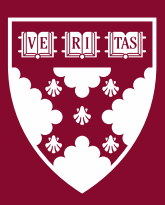
Working Paper 26-049

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Hidden Risk*

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Abstract

This paper investigates the agency problems that arise when investors cannot observe the risks taken by their asset managers. Using a unique regulatory dataset spanning most U.S. hedge fund assets, we find that the scope for agency problems is large, as managers possess valuable information about fund risk taking beyond what investors can infer from past returns. Investor flows respond to this information only when it is beneficial to managers, suggesting that contracting and reputation do not solve the asymmetric information problem. We estimate that 10-20% of hedge fund flows over the past decade may have been allocated differently had investors better understood fund risk taking. Such agency frictions are likely more severe in other parts of asset management, where risks are harder to measure.

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1 Introduction

Financial intermediation in the United States has changed dramatically over the last forty years. While traditional banks once dominated the financial system, the role of asset managers in intermediation has grown enormously (Greenwood et al., 2024). At a more fundamental level, intermediation has shifted towards more arms-length transactions, with investors increasingly entrusting their capital to external fund managers operating under a variety of complex contractual arrangements. The benefits of this evolution are clear. With deeper and more efficient capital markets, firms can now raise financing from a broader set of investors at lower cost. The proliferation of capital markets has also increased opportunities for diversification and facilitated global risk sharing.

Nevertheless, the growth of asset management also carries costs. Layers of financial intermediation, coupled with less transparent investment vehicles, can hinder investors' ability to monitor the risks taken by their asset managers (Rajan, 2005; Acharya et al., 2016). Fund managers thus face strong incentives to take risks that investors do not recognize. This agency problem underlies much of the theoretical work on both the limits of arbitrage (Shleifer and Vishny, 1997) and intermediary asset pricing (He and Krishnamurthy, 2011, 2013).

Although the potential for such agency problems in the modern financial system is widely acknowledged, gauging their quantitative significance is difficult. The primary challenge lies in measurement: in most datasets, it is not possible to determine the scale of the informational asymmetry between asset managers and their investors. Moreover, holding fixed the size of the asymmetry, it is theoretically unclear whether contracting, reputation, and other tools mitigate the problem. In some models, the private information of agents is ultimately fully revealed in equilibrium (e.g., Stein, 1989; Milgrom, 1981), while in others, information remains concealed because there is either a pooling equilibrium or principals are unsophisticated (e.g., DeMarzo and Duffie, 1999; Dang et al., 2017).

In this paper, we make progress on measuring agency problems in asset management

using regulatory data from Securities and Exchange Commission (SEC) Form PF. These data encompass the vast majority of the U.S. hedge fund industry, which managed around $5 trillion in net assets and $10 trillion in gross assets as of September 2023.[1] Form PF is uniquely suited for studying agency frictions because it requires hedge fund managers to report to the SEC their perceived exposures to various risk factors (e.g., public equity markets). Crucially, however, the SEC does not share this information with investors. Thus, we can compare managers' private assessments of risk with estimates that are readily available to investors, namely those implied by past fund returns.

Throughout our analysis, risk is defined as CAPM beta with respect to public equity markets, a simple, common form of risk adjustment.[2] On Form PF, funds must report how their portfolio values will be affected by changes in equity prices of -20%, -5%, 5%, and 20%, which we use to infer managers' perceived CAPM betas. We label as the beta gap the difference between manager-perceived betas (β^R) and those implied by historical returns ($\hat{\beta}$). The average beta gap is small, but there is substantial variation around the mean: the standard deviation of the beta gap is over 0.3. For an equity premium of 10%—roughly the realized annual excess return in our sample—a beta gap of 0.3 implies the manager views the fund's alpha as 3 percentage points lower than historical returns suggest.

Our analysis proceeds in two steps. First, we establish that manager beliefs contain incremental information about future risk, a necessary condition for an asymmetric information problem to exist. In particular, through a series of forecasting regressions, we show that manager-perceived betas strongly predict their funds' future equity market exposure, even after controlling for CAPM betas estimated from historical returns. The scope for agency problems could therefore be large in our setting, as managers possess useful information about risk that investors cannot easily infer from past returns.

Second, we ask whether contracting and reputation overcome the information asym-

[1] See SEC Private Fund Statistics: https://www.sec.gov/files/investment/private-funds-statistics-2024-q3.pdf.

[2] This focus is further supported by Berk and van Binsbergen (2016), Barber et al. (2016), and Agarwal et al. (2018), who show that CAPM-based risk adjustments best explain the behavior of investors in mutual funds and hedge funds.

metry by testing if investors incorporate managers' information into their asset allocation decisions. In the spirit of Barber et al. (2016) and Berk and van Binsbergen (2016), we take a revealed preference approach that links net flows into a fund in quarter $q+1$ ($flow_{q+1}$) to its CAPM alpha estimated from its recent returns ($\hat{\alpha}_q$). Our innovation is to augment standard flow-performance regressions with the product of the beta gap ($\beta_q^R - \hat{\beta}_q$) and the recent market return (μ_q^M), which captures differences between the manager's and investors' perceptions of the manager's skill:

$$flow_{q+1} = \kappa_0 + \kappa_1 \hat{\alpha}_q + \kappa_2 (\beta_q^R - \hat{\beta}_q)\mu_q^M + \varepsilon_{q+1}.$$

To see the intuition, consider a fund with a positive beta gap during a period of strong market returns, meaning $(\beta_q^R - \hat{\beta}_q)\mu_q^M > 0$. Because the manager perceives more equity exposure than implied by historical returns ($\beta_q^R > \hat{\beta}_q$