $r_\lambda = x^\top \lambda$, where λ is a vector capturing exogenous investor demand for specific assets.

The model timing is as follows. At $t = 0$, the manager chooses portfolio weights x to maximize his expected utility. Investor flows related to ex-ante return expectations, r_λ are realized. At $t = 1$, asset returns are realized and flows respond to realized returns. There is no time discounting. Thus, the wage function is:

$$w = \hat{a} r_x + b\,(r_x - r_\mathbf{b}) + cf \cdot (r_x - r_\mathbf{c}) + c r_\lambda = a r_x - b r_\mathbf{b} - cf\, r_\mathbf{c} + c r_\lambda \tag{1}$$

where a, b, and c and the weights on absolute returns, returns relative to a benchmark, and fund flows respectively.

2.2 Analysis

2.2.1 Portfolio choice

At $t = 0$, the manager chooses a portfolio of risky assets x and the risk-free bond holdings to maximize:

$$-E \exp\{-\gamma\,[a r_x - b r_\mathbf{b} - cf\, r_c + c r_\lambda]\} \tag{2}$$

[8]Adding a fixed component of compensation has no effect on portfolio choice in this CARA-Normal setting.

We show in the appendix that the portfolio choice rule implied by this objective function is:

$$x^* = \frac{1}{a}\left(\underbrace{\frac{\mu}{\gamma}\Sigma^{-1}}_{\substack{\text{Subjective}\\\text{return beliefs}}} + \underbrace{\underbrace{b\theta_b}_{\substack{\text{Benchmark}\\\text{hedging}}} + \underbrace{cf\,\theta_c}_{\substack{\text{Competition}\\\text{hedging}}}}_{\text{Hedging incentives}} + \underbrace{\frac{c}{a}\frac{\lambda}{\gamma}\Sigma^{-1}}_{\text{Catering}} \right) \tag{3}$$

This expression has four terms. The first term ($\frac{\mu}{\gamma}\Sigma^{-1}$) reflects the manager's subjective beliefs about the distribution of returns and is a standard feature of mean-variance analysis. The remaining three terms represent deviations from the standard portfolio choice rule that are driven by managers' compensation structure.

The second and third terms depend on the portfolio of a fund's benchmark (θ_b) and competitors (θ_c). These terms arise because the manager is exposed to the risk of their benchmark and competitors performing well when the manager does poorly. Because the manager is risk averse, he hedges this risk by tilting his portfolio towards his benchmark and competitors' portfolios. We refer to these two terms as benchmark and competition hedging incentives respectively.

The fourth term is increasing in investors' ex-ante demand for specific assets (λ). This term essentially increases the expected return of an asset since the manager receives valuable inflows at $t = 0$. However, because they must hold the asset until $t = 1$, the incentive to add these assets is declining in the perceived risk of the asset. We refer to this term as catering.

The entire portfolio choice expression is multiplied by by $\frac{1}{a}$. Since higher a scales the manager's whole wage and exposes them to more risk, the manager reduces their aggregate risk asset holdings as a increases.

2.2.2 Predictions

Our framework makes testable predictions which relate portfolio choice to competitive hedging incentives. All derivations are in the appendix.

Prediction 1. *Managers with stronger direct performance incentives* (a) *compared to relative performance* (b) *and flow* (c) *incentives hedge less aggressively in response to the portfolio choice of their competitors* (θ_c).

Intuitively, a manager with stronger direct performance incentives places greater weight on their own beliefs about returns (since they drive absolute returns) and smaller weight on their competitiors' portfolios and catering because they are less concerned with outperforming their peers and fund flows.

Prediction 2. *Managers who face a stronger flow performance relationship* (f) *hedge more aggressively in response to the portfolio choice of their competitors* (θ_c).

In our model, managers tilt towards their competitors' portfolios to hedge the risk that they underperform their peers and face outflows. It follows that managers with fund flows that are highly sensitive to relative performance should hedge more aggressively.

Prediction 3. *Among managers who manage multiple funds with the same benchmark, the funds with more competitors adopting crypto* (θ_c) *are more likely to adopt crypto themselves.*

In our empirical analysis below, we test these predictions and we provide evidence consistent with the idea that hedging incentives play an important role in manager's portfolio choice.

2.2.3 Extensions

The portfolio choice expression derived above comes from a static model in which competitors' holdings are taken as exogenous. In the appendix, we derive an expression for portfolio choice which endogenizes the competitor portfolio by having multiple managers choose their portfolios while accounting for their competitors' holdings. This allows us to analyze how a change in competitors' beliefs and incentives affect a manager's decisions. The model delivers the intuitive result that a manager's crypto portfolio weight is increasing in the crypto optimism of their peers, and the strength of the effect depends on the strength of the competition hedging incentives and the flow-performance relationship.

We also derive and simulate a multi-period version of the model in which managers update their holdings every period according to their portfolio choice rule.[9] Managers begin period one with zero crypto holdings. In period two, crypto optimists begin holding crypto and pessimists

[9]Details of this simulation are included in the appendix.

hold no crypto.[10] In the subsequent periods, the fraction of crypto holders and the average portfolio weight in crypto increases even though all managers' beliefs about returns remain fixed. The growth in crypto adoption following period two is driven by managers' competition hedging incentives – managers with weakly negative beliefs about crypto returns begin holding crypto to hedge the risk of underperformance. This increases the average crypto portfolio weight that all funds use in period three to determine their holdings, and this dynamic continues in future periods. Eventually the fraction of managers holding crypto asymptotes - intuitively, some managers are so pessimistic about crypto that no amount of competitor adoption will lead them to adopt crypto. The exact limit and number of periods required to approach it depend on the distribution of return beliefs and the strength of benchmarking incentives.

The multi-period model also allows us to capture richer dynamics in manager choices over time. For instance, if a manager believed that crypto would have a huge run-up followed by a huge crash, so that $\mu_0 >> 0 >> \mu_1$, then all else equal, the manager would go long crypto in period 0 and short crypto in period 1. Time-varying pressure from clients or competitors – parameterized by λ_t and θ_{ct}, respectively – could create similar patterns.

In our empirical analysis, we explore the timing of manager investment in crypto – and in particular, whether they appropriately time exit – as an additional way of understanding the motivations behind crypto investment.

3 Data

3.1 Mutual fund holdings and characteristics

3.1.1 Measuring crypto holdings

Mutual funds can gain exposure to crypto in three ways: i) buying cryptocurrencies like Bitcoin from crypto exchanges, ii) buying structured products like ETFs which track the performance of crypto futures, and iii) buying shares in stocks like Coinbase which are related to the crypto

[10]Managers do not hold a negative weight in crypto due to short sales constraints. This assumption strengthens the competitive hedging incentive because it means that the average portfolio weight held by managers is positive. If managers were allowed to short crypto, then with a symmetric distribution of beliefs centered around zero, the average portfolio weight in crypto would be zero and all managers would shade their holdings towards zero.

industry. Mutual funds' direct holdings of cryptocurrencies are private, but their regulatory filings include data on ETFs, trusts, and common shares which we use measure crypto exposure. We manually construct a list of popular ETFs and trusts that managers use to gain cryptocurrency exposure.[11] We also include a small set of large companies with cryptocurrencies as their primary business to capture exposure through crypto-related stocks.[12]

3.1.2 Fund and manager characteristics

Our primary data set is the Thomson Reuters S12 database of quarterly holdings by U.S.-domiciled mutual funds. Our sample period covers 2015Q1-2022Q2, which covers three crypto cycles, including the most recent boom and bust.[13] We supplement this with additional data on fund characteristics such as investment objectives, returns, and flows from CRSP Mutual Fund and Morningstar. We aggregate these data from the share class level to the portfolio level since we are interested in the managers' portfolio level decisions.

We also gather data from mutual funds' Statement of Additional Information (SAI) filings with the SEC, which report dollar ranges of manager investment up to one million dollars. We group managers to the fund level and create an indicator for whether at least one fund manager invests their personal wealth in the fund.

3.1.3 Defining competitor funds

Morningstar groups mutual funds into categories based on their holdings and risk-return profiles - for example, funds are grouped based on the factor characteristics of their holdings (e.g. small growth, large value, mid blend, etc.) as well as their sector (e.g. technology, finance). Morningstar

[11]Most of these products track the returns of Bitcoin, and some track other coins like Ethereum or Litecoin. The full list of tickers is GBTC, BITW, OBTC, BTCF.X, ETHE, GDLC, GDLCF, BITO, BTF, XBTF, RAAX, BITS, LTCN, BCHG, and ETCG.

[12]Specifically, we include Coinbase, a cryptocurrency exchange platform, and MicroStrategy, a business strategy company that pivoted to almost exclusively holding Bitcoin during the crypto run up. In unreported results, we constructed a broader measure of crypto stocks by estimating quarterly stock betas with respect to a cryptocurrency index, FF3, and momentum factors using daily data, then defining "crypto stocks" as those with a cryptocurrency beta above a certain cutoff. However, we found these betas to be highly volatile across time. For example, in 2021 it was revealed that Elon Musk invested $1.5B in Bitcoin. Tesla's return correlation with Bitcoin jumped from 0 before 2019 to 0.3 in 2021. It is unlikely that all of Tesla's existing shareholders chose to increase their crypto exposures at that point. Therefore, we opt for our more transparent metric, with the understanding that we are likely underestimating the true extent of crypto exposure.

[13]These cycles occured in 2017-2018, 2019, and 2020-2022.

also assigns funds a rating from 1 to 5 based on their past returns. Previous research finds that many investors use these Morningstar categories to make investment decisions and that Morningstar ratings drive fund flows (Del Guercio and Tkac (2008), Evans and Sun (2020)). Given this, it is natural to define funds in the same Morningstar category as competitors.

3.1.4 Sample selection

We restrict our sample to active mutual funds because we are interested in managers' portfolio choice decisions rather than passive index strategies. We also remove funds which have strategies that preclude holding crypto by mandate (e.g. corporate and municipal bond funds, money market funds).

3.2 Summary statistics and aggregate holdings

Table 1 presents summary statistics for our primary dataset. The median fund has net assets of $321 million, and it is managed by two male managers with roughly 5 years of experience each. Approximately 60% of funds have at least one manager investing in the fund.[14]

On average, 3% of funds have exposure to crypto. Crypto portfolio weights are highly skewed – although the median fund holds no crypto, some funds hold as much as 35% of their portfolio in crypto. Table 2 reports summary statistics that are averaged at the Morningstar category × quarter level. Since Morningstar categories group funds by investment style and holdings, differences across categories speak to the scope of cryptocurrency investment. There is significant variation in crypto holdings across categories – the average category has 2% of funds holding crypto, with a standard deviation of 5% and a maximum of 75%.

Next, we summarize time series variation in crypto holdings. Figure 1 shows that the fraction of mutual funds holding crypto tripled from 2% in 2020Q1 to 6% by 2021Q4. The fraction of mutual fund AUM in crypto increased from essentialy zero to 0.05% over the same time period. The magnitude of the crypto AUM share shrinks towards zero because most funds have no crypto exposure. Conditional on holding a positive amount of crypto, the average crypto portfolio share

[14]The median amount of investment (conditional on any investment) is $100,000-$500,000. The ideal measure of the strength of manager incentives is the fraction of their wealth that is invested in the fund, we do not observe wealth. However, we note that the median financial manager salary in the U.S. in 2021 was $130,000, so observed investment levels are a non-trivial share of a manager's annual salary.

in 2021Q4 is 1.1% with a standard deviation of 3%.

Figure 2 presents crypto adoption patterns over time within Morningstar categories. It shows that funds in categories like Small Growth, Technology, and Financial were early adopters of crypto before the run-up in 2020Q4, and that other funds in these categories also adopted crypto aggressively during the run up in 2021. It also shows that crypto adoption expanded in funds across wider range of categories, such as Large and Mid-Cap Growth and Multialternative.

It is important to note that, despite the increased adoption of crypto by mutual funds during this time period, they remained a relatively small share of total investment in the crypto market. Figure 3 shows that mutual funds held about 1.5% of the shares outstanding of Grayscale Bitcoin Trust, a popular investment vehicle for Bitcoin exposure. Given this, our results are not intended to speak to the causal effect that mutual fund managers had on the crypto bubble. Rather, we seek to understand the investment decisions of managers, taking the price patterns as given.

4 Empirical Results

4.1 Characteristics of early adopters

We begin by documenting the incentives of fund managers that invested in cryptocurrencies before the early Bitcoin price boom in 2017. We examine two characteristics of managers which affect their incentives. The first is whether the manager invests their personal wealth in the fund that they manage, otherwise known as "skin in the game". Previous research has shown that skin in the game aligns the incentives of fund management with shareholder interests by creating stronger performance incentives (Cremers et al. (2009)). The second is whether a fund is sold directly to investors or whether it sold by a broker. Del Guercio and Reuter (2014) show that broker-sold active funds underperform index funds whereas directly-sold funds do not underperform. They attribute this to manager of directly-sold funds having stronger incentives to generate alpha, which drives them to invest more in active management. Table 3 presents a regression of whether a manager holds crypto or not on these two characteristics and additional fund level controls on a sample of funds from 2016, before the first crypto run up. Column 1 shows that managers with skin in the game were 1.3 percentage points (30%) more likely to hold crypto than managers without skin in the game, and that directly-sold funds were 1.6

percentage points (37%) more likely to hold crypto than broker-sold funds.

We also examine assets that managers hold along with cryptocurrencies to provide a clearer picture of the broad investment styles of these managers. We regress a fund's portfolio weight in cryptocurrency on a Morningstar category fixed effect for the sample before 2017. Since Morningstar categories group funds based on the broad style of their holdings, this analysis tells us what the funds co-hold with cryptocurrencies. Figure 4 shows that funds which held small cap, growth, and technology stocks had larger portfolio weights in cryptocurrencies. These stocks have similar characteristics to cryptocurrencies, which were also small growth assets in the technology space.

Taken together, these two facts suggest that early cryptocurrency were small-cap, growth, and technology fund managers who had strong incentives to do research and invest according to their beliefs.

4.2 Incentives to adopt during the price run up

In this section, we examine whether managers' relative performance and fund flow incentives affected their cryptocurrency investment decisions during the crypto price run up. In a standard portfolio choice setting with no agency frictions, investment decisions are purely a function of manager beliefs. Under this benchmark, the fact that Small Growth funds are more likely to adopt crypto following their peers than Large Value funds would be interpreted as managers with different beliefs choosing to invest in different strategies. By contrast, our framework suggests that Small Growth managers may wish to adopt crypto to hedge underperformance relative to their peers who hold crypto, or to cater to investors who want to invest in funds that hold crypto. In the following analyses, we test whether the patterns of crypto adoption we observe are consistent with a competition hedging motive.

4.2.1 Manager direct performance incentives

Recall Prediction 1, that managers with stronger direct performance incentives compared to relative performance and flow incentives hedge less aggressively in response to the portfolio choice of their competitors. Testing this prediction requires variation in the strength of direct performance incentives across managers. We use data on whether managers invest their personal wealth in the funds that they manage as a measure of their direct performance incentives. The intuitive idea is that managers with skin in the game invest in assets based on their return beliefs because they bear more of the risk and potential rewards of the asset's absolute performance.

To test whether managers with strong direct performance incentives are less responsive to their competitors' crypto investments, we examine crypto adoption by manager skin in the game and competitor crypto holdings. Specifically, we take the set of funds which had not yet adopted crypto by 2020Q4 and we group them by (i) whether the fund's manager invests in the fund or not and (ii) the fraction of the fund's competitors that held crypto in 2020Q4. Figure 5 reports the crypto adoption of these groups of funds over time. It shows that funds in categories where more competitors held crypto in 2020Q4 are more likely to adopt crypto over the next year, and that this effect is significantly more pronounced for managers who do not invest personal money in their funds. Table 4 in the appendix confirms the statistical significance and magnitude of this result. Column 1 shows that a one standard deviation increase in the fraction of competitors holding crypto increases the probability that a fund holds crypto by 1.2 percentage points (30%) if the manager invests in their fund (though the estimate is insignificant), and by 3.1 percentage points (77%) if the manager does not invest in their fund. In other words, the effect of competitors' cryptocurrency holdings on a fund's probability of adopting crypto is two and a half times larger for managers without skin in the game.[15]

A natural concern with interpreting this analysis as causal is that managers choose whether or not to invest in their funds, and their decision could be correlated with other factors which drive sensitivity to competitors. For example, Figure 6 shows that older managers are more likely to invest in their funds, perhaps because they have more financial wealth than younger managers on average. If younger managers are also more sensitive to their competitors' portfolios than older managers (e.g. because their beliefs update aggressively in response to information as in Nagel and Xu (2021)), then manager investment is a proxy for age rather than a measure of direct performance incentives. To address this concern, we begin by regressing manager investment on a wide range of characteristics. We find that funds with longer manager tenure, higher expense ratios, and larger assets under management are more likely to have managers who invest, and

[15]In our main analyses, we use linear probability models instead of logit due to the inclusion of fixed effects and the incidental parameters problem. We find similar results with probit and logit regressions in specifications without fixed effects.

younger funds are less likely to have investment. To account for these covariates, in Table 4 we include linear controls for these characteristics in Column 2, and linear controls along with the characteristics' interaction with the competition measure in Column 3. We find that none of the additional interaction terms are significant, whereas the interaction between competition and manager skin in the game remains stable and significant. This suggests that fund managers' investment affects direct performance incentives in a way that is unrelated to tenure and fund size effects.

This finding has an additional implication for the composition of cryptocurrency investors over time. Figure 7 shows that early cryptocurrency holders were primarily managers who had skin in the game, but that late adopters in the same categories as the early holders were managers without skin in the game. In other words, as the bubble spread, the set of cryptocurrency investors shifted from investors with strong direct performance incentives and conviction in cryptocurrencies to those who were more likely to have strong relative performance incentives.

Next, to understand how a manager's relative performance incentives affect their portfolio choice, we examine how fund flows respond to returns relative to peer returns.

4.2.2 Flow-performance relationship

Prediction 2 of our framework is that managers tilt towards their competitors' portfolios to hedge the risk that they underperform their peers and face outflows. It follows that managers with fund flows that are highly sensitive to relative performance should hedge more aggressively. One determinant of a fund's flow performance sensitivity is its past returns. Figure 8 plots average quarterly dollar flows for funds by their Morningstar rating, which are within-category quantiles of past returns that are known to drive fund flows (Del Guercio and Tkac (2008)). The ratings range from 1 to 5, with 1 corresponding to the bottom decile and 5 corresponding to the top decile. Our focus is on the local slope of the flow performance relationship that funds with different levels of past returns face. For example, 4 star funds face strong flow performance incentives – if they perform slightly better and become 5 star funds, they can expect an additional quarterly inflow of $75 million. If they perform slightly worse and become 3 star funds, they can expect a net quarterly outflow of $10 million. In contrast, 2 star funds face relatively weak flow performance incentives. Whether they perform well and become 3 star funds or poorly and become 1 star funds, their flows remain similar.

Our model implies that if funds are engaging in competitive hedging ($c > 0$), then funds with greater flow performance sensitivity should be more responsive to competition.[16] The regression in Table 5 tests this prediction by examining heterogeneity in funds' responsiveness to their competitors by their Morningstar rating. Column 1 shows that a one standard deviation increase in the fraction of competitors holding crypto increases the probability that 3 and 4 star funds adopt crypto 2.1 percentage points (50%) and 2.9 percentage points (70%) respectively, but that there is no significant effect for 2 and 5 star funds. We control for fund characteristics as well as fund benchmark, Morningstar category, and fund benchmark by Morningstar category fixed effects in Columns 2, 3, and 4, and we find similar results. Thus, the funds which have the most to gain from outperforming their peers (as well as the most to lose by underperforming) are the most responsive to their competitors' cryptocurrency holdings.[17]

Thus far, our analyses have shown how variation in incentives across managers explains variation in their cryptocurrency adoption decisions. While we have robustness tests which control for other manager characteristics which might be correlated with incentives, one might still be concerned that unobserved manager beliefs could be driving our results. Prediction 3 motivates a clear empirical test which addresses this issue by varying incentives while holding fixed beliefs.

4.2.3 Multi-fund managers

Prediction 3 of our framework is that if we compare a manager who manages two funds in different Morningstar categories, any differences in the two funds' crypto holdings are not driven by differences in manager beliefs. Furthermore, due to Morningstar's methodology for classifying funds, funds can have the same prospectus benchmark and be in different Morningstar categories. By controlling for a fund's benchmark as well, any remaining variation in crypto holdings across two funds in different categories is driven by category-specific factors such as competitor adoption or catering. As an example of this comparison, Rydex Funds (owned by Guggenheim Partners) offers multiple funds managed by Michael Byrum and Ryan Harder. Among other products, they offer the Rydex Technology Fund, Rydex Financial Services Fund, and the Ry-

[16]Formally, the prediction is that $\frac{\partial x^*}{\partial f \partial \theta_c} > 0$ if $c > 0$.

[17]These results are robust to alternative measurement periods of past performance, including deciles of cumulative returns over the previous 1, 3, and 5 years.

dex Multi-Hedge Strategies Fund. All of these funds have the S&P 500 as their benchmark. In 2020Q4, none of these funds had any crypto exposure. By 2021Q4, the Technology and Financial Services fund adopted crypto, but the Multi-Hedge strategies fund had not. The funds which adopted crypto were in Morningstar categories with high levels of competitors holding crypto – 8% of technology and 8% of financial services funds held crypto in 2020Q4, whereas zero multistrategy funds had adopted crypto. Table 6 presents regressions based on this idea. Column 1 reports a regression of the probability that a fund adopts crypto on the fraction of competitors that hold crypto and other fund characteristics. The coefficient on competition is positive, but it is potentially confounded by unobserved manager characteristics which affect crypto adoption decisions. In Column 2 we include manager fixed effects which absorb the unobserved manager characteristics, but two funds with the same manager may have two different benchmarks (e.g. S&P 500 vs. the Nasdaq) which drive different investment behavior. Column 3 is our preferred specification in which we compare two funds offered by the same firm, managed by the same investment manager, with the same benchmark in their prospectuses. It shows that a one standard deviation increase in the fraction of competitors holding crypto increases the probability of crypto adoption by 15 percentage points (157%), suggesting that manager incentives have a large effect on portfolio choice.

One potential concern with this analysis is that differences in investment mandates differ across categories, so managers are allowed to hold crypto in some categories but not others. To provide some reassurance that this issue isn't driving the result above, we restrict the sample to Morningstar categories in which at least 5% of funds held crypto in 2020Q4 or at least 5% of funds which didn't hold crypto in 2020Q4 began holding crypto by 2021Q4. The purpose of this is to condition on categories where we know crypto holdings are feasible (either because funds hold crypto before the run up or because funds adopt during the run up), and then use variation in the intensive margin to explain adoption. In the earlier example of Rydex funds, we find that by 2021Q4, the multistrategy category had 9% of other funds adopting crypto, which suggests that there were no structural differences between these categories of funds which would have led Rydex to adopt in technology and financial services and not in multistrategy. Column 4 of Table 6 generalizes this example by restricting the manager × benchmark fixed effects regression to the high crypto Morningstar category sample. The statistical power is slightly weaker due to the small sample, but the effect of competition on fund crypto adoption remains large and positive.

Overall, our results suggest that manager incentives play an important role in their decision to adopt crypto during the boom. Managers with skin in the game are significantly less likely to adopt crypto following their peers' adoption relative to managers with no skin in the game, suggesting that direct performance incentives reduce incentives to follow the crowd. Managers whose fund flows are highly sensitive to performance are more responsive to their competitors' adoption, reflecting incentives managers face to grow fund size. These findings examine variation across managers, but we also find evidence that incentives matter *within* manager. The same manager, when operating two funds with the same benchmark in two different categories, is more likely to adopt crypto in the fund that faces more competitors holding crypto.

4.3 Are managers hedging competitive risks or catering to clients?

While the results above speak to the importance of incentives generally, they do not identify which of the incentives in our model are driving manager behavior. All of the patterns are consistent with either competitive hedging or catering. Managers without skin in the game are more likely to hedge or cater because they place less weight on absolute returns. Managers with strong incentives to grow their fund size can do so either by hedging or by catering to investor demand. The same manager might hold crypto in one fund but not the other, either because more of the fund's peers are holding more crypto or because investors in one category demand more crypto than other investors. The key identification challenge is analogous to estimating peer effects (Manski (1993)), which we formalize as follows:

$$y_{i,b,c} = ax_{i,b,c} + b\theta_b + c\theta_c + \lambda_c + \epsilon_{i,b,c}$$

where $y_{i,b,c}$ is an indicator for whether fund i with benchmark b in category c holds crypto, $x_{i,b,c}$ are fund i characteristics, θ_b is the fraction of funds in the benchmark holding crypto, θ_c is the fraction of competitors in the Morningstar category holding crypto, and λ_c is an unobserved category-level characteristic. We are interested in testing whether managers engage in competitive hedging ($c > 0$). However, the unobserved λ_c term affects both fund i's decision to hold crypto ($y_{i,b,c}$) and the fund i's competitors' decisions to hold crypto θ_c. For example, unobserved investor demand for funds holding crypto which varies across categories would be captured by λ_c.

Separately identifying these two incentive channels is interesting for two reasons. First, they are two distinct mechanisms with different implications for how speculation spreads across fund managers. Under the catering mechanism, sophisticated managers adopt crypto to exploit naive investors' demand. The extent of speculation is driven by the extent of demand for cryptocurrencies (which itself may not be driven by well-specificed return expectations) – for there to be significant returns to catering, there needs to be enough investors who demand crypto. Under the hedging mechanism, flow-chasing investors motivate sophisticated managers adopt crypto in response to their peers' holdings. This can generate a cycle in which a small number of optimistic managers begin holding crypto, then their peers begin holding crypto to hedge underperformance risk. This new adoption generates a second wave of adoption among a broader set of peers, and the cycle continues. Second, understanding these channels separately is important for understanding manager behaviors in contexts without strong catering incentives. For example, university endowments are an example of managers who do not experience significant inflows or outflows related to their portfolio composition, but might face strong incentives to not fall behind peer universities.

We recognize that the separation between competitive hedging and catering is less well-defined in the case of mutual funds because both incentives are partly driven by the same investor behavior. Investors who search for crypto-holding funds to invest in are also likely to chase returns and switch to mutual funds which perform well. This means that managers might begin catering to investors in response to their competitors' catering.

In absence of a natural experiment which generates random variation in cryptocurrency holdings, we cannot definitively identify the causal effect of a competitor's crypto holdings on a fund's decision to adopt crypto. Instead, we conduct a series of tests to see whether funds appear to be catering to investor demand by holding crypto. The purpose of our tests is not to definitively rule in or out the possibility that managers are catering. Rather, we aim to understand whether our main results which we interpret as being driven by competition hedging are instead largely driven by catering.

4.3.1 Fund advertising

A natural starting point to determine whether managers are catering is to ask whether funds are communicating their crypto holdings to their investors. After all, managers cannot be catering to investors if the investors do not know that the funds hold crypto.

One place that mutual funds are likely to advertise is in their prospectus, which is a document published by the fund which details its investment objectives and strategies.[18] We gather text data from mutual fund prospectuses from the SEC covering 2020Q1-2022Q4. We observe each fund's description of their investment objective, investment strategy, and the risks associated with investing in the fund. Then, we link the prospectuses to our mutual fund dataset and identify the prospectuses of funds which hold crypto. We are interested in whether crypto-holding funds explicitly discuss their crypto holdings in their prospectuses. We are also interested in *where* the funds mention crypto holdings. Funds can either discuss crypto in the risk/return summary section of prospectus, which is salient for readers as it tends to be one of the earliest sections in the prospectus, or they can mention it towards the end of the prospectus in a less salient section.

For example, the ARK Innovation ETF prospectus says that the fund invests in"Next Generation Internet Companies or Fintech Innovation Companies" which include "peer-to-peer lending, blockchain technologies, intermediary exchanges, asset allocation technology, cryptocurrency". It also mentions that the fund "may have exposure to cryptocurrency, such as bitcoin, indirectly through an investment in a grantor trust". In contrast, the Morgan Stanley Insight Fund says that the fund invests "primarily in a portfolio of common stocks of companies with market capitalizations... between \$8.6 million and \$2.7 trillion". There is no mention of cryptocurrencies or bitcoin anywhere, despite the fact that the fund held \$80M of Grayscale Bitcoin Trust in 2022.

Among the funds that hold crypto, we find that only 4% of funds explicitly mention key words related to crypto in the description of the fund's investment strategy.[19] These funds include explicitly Bitcoin-based ETFs and funds which market themselves as "technological innovation" or "transformational data sharing" funds. In contrast, 94% of funds which hold crypto mention the key words elsewhere in the prospectus. This gap suggests that the majority of funds which

[18]Existing evidence suggests that prospectuses are an important way that managers try to influence investor perceptions about their funds. For example, deHaan, Song, Xie, and Zhu (2021) find that fund managers use complexity in mutual fund summary prospectuses to make their products appear more attractive.

[19]The key words are crypto, blockchain, bitcoin, non-fungible, web3, and metaverse.

hold crypto are not actively communicating their holdings to investors.

Another place where managers might advertise is through their fund's name. Previous research documents that companies and mutual funds changed their names during the tech bubble, which led to sharp increases in returns and flows respectively (Cooper et al. (2005)). We do find specific examples of this in our data: the Emerald & Banking Finance Fund is an example of a fund that is actively catering to investors who demand crypto. Figure 9 shows that the fund faced large outflows due to poor returns in the months leading up to the crypto run up. During the run up, its crypto portfolio share increased from zero to 15% at its peak, and its fund size doubled in 2021. In mid-2021, the fund changed its name to the Emerald Finance & Banking Innovation Fund, reflecting its new investment strategy. We test whether this behavior is systematic across funds by examining the likelihood of recent name changes by crypto and non-crypto funds at the peak of the bubble. Table 7 presents a regression of an indicator for whether a fund has changed its name in the past 1, 2, or 3 years on an indicator for crypto holdings. It shows that funds which held crypto at the peak of the bubble were no more likely to have changed their names than non-crypto funds. This analysis rules out a strong form of catering in which a significant number of funds adopted crypto and changed their names to attract inflows.

4.3.2 Investor clientele demand

Our second test is to examine crypto holdings by funds' investor clientele. If funds face investors who do not demand crypto, then there should be no difference in the crypto holding behavior of managers with and without skin in the game. If investors have strong demand for crypto, then we should see managers without skin in the game catering aggressively and managers with skin in the game abstaining.

Testing this prediction requires measuring variation in investor demand for crypto. One way of doing this is by looking at the composition of each fund's investor base. Using data on each fund's retail and institutional share classes, we calculate the fraction of a fund's total AUM that comes from each group of investors. We assume that retail investors had stronger catering demand for crypto than institutional investors during the crypto run up, consistent with the view that retail demand for crypto surged in 2020 and drove the bubble. In Table 8, Column 1 presents results from a regression of crypto holdings on manager skin in the game interacted with the fraction of fund AUM from retail investors. The interaction term between retail share and manager skin in the game is not statistically significant, implying that managers with a greater incentive to cater do not appear to do so. We find similar results when we include controls for additional fund characteristics and Morningstar category fixed effects in Columns 2 and 3.

In sum, our tests fail to find substantial evidence that managers were systematically catering to investor demand by holding cryptocurrencies.

4.4 Market timing during the price crash

In this section, we examine managers' trading behavior as the price of cryptocurrencies fell by nearly 75% in 2022. Understanding whether managers were able to time the bubble and exit before the crash provides insight into managers' beliefs about cryptocurrencies.

One possibility is that managers who adopted cryptocurrencies had overoptimistic beliefs about their future returns. Many models of bubbles emphasize extrapolative beliefs (Barberis, Greenwood, Jin, and Shleifer (2018)) and some empirical evidence suggests that even sophisticated informed investors can hold overoptimistic beliefs during bubbles (Cheng, Raina, and Xiong (2014)). Another possibility is that these managers believed that crypto was overvalued, but they believed they could profit from the bubble by buying crypto during the boom and selling before the bust. Managers would have adopted this approach if they were concerned that retail investors would continue to drive high returns in the short run before prices crashed (De Long et al. (1990)). Brunnermeier and Nagel (2004) show that hedge funds used this strategy to profit from tech stocks during the dot-com bubble.

4.4.1 Aggregate crypto bubble

We begin by examining aggregate cryptocurrency flows and prices, with a particular focus on whether managers with different incentives had different abilities to time the crypto bubble. Of the 255 mutual funds which held cryptocurrencies at the peak of the price run up in 2021Q4, nearly 40% had exited their crypto positions after the crash by 2022Q2. To analyze the timing of exit, the top panel of Figure 10 plots the cryptocurrency portfolio share and flows separately for managers that do and do not invest in their funds. Two broad patterns emerge.

First, managers with skin in the game held significantly higher crypto portfolio shares than managers with no skin in the game. At the crypto price peak in 2021Q4, managers with no skin in the game held 0.1% of their portfolios in crypto, whereas managers with skin in the game held more than three times that amount. Through the lens of our model, managers with no skin in the game are more likely to hold crypto for hedging purposes rather than because they believe crypto has high returns. This implies that they should hold less crypto than managers with skin in the game, who will be crypto optimists conditional on investing in crypto.

Second, we find that managers with skin in the game timed the bubble much more aggressively than managers without skin in the game. The bottom panel of Figure 10 shows that the former group exhibits large crypto inflows in early 2020 before prices begin to rise dramatically, whereas the latter group is largely inactive in this period. As crypto prices peak in 2021Q4, managers with skin in the game invest 0.4% of AUM in crypto whereas managers without skin in the game only invest 0.15% of AUM. Perhaps most interestingly, in 2022Q1 as crypto returns begin to fall, managers who invest in their funds exhibit an outflow of 0.1% of AUM, whereas managers who do not invest in their funds exhibit moderate inflows of 0.05% of AUM. It appears that managers with skin in the game were able avoid some of the crash by pulling out before 2022Q2 whereas managers without skin in the game failed to do so. Table 9 confirms the statistical significance of this pattern. One interpretation of these results is that these managers had stronger views on crypto returns because they were investing according to their beliefs, whereas the managers who engaged in competitive hedging were simply investing with the crowd and so they did not anticipate the crash.

4.4.2 Individual crypto assets

Next, we move beyond the aggregate crypto bubble and analyze the trading behavior of managers in individual crypto assets. Specifically, we examine holdings around the price peak of individual assets and see whether managers decreased their exposure before prices fell. We find mixed evidence of market timing across different assets.

Consider Grayscale Bitcoin Trust (GBTC), the largest Bitcoin fund as of 2021Q4 with $37 billion in assets. It was popular among mutual fund managers because it provided simple direct exposure to Bitcoin (unlike other products which are based on Bitcoin futures), so it is a useful asset for us to understand whether fund managers were able to time GBTC's returns. Figure 11 presents the fraction of GBTC's shares outstanding that mutual funds held from 2020Q1 to 2022Q3, along with GBTC's cumulative return over the same period. It shows that GBTC's returns increased rapidly and peaked in 2021Q2 before falling over the next year. It also shows that mutual fund managers' holdings of GBTC tracked its cumulative returns closely – managers increased their holdings from 1.25% to 2% of shares outstanding up to the peak, then sold their shares after prices began to fall. If managers were timing the bubble, they would have sold before the crash. To highlight the behavior of individual managers, we report the holdings of the top five mutual fund investors in GBTC. Figure 12 shows that ARK, the largest mutual fund holder of GBTC, increased their exposure during the run up and only slowly decreased their holdings after the crash began. Kinetics, the second-largest holder, decreased its exposure in the four quarters before the price peak, then kept their exposure flat during the entire crash.

While there is little evidence of mutual fund managers as a group timing the GBTC boom and bust, we do find instances of specific managers timing individual stocks. Figure 13 plots the mutual fund holdings of MicroStrategy, a business software vendor which pivoted to holding Bitcoin in August 2020. At the end of 2022 it held 132,500 BTC, worth around $2.1 billion. Since MicroStrategy switched from being a non-crypto stock to a crypto-stock in 2020, we split mutual fund managers by whether they held the stock before 2020 or not and examine their trading behavior after 2020. We find that funds which held MicroStrategy before 2020 reduced their holdings from 10% of shares outstanding to 2.5% two quarters after the firm announced that it held crypto. Funds which held MicroStrategy only after 2020 increased their exposure after the price peak – they went from holding 2.5% in 2021Q1 to holding over 15% by 2022Q1, and they were exposed to sigificantly negative returns in 2022Q2. We also find evidence that Morgan Stanley appeared to have timed the bubble well – they quickly took a large stake in MicroStrategy in 2020Q4 after Bitcoin holdings were announced and profited from the run up, then sold their stake during the peak in 2021Q1.

In sum, we find that mutual fund managers as a whole did not time the cryptocurrency bubble. We do find that specific groups of managers were better at timing the bubble than others. Managers with skin in the game were more successful at investing before the run up and exiting before the crash, and specific managers like Morgan Stanley timed the bubble in individual stocks like MicroStrategy.

5 Conclusion

Speculative bubbles have negative effects on the real economy: capital is allocated to inefficient firms during price run ups, investors lose their savings during price crashes, and pecuniary externalities can lead to economy-wide downturns. An important question is why sophisticated investors not only fail to trade against speculative bubbles, but in some cases, actively participate in them. Existing theories emphasize that these investors can hold incorrect beliefs about asset values, and that they face limits to arbitrage which prevent short-selling. In this paper, we find evidence consistent with the idea that competition among investment managers is an important driver of speculative demand. Asset managers whose compensation depends on their performance relative to peers have incentives to mimic their competitors' portfolios. These incentives expand the scope of speculative demand, as the investment decisions of early speculators influence the portfolio choice of other investors.

We examine three periods during the 2020-2022 cryptocurrency bubble – the period before run up, the run up during 2021, and the crash in 2022. We find that managers which held crypto before the run up had skin in the game and operated directly-sold funds, both of which create strong direct performance incentives. During the crypto run up, these early adopters enjoyed high returns. However, this placed pressure on their competitors to increase returns as well. Consistent with our framework, we find that managers with no skin in the game and strong flow-performance incentives adopted cryptocurrencies after their peers, whereas managers with skin in the game and weak flow-performance incentives did not. During the crash, the early investors with skin in the game were more successful at exiting their positions before the largest crash, whereas the late investors with no skin in the game failed to exit in time.

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6 Appendix

6.1 Figures

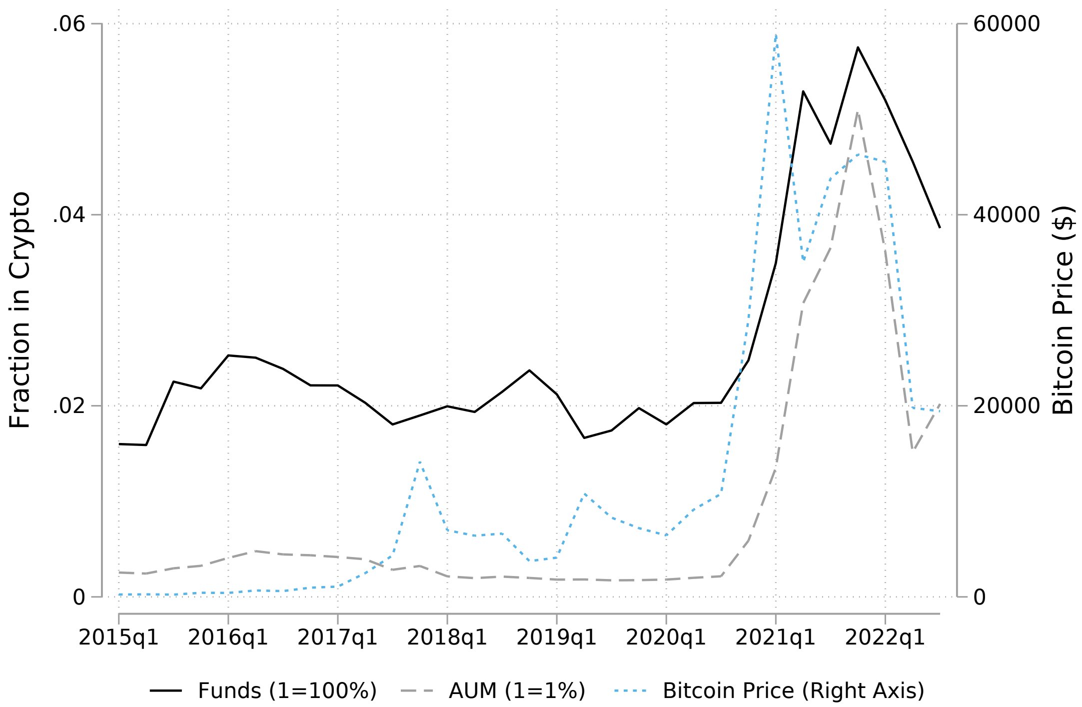


Figure 1: This figure presents an aggregate time series of i) the fraction of mutual funds with any crypto holdings (black), ii) the fraction of mutual fund AUM in crypto assets (grey), and iii) the price of Bitcoin (blue).

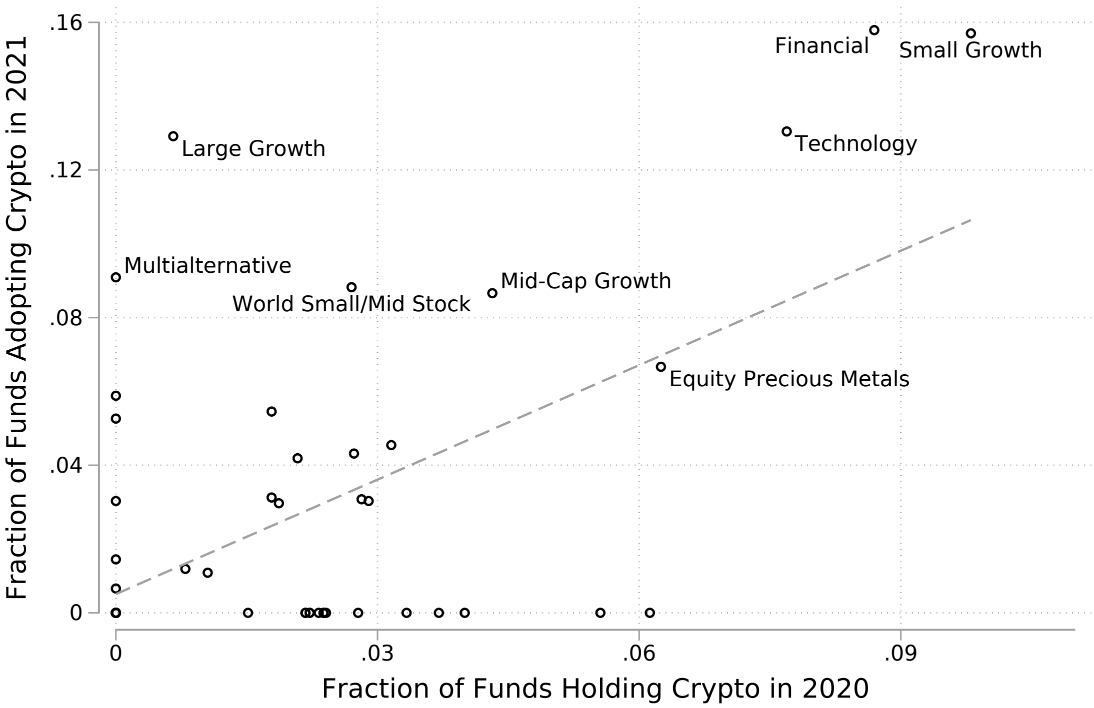
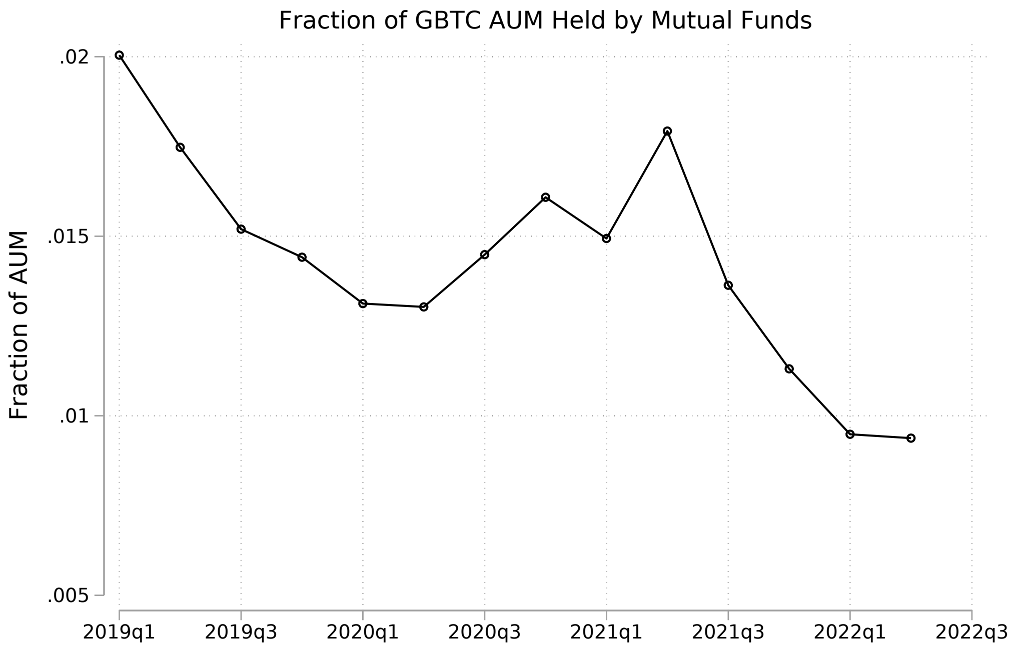


Figure 2: This figure presents crypto adoption patterns over time within Morningstar categories. The x-axis is the fraction of funds in a Morningstar category which held crypto in 2020Q4. The y-axis is the fraction of funds in a category which did not hold crypto in 2020Q4 which adopted crypto by 2021Q4.

(a) Mutual Funds



(b) 13F Institutions

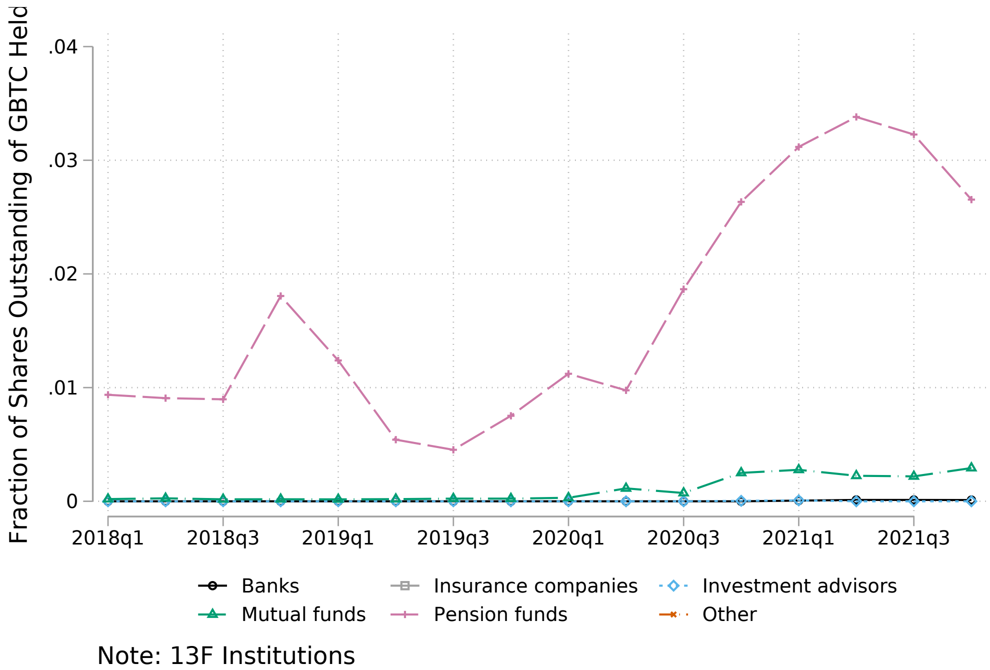


Figure 3: This figure plots the fraction of Grayscale Bitcoin Trust's AUM held by institutional investors. Panel (a) plots this fraction for all mutual funds using the S12 mutual fund holdings data, and panel (b) plots this fraction for 13F institutions which include large mutual fund managers.

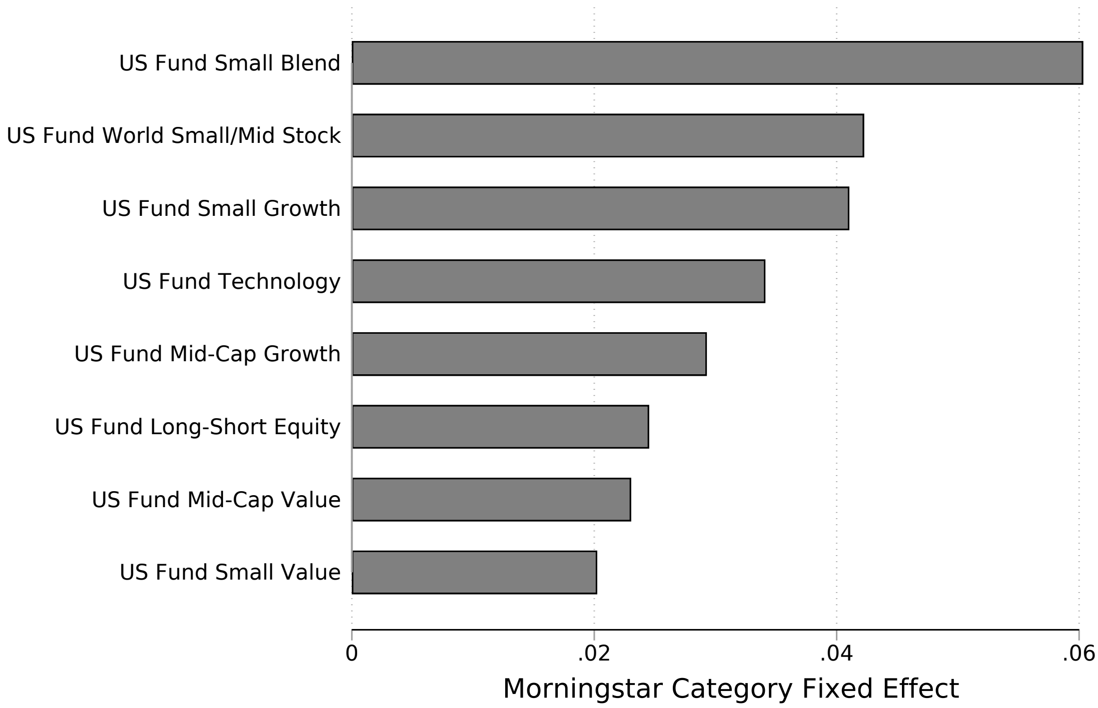


Figure 4: This figure plots the estimated fixed effects from a fund-level regression of cryptocurrency portfolio weight on Morningstar category fixed effects on a sample of funds from 2015-2016. We report the eight categories with the largest fixed effects.

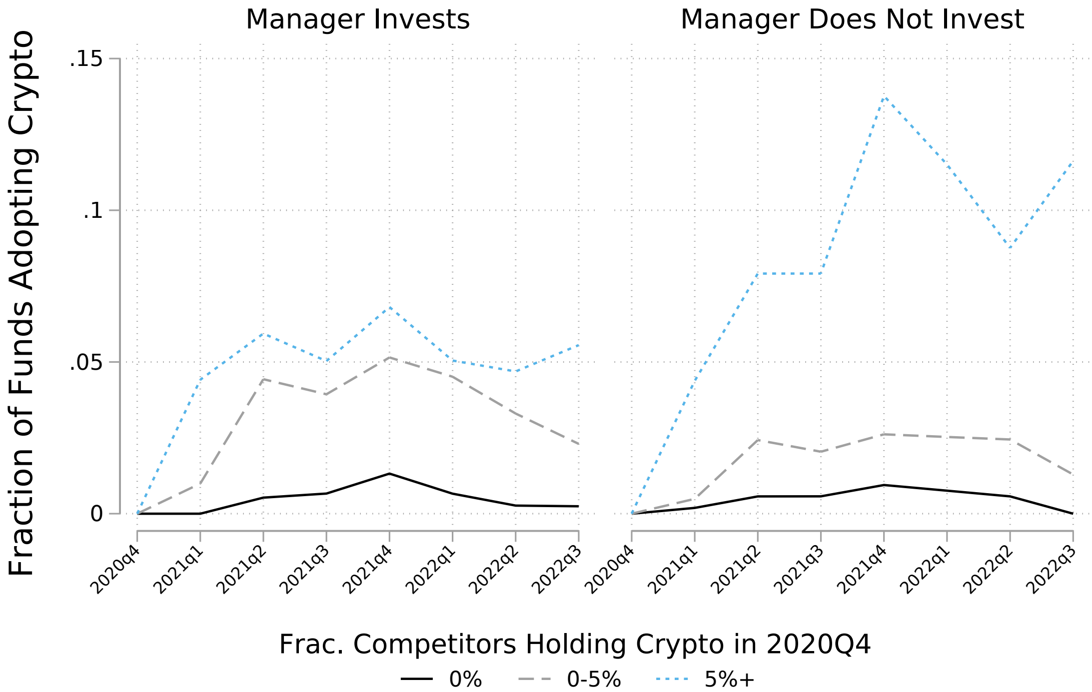


Figure 5: This figure plots the fraction of funds adopting cryptocurrencies from 2020Q4 to 2022Q3, separately by fund manager characteristics and fund competitors. The sample is funds which have yet to adopt cryptocurrencies by 2020Q4. The left panel is funds in which the manager invests personal wealth in the fund, and the right panel is funds in which the manager does not invest. The black, gray, and blue lines split funds into three groups based on the fraction of the funds competitors which held cryptocurrencies in 2020Q4.

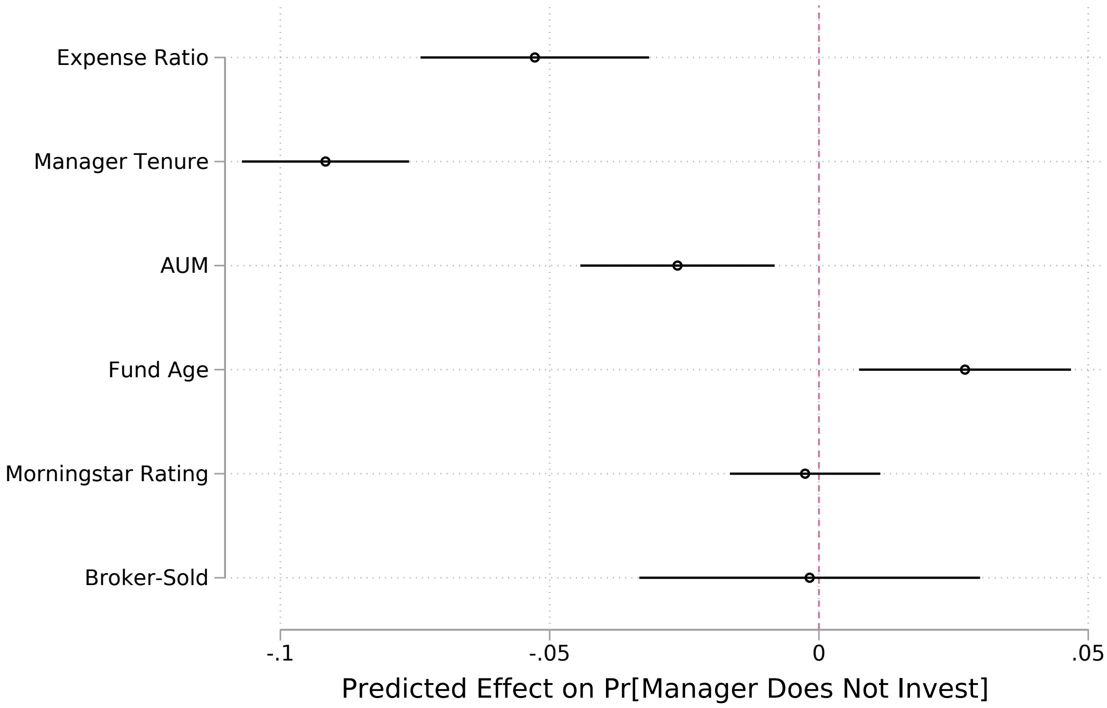


Figure 6: This figure plots coefficients from a regression of an indicator for whether a manager does not invest personal wealth in their fund on manager and fund characteristics. The sample is all funds from 2015-2022.

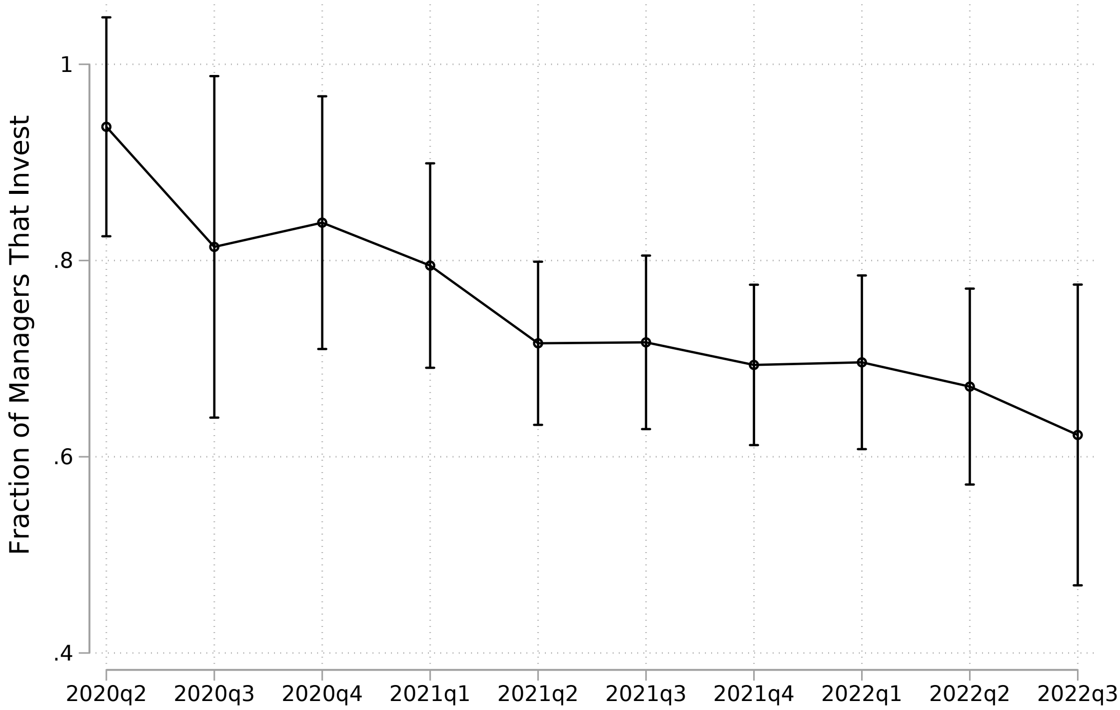


Figure 7: This figure plots the fraction of managers who invest in their funds among a sample of funds which hold cryptocurrencies. The sample is restricted to funds in categories where at leat 5% of funds newly adopted cryptocurrencies in 2021, and where there were some funds which held cryptocurrencies in 2020. These categories are US Fund Technology, US Fund Small Growth, US Fund Financial, US Fund Equity Precious Metals, US Fund Large Growth, US Fund Mid-Cap Growth, and US Fund World Small/Mid Stock.

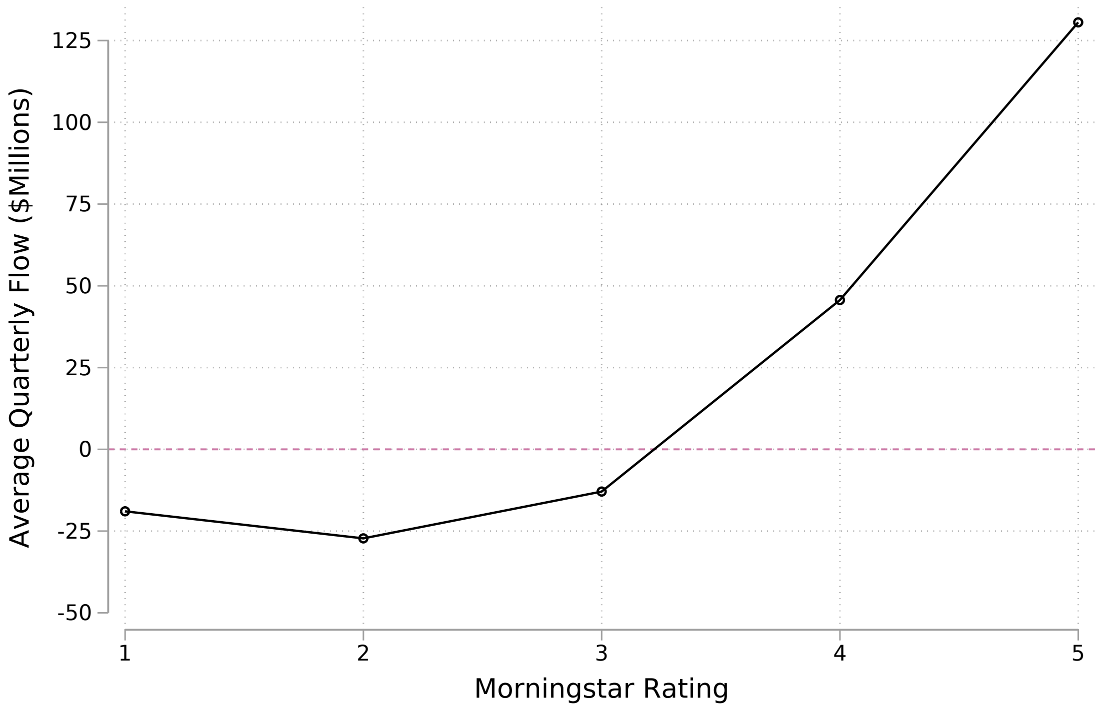


Figure 8: This figure plots average quarterly dollar flows by fund Morningstar rating. The sample is all funds from 2015-2022.

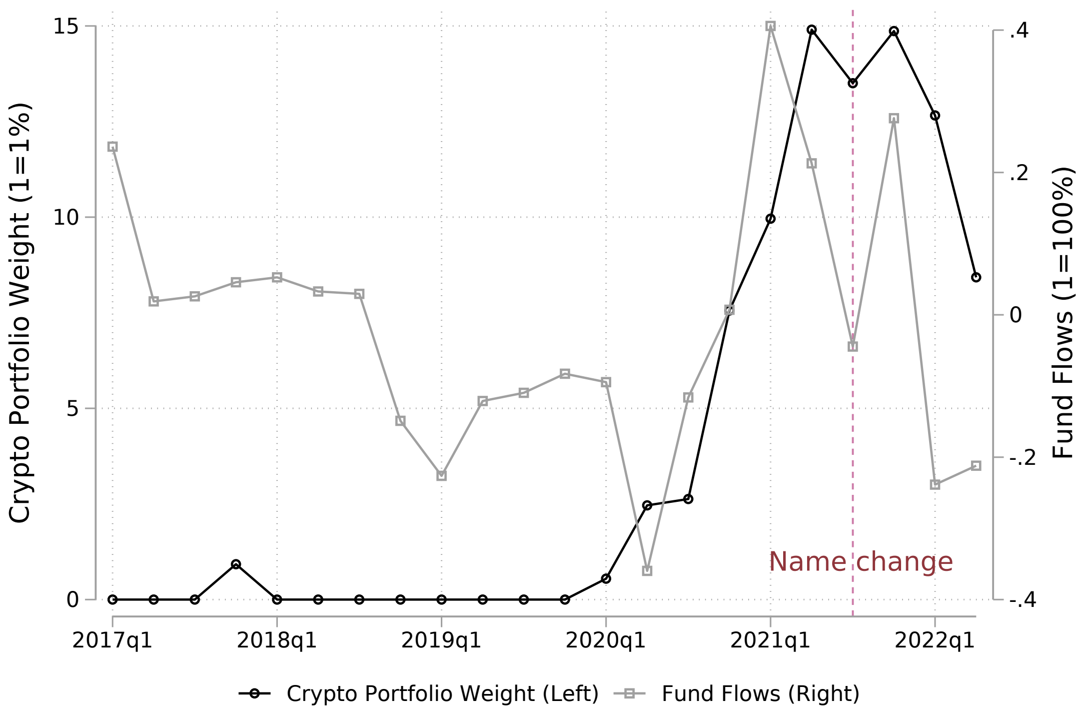


Figure 9: This figure plots the cryptocurrency portfolio weight (left) and flows (right) of the Emerald Banking & Finance Fund. In 2021, the fund changed its name to the Emerald Finance & Banking Innovation Fund.

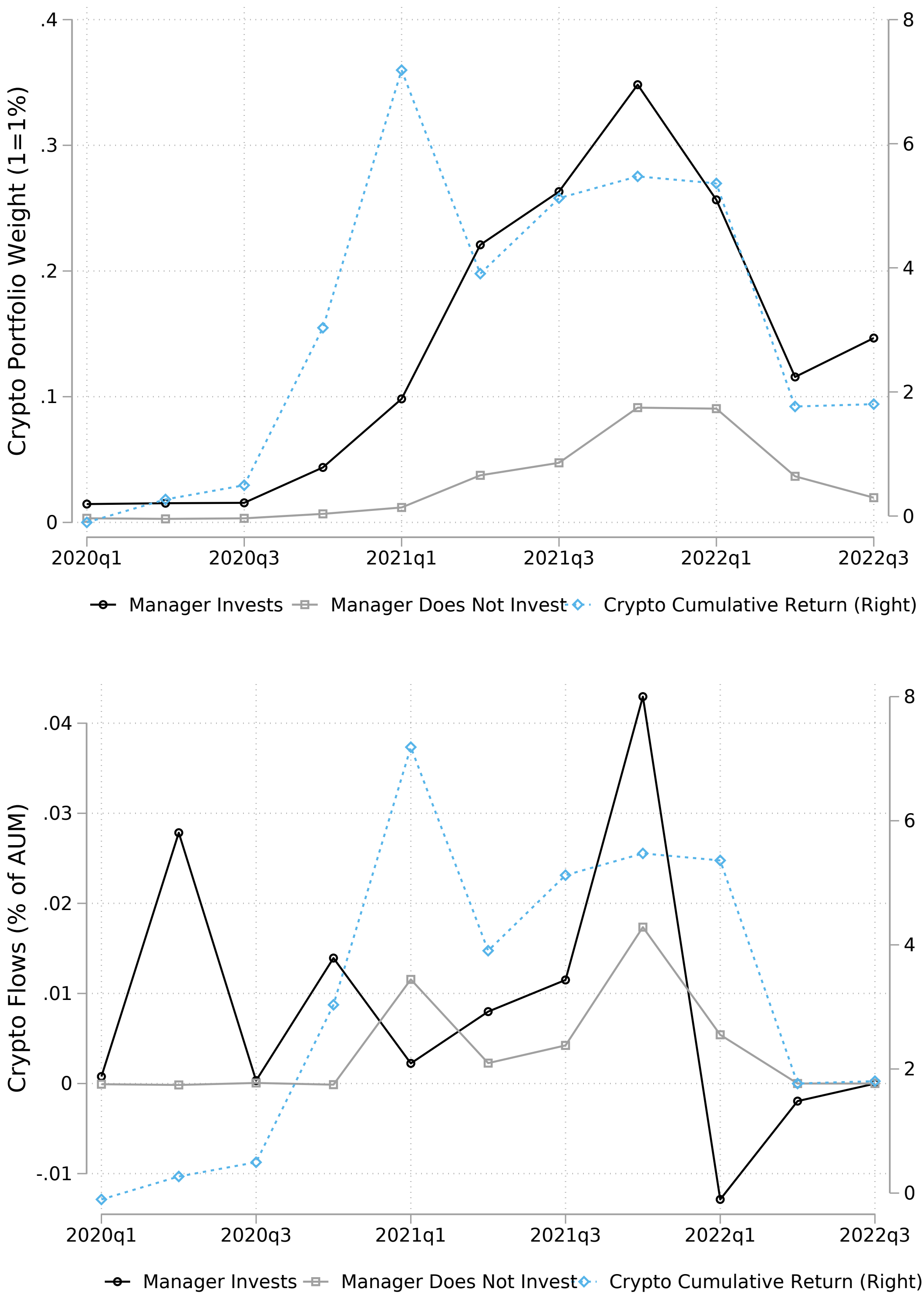


Figure 10: This figure plots the value-weighted cryptocurrency portfolio weight (top panel) and flows (bottom panel) of mutual funds, separately for funds in which the managers invests and not.

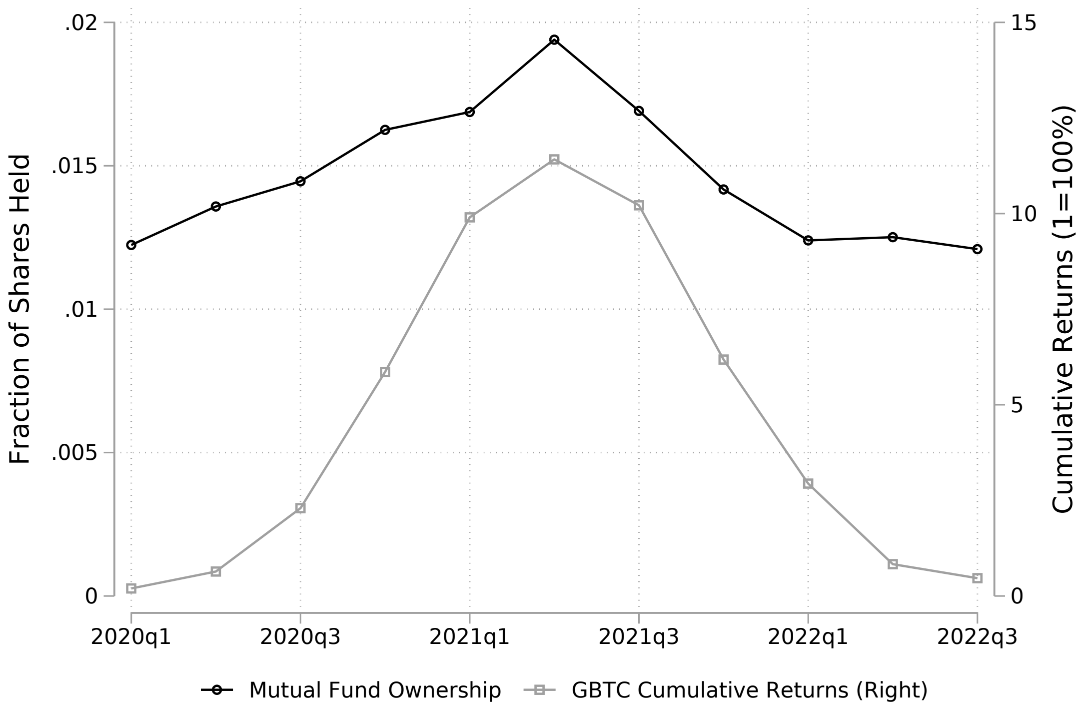


Figure 11: This figure plots the fraction of outstanding Grayscale Bitcoin Trust (GBTC) shares held by mutual funds (black) along with the cumulative returns to GBTC from 2020Q1 to 2022Q3 (grey).

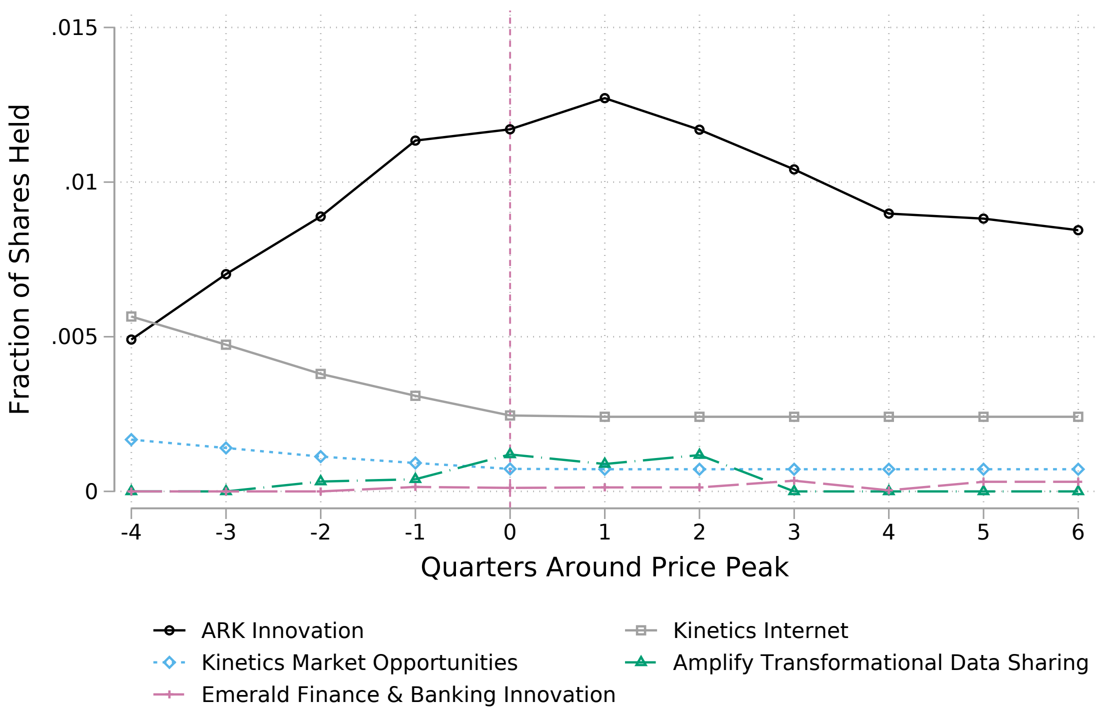


Figure 12: This figure plots the fraction of outstanding Grayscale Bitcoin Trust (GBTC) shares held by the five mutual funds with the largest GBTC holdings.

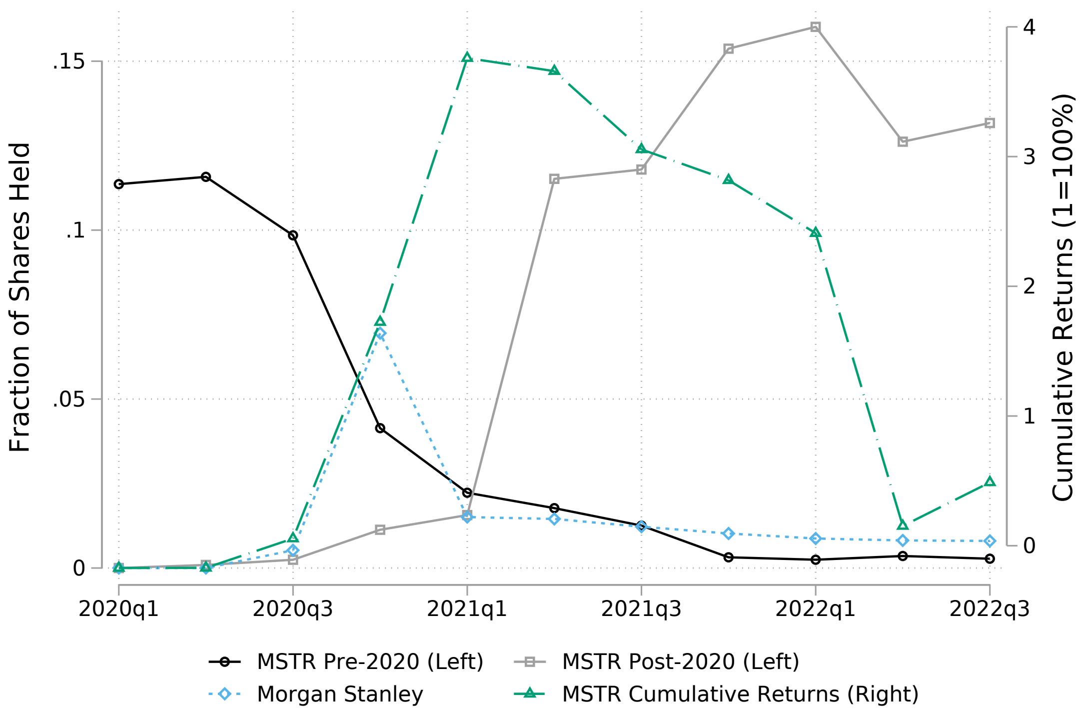


Figure 13: This figure plots the fraction of MicroStrategy's shares outstanding held by three groups of funds - funds which held MicroStrategy shares before 2020, funds which did not hold hold MicroStrategy shares before 2000, and Morgan Stanley funds. It also plots the cumulative returns of MicroStrategy stock from 2020Q1 to 2022Q3.

6.2 Tables

Table 1: Fund-Level Summary Statistics

VARIABLES	(1) N	(2) mean	(3) p50	(4) sd	(5) min	(6) max
TNA (millions)	125,616	2,149	321	8,455	0	295,455
I[Holds crypto]	118,519	0.027	0	0.16	0	1
Crypto share (%)	118,519	0.022	0	0.45	0	34.4
Fund age (quarters)	119,766	49.9	40	44.5	0	391
Average manager tenure (quarters)	103,476	23.6	18.7	19.6	0	169
Maximum manager tenure (quarters)	111,572	34.3	28	26.6	0	221
I[Manager invests]	125,616	0.59	1	0.49	0	1
Number of fund managers	111,538	2.97	2	2.01	1	11
Male managers (%)	111,538	88.9	100	21.4	0	100
Expense ratio (bps)	118,881	102	103	52.4	-11	1,515
Morningstar rating	93,505	3.12	3	1.06	1	5
Family retail share (%)	94,185	54.8	56.3	37.0	0	100

This table reports summary statistics for the mutual funds in our data. Observations are at the fund-quarter level from 2015Q1 to 2022Q2.

Table 2: Morningstar Category-Level Summary Statistics

VARIABLES	(1) N	(2) mean	(3) p50	(4) sd	(5) min	(6) max
Number of funds	3,201	39.2	17	57.7	1	331
Category TNA (millions)	3,201	84,343	12,605	198,425	0.73	2.12e+06
I[Holds crypto]	3,168	0.018	0	0.053	0	0.75
Crypto share (%)	3,168	0.013	0	0.074	0	1.28
Fund age (quarters)	3,095	51.7	50	24.1	0	129
Average manager tenure (quarters)	3,049	21.7	20.7	10.9	0.080	77.3
Maximum manager tenure (quarters)	3,128	32.9	32.5	13.6	0	85
I[Manager invests]	3,201	0.40	0.50	0.32	0	1
Number of fund managers	2,995	2.80	2.88	0.98	1	8
Male managers (%)	2,995	87.8	89.2	10.3	50	100
Expense ratio (bps)	2,383	105	113	39.3	12.3	196
Morningstar rating	2,803	3.19	3.17	0.48	1	5
Family retail share (%)	2,217	56.2	53.5	22.4	0.45	100

This table reports summary statistics for the mutual funds in our data. Observations are at the Morningstar category-quarter level from 2015Q1 to 2022Q2.

Table 3: Early Adopter Incentives

VARIABLES	(1) Pr[Crypto]	(2) Pr[Crypto]
Manager Invests	1.303**	0.855
	(0.613)	(0.598)
Broker Sold	-1.616***	0.0884
	(0.623)	(0.470)
Log[AUM]	0.0125	0.178
	(0.134)	(0.156)
Fund Age (Quarters)	-0.00413	0.0168**
	(0.00552)	(0.00803)
Average Manager Tenure (Quarters)	0.0152	0.0268
	(0.0215)	(0.0176)
Number of Managers	0.221	0.690***
	(0.191)	(0.193)
Frac. Managers Male	-3.399	-0.0276
	(2.597)	(1.436)
Constant	4.399	-0.263
	(2.708)	(1.541)
Observations	8,087	16,629
R-squared	0.007	0.008
Sample	2016	2021

The dependent variable is an indicator which equals 100 if a fund holds cryptocurrencies and 0 otherwise. Standard errors clustered at the fund level. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 4: Manager Investment and Competitive Hedging

	(1)	(2)	(3)
VARIABLES	Pr[Adopt Crypto]	Pr[Adopt Crypto]	Pr[Adopt Crypto]
Frac. Competitor	1.263	1.412	1.360
	(1.068)	(1.054)	(1.234)
I[Manager Does Not Invest]	-0.686	-0.797	-0.804
	(0.882)	(0.816)	(0.805)
Frac. Competitor x I[Manager Does Not Invest]	2.825**	2.034**	2.032**
	(1.374)	(0.867)	(0.852)
Expense Ratio		0.700	0.705
		(0.446)	(0.428)
Fund Age		0.613*	0.624*
		(0.331)	(0.343)
Manager Tenure		-0.856***	-0.861***
		(0.284)	(0.273)
AUM		1.495**	1.493**
		(0.743)	(0.694)
Frac. Competitor x Expense Ratio			0.119
			(0.548)
Frac. Competitor x Fund Age			0.148
			(0.593)
Frac. Competitor x Manager Tenure			-0.00619
			(0.438)
Frac. Competitor x AUM			-0.0195
			(0.775)
Constant	4.273***	4.259***	4.249***
	(1.110)	(1.104)	(1.084)
Observations	4,131	3,762	3,762
R-squared	0.014	0.018	0.018
Sample	2021Q4	2021Q4	2021Q4

Sample is 2021Q4, funds holding no crypto by 2020Q4. The dependent variable is an indicator which equals 100 if a fund holds cryptocurrencies and 0 otherwise. Linear controls include fund age, log fund AUM, expense ratio, and manager tenure. Interaction controls include all the variables above interacted with the competition variable. All independent variables are standardized except for the manager investment indicator. Standard errors clustered at the Morningstar category level. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 5: Crypto Adoption by Flow Performance Sensitivity

	(1)	(2)	(3)	(4)
VARIABLES	Pr[Adopt Crypto]	Pr[Adopt Crypto]	Pr[Adopt Crypto]	Pr[Adopt Crypto]
Frac. Competitor	0.381	-0.149		
	(0.985)	(1.709)		
2 Star Fund	-1.649	-0.274	-1.286	-0.585
	(1.014)	(1.068)	(1.005)	(0.921)
3 Star Fund	-1.195	-0.536	-0.824	-0.0656
	(1.050)	(1.086)	(0.855)	(0.961)
4 Star Fund	0.0384	0.651	0.470	1.302
	(1.523)	(1.710)	(1.268)	(1.661)
5 Star Fund	2.959	3.763*	3.991	5.235**
	(2.046)	(2.184)	(2.412)	(2.437)
Frac. Competitor x 2 Star Fund	0.495	2.051**	1.435	2.438***
	(1.039)	(1.007)	(1.009)	(0.851)
Frac. Competitor x 3 Star Fund	2.095***	2.758***	1.926**	3.169***
	(0.777)	(0.858)	(0.854)	(0.846)
Frac. Competitor x 4 Star Fund	2.954*	2.947**	2.749*	3.144**
	(1.493)	(1.434)	(1.401)	(1.450)
Frac. Competitor x 5 Star Fund	2.253	3.179	2.519	3.103
	(2.525)	(2.156)	(2.498)	(2.274)
Constant	4.204***	3.751***	3.806***	3.478***
	(1.280)	(0.744)	(0.544)	(0.541)
Observations	3,762	3,407	3,760	3,177
R-squared	0.023	0.095	0.072	0.150
Fixed Effects	None	Benchmark	MC	Benchmark x MC
Sample	2021Q4	2021Q4	2021Q4	2021Q4
Controls	Yes	Yes	Yes	Yes

Sample is 2021Q4, funds holding no crypto by 2020Q4. The dependent variable is an indicator which equals 100 if a fund holds cryptocurrencies and 0 otherwise. The independent variables are the fraction of a fund's competitors in the same Morningstar category which held crypto in 2020Q4, and the fund's Morningstar rating in 2020Q4. Controls include fund age, log fund AUM, expense ratio, and manager tenure, and all independent variables are standardized. Standard errors are clustered by Morningstar category. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 6: Crypto Adoption within Manager × Benchmark

	(1)	(2)	(3)	(4)
VARIABLES	Pr[Adopt Crypto]	Pr[Adopt Crypto]	Pr[Adopt Crypto]	Pr[Adopt Crypto]
Frac. Competitor Crypto in MC	1.950*	5.113**	14.92**	27.07*
	(1.046)	(2.165)	(6.790)	(12.37)
Expense Ratio	0.802*	-2.127*	-1.052	-0.0614
	(0.404)	(1.117)	(1.646)	(1.887)
Fund Age	0.614*	0.921	0.976	1.980
	(0.338)	(0.619)	(0.776)	(3.557)
Manager Tenure	-0.762**	-0.928	0.0718	11.47
	(0.300)	(1.335)	(1.936)	(7.274)
AUM	1.549**	1.369	-1.637	-11.90
	(0.770)	(0.979)	(1.915)	(7.966)
Constant	3.884***	5.404***	9.588***	10.08*
	(0.870)	(0.489)	(1.441)	(5.492)
Observations	3,762	942	391	70
R-squared	0.015	0.764	0.868	0.843
Sample	Full	Full	Full	Crypto MC
FE	None	Manager	Manager x Benchmark	Manager x Benchmark
Controls	Yes	Yes	Yes	Yes

Sample is 2021Q4, funds holding no crypto by 2020Q4. The dependent variable is an indicator which equals 100 if a fund holds cryptocurrencies and 0 otherwise. All independent variables are standardized. Standard errors clustered by Morningstar Category. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 7: Fund Name Changes

	(1)	(2)	(3)
VARIABLES	Δ Name in 2021	Δ Name Since 2020	Δ Name Since 2019
I[Crypto]	2.449	2.784	-0.582
	(2.892)	(3.434)	(3.732)
Expense Ratio	0.408	0.842	0.569
	(0.603)	(0.731)	(0.819)
Fund Age	-1.108**	-1.136*	-1.260*
	(0.550)	(0.640)	(0.751)
Manager Tenure	-1.843***	-2.576***	-3.459***
	(0.499)	(0.610)	(0.714)
AUM	-1.183**	-0.987	-0.837
	(0.568)	(0.671)	(0.760)
Constant	10.59***	16.24***	22.64***
	(0.511)	(0.610)	(0.690)
Observations	3,760	3,760	3,760
R-squared	0.031	0.039	0.046
Fixed Effects	MC	MC	MC
Sample	2021Q4	2021Q4	2021Q4

The dependent variables are indicators which equal 100 if a fund has changed its name in 2021 (Column 1), from 2020 to 2021 (Column 2), and from 2019 to 2021 (Column 3) and 0 otherwise. Robust standard errors in parentheses. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 8: Manager Investment and Competitive Hedging by Fund Investor Composition

VARIABLES	(1) Pr[Adopt Crypto]	(2) Pr[Adopt Crypto]	(3) Pr[Adopt Crypto]
Retail AUM Share	3.939***	3.770***	3.032**
	(1.207)	(1.378)	(1.333)
I[Manager Does Not Invest]	-0.0391	-0.151	0.564
	(1.384)	(1.183)	(1.405)
Retail AUM Share x I[Manager Does Not Invest]	-2.601	-2.093	-1.978
	(1.830)	(1.893)	(2.171)
Expense Ratio		1.236***	0.998**
		(0.434)	(0.497)
Fund Age		0.697	0.485
		(0.454)	(0.507)
Manager Tenure		-0.549**	-0.824***
		(0.249)	(0.259)
AUM		1.425**	1.282**
		(0.651)	(0.531)
Constant	2.369**	1.995**	2.212***
	(0.990)	(0.973)	(0.687)
Observations	3,124	2,999	2,995
R-squared	0.005	0.015	0.062
Fixed Effects	None	None	Morningstar Category

Sample is 2021Q4, funds holding no crypto by 2020Q4. The dependent variable is an indicator which equals 100 if a fund holds cryptocurrencies and 0 otherwise. Controls include fund age, log fund AUM, expense ratio, and manager tenure. All independent variables are standardized except for the manager investment indicator. Standard errors clustered at the Morningstar category level. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

Table 9: Market Timing by Manager Investment

	(1)	(2)
VARIABLES	Crypto Flows	Crypto Flows
Manager Invests	1.798**	-1.269**
	(0.884)	(0.538)
Fund Age (Quarters)	-0.0120	0.00666
	(0.00770)	(0.00496)
Retail Share of AUM (%)	4.146*	-3.116**
	(2.304)	(1.271)
Frac. Male Managers	2.544*	-0.449
	(1.302)	(0.989)
Number of Managers	0.686*	-0.274
	(0.395)	(0.202)
Constant	-5.674*	2.119
	(3.130)	(1.633)
Observations	12,423	3,273
R-squared	0.002	0.005
Sample	2020	2022Q1

The dependent variable is a fund's crypto flow as a percentage of fund AUM multiplied by 100. Observations are at the fund × quarter level. Standard errors clustered by fund. 1%, 5%, and 10% statistical significance are indicated by ***, **, and *, respectively.

6.3 Proofs

Portfolio choice

We take the objective function given in Equation 2 and transform it into a mean-variance optimization problem by multiplying by negative one, taking a log, and minimizing the resulting objective function:

$$\begin{aligned}&\min_x \log E[\exp\{-\gamma\,[ar_x - br_{\mathbf{b}} - cf\,r_{\mathbf{c}} + cr_\lambda]\}] \\ &\quad = (ax^\top - b\theta_b^\top - cf\,\theta_c^\top)\mu + cx^\top\lambda - \frac{\gamma}{2}\left[(ax - b\theta_b - cf\,\theta_c)^\top \Sigma(ax - b\theta_b - cf\,\theta_c)\right]\end{aligned} \tag{4}$$

Taking a derivative with respect to x and rearranging yields the portfolio choice rule:

$$\frac{d}{dx} : a\mu + c\lambda - \frac{\gamma}{2}\cdot 2(ax - b\theta_b - cf\,\theta_c)a\Sigma = 0$$

$$a\mu + c\lambda - \gamma(ax - b\theta_b - cf\,\theta_c)a\Sigma = 0$$

$$a\mu + c\lambda = \gamma(ax - b\theta_b - cf\,\theta_c)a\Sigma \tag{5}$$

$$\frac{\mu}{\gamma}\Sigma^{-1} + \frac{c\lambda}{a\gamma}\Sigma^{-1} = ax - b\theta_b - cf\,\theta_c$$

$$\frac{\mu}{a\gamma}\Sigma^{-1} + \frac{c\lambda}{a^2\gamma}\Sigma^{-1} + \frac{b\theta_b}{a} + \frac{cf\,\theta_c}{a} = x^*$$

Model predictions

Proposition 1: Managers with stronger direct performance incentives (a) compared to relative performance (b) and flow (c) incentives hedge less aggressively in response to the portfolio choice of their competitors (θ_c).

Proof: we normalize the weights so that $(a+b+c) = 1 \implies c = 1-a-b$. Taking a derivative of the portfolio choice expression with respect to a yields:

$$\begin{aligned}\frac{\partial x^*}{\partial a} = &-\frac{1}{a^2}\left[\frac{\mu}{\gamma}\Sigma^{-1} + b\theta_b + (1-a-b)f\,\theta_c + \frac{1-a-b}{a}\frac{\lambda}{\gamma}\Sigma^{-1}\right] \\ &-\frac{1}{a}\left[f\,\theta_c + \frac{\lambda}{\gamma}\Sigma^{-1}[\frac{1-2a-b}{a^2}]\right]\end{aligned}$$

The first term shows that the entire portfolio scaled down by $\frac{1}{a}$ in proportion to original weights, and the second term shows that the weights on θ_c and λ are scaled down by an additional term.

Proposition 2: Managers who face a stronger flow performance relationship (f) hedge more aggressively in response to the portfolio choice of their competitors (θ_c).

Proof: $\frac{\partial x^*}{\partial f\,\partial\theta_c} = \frac{c}{a} > 0$ if $c > 0$.

Proposition 3: Managers whose competitors hold more crypto (θ_c) are more likely to adopt crypto themselves, holding fixed their beliefs $\frac{\mu}{\gamma\Sigma}$ and fund benchmark θ_b.

Proof: $\frac{\partial x^*}{\partial \theta_c} = \frac{cf}{a} > 0$ if $c > 0$ and $f > 0$.

Endogenous competition. In Equation 3, the competitor's portfolio is taken as exogenous. We derive an expression for portfolio choice in a simplified setting which endogenizes the competitor's portfolio. This allows us to analyze how a change the primitives of the model (e.g. a change in competitors' beliefs and incentives) affect a fund's decisions.

Consider two managers, 1 and 2. Managers are allowed to differ in their view of mean asset returns μ and contract incentives. We make the simplifying assumptions that managers have the same risk aversion and beliefs about the covariance of returns, and that there are no benchmark hedging or catering effects. We also assume that managers believe that crypto is uncorrelated with all other assets, and that the variance of crypto returns is σ. Each manager's portfolio share in crypto is (suppressing subscripts):

$$x_1 = \frac{\mu_1}{a_1\gamma\sigma} + c_1 f_1 x_2 \quad , \quad x_2 = \frac{\mu_2}{a_2\gamma\sigma} + c_2 f_2 x_1 \tag{6}$$

Substituting manager 2's portfolio choice into manager 1's problem and simplifying yields:

$$\begin{aligned} x_1 &= \frac{\mu_1}{a_1\gamma\sigma} + c_1 f_1 [\frac{\mu_2}{a_2\gamma\sigma} + c_2 f_2 x_1] \\ &= \frac{\mu_1}{a_1\gamma\sigma} + c_1 f_1 \frac{\mu_2}{a_2\gamma\sigma} + c_1 c_2 f_1 f_2 x_1 \\ &= [\frac{\mu_1}{a_1\gamma\sigma} + c_1 f_1 \frac{\mu_2}{a_2\gamma\sigma}] \cdot [1 - c_1 c_2 f_1 f_2]^{-1} \end{aligned} \tag{7}$$

Taking a derivative with respect to μ_2, manager 2's beliefs about the mean return of crypto:

$$\frac{\partial x_1}{\partial \mu_2} = \frac{c_1 f_1}{a_2\gamma\sigma \cdot (1 - c_1 c_2 f_1 f_2)} \tag{8}$$

This derivative is positive as long as c_1, c_2, f_1, and f_2 are between zero and one. The parameters c are between zero and one because the incentive weights sum to one. The strength of flow-performance incentives can also be normalized to be between zero and one without loss of generality. Manager 1 is more likely to hold crypto if manager 2 becomes more optimistic about crypto, holding fixed manager 1's beliefs.

Model dynamics. The current version of the model is a static portfolio choice problem. To demonstrate how competition hedging can lead to amplification, we clarify the assumptions under which the dynamic portfolio choice is a repeated version of the static portfolio choice, and we simulate a multi-period version of the model.

We modify the setup described in Section 2. First, there are three periods, $t = 0, 1, 2$. Managers make asset allocation decisions in periods 0 and 1, denoted x_t. Investments return risky cash flows $\tilde{D}_{t+1} \sim N(\mu_t, \Sigma)$. The outcomes of period-0 investment decisions are observed in period 1, and the outcomes of period 1 investment decisions are observed in period 2. Second, we assume that risky cash flows $\tilde{D}_{t+1}$ are iid across periods, so the realized cash flow of asset i in period 1 does not provide information about asset i's cash flow in period 2. Third, we assume beliefs about mean returns μ_t, competitor portfolios θ_{ct}, ex-ante investor demand λ_t, flow-performance f_t, and compensation weights a_t, b_t, c_t may vary over time, while beliefs about covariance Σ, absolute risk aversion γ, and benchmark portfolios θ_b remain fixed. Fourth and finally, we assume that the strength of absolute performance incentives when making asset allocation choices in period 1 do not depend on realized absolute performance in period 1.[20]

These assumptions imply that the optimal portfolio choice is just a repeated version of the

[20]Since absolute performance is meant to proxy for direct manager investment in the fund (see description in section 4.2), good period-1 performance could increase the manager's wealth available to allocate when making period-1 portfolio allocation choices. This assumption rules out such an effect. It could represent a requirement that a manager invest a fixed dollar value in their porfolio each period, in which case the manager skims off excess returns or deposits additional funds to maintain a fixed dollar investment in each period.

rule derived in section (2.2.1):[21]

$$x_t^* = \frac{1}{a_t}\left(\frac{\mu_t}{\gamma}\Sigma^{-1} + b_t\theta_b + c_t f_t \theta_{ct} + \frac{c_t}{a_t}\frac{\lambda_t}{\gamma}\Sigma^{-1}\right) \tag{9}$$

Simulation. We have N managers with heterogeneous beliefs about the average return of a single asset μ_i. Beliefs about the mean return are distributed standard normal. Managers place equal weight on their beliefs and on competition hedging, $a = c = \frac{1}{2}$. We make the following simplifying assumptions: i) managers all believe that the variance of asset returns $\sigma^2 = 5$, ii) managers have homogeneous risk aversion $\gamma = 1$, and iii) the benchmark hedging (b) and catering (λ) terms both equal zero. We define θ_c as the average portfolio weight of competitor funds in crypto.

All managers begin with zero crypto holdings. In the first period, managers choose their portfolios based on their subjective return beliefs $\frac{\mu_i}{\gamma}\Sigma^{-1}$. All managers with positive μ_i hold a positive weight in crypto, and all managers with weakly negative μ_i hold zero weight in crypto due to short-sales constraints. There is no competitive hedging incentive since none of their peers hold crypto. In all subsequent periods, managers update their portfolios, accounting for the fact that their peers' crypto holdings have changed. Figure 14 presents the results of the simulation.

[21]The result for the period-1 investment is obvious. The period-0 investment rule might differ from the expression in equation (3) for three reasons. First, period-1 adjustment may not be possible, which we assume away. Second, if returns are serially correlated, then the period-0 asset allocation must consider the correlation between period-1 wealth and period-1 investment opportunities. Our assumption that returns are iid shuts down this motive. Third, if wealth grows or shrinks based on returns, then the period-0 investment allocation may consider how realized period-1 wealth will impact absolute performance incentives. Assuming that managers adjust the personal assets they invest in their fund in period 1 shuts down this incentive.

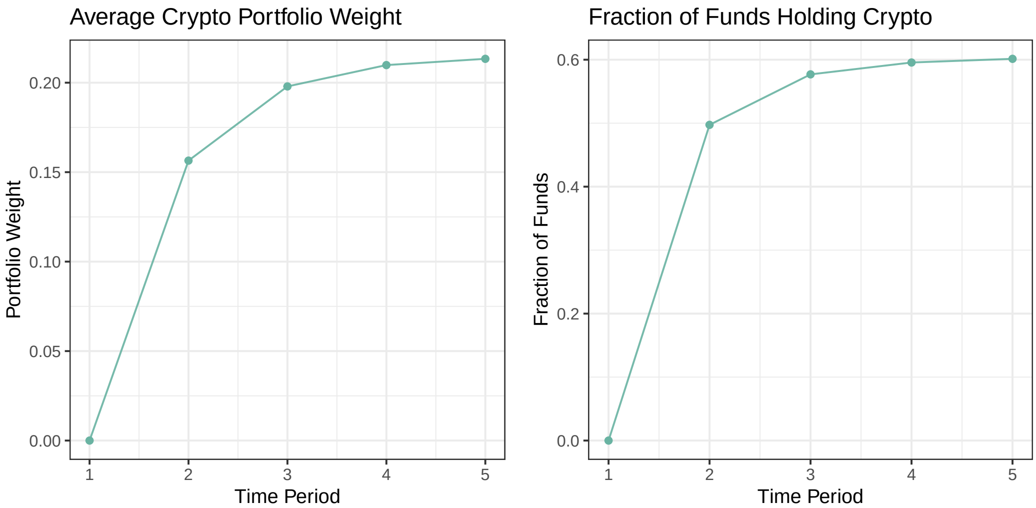


Figure 14: This figure presents simulations of the dynamics of cryptocurrency adoption. The left panel plots the average crypto portfolio weight across all funds over time. The right panel plots the fraction of funds with any crypto exposure over time.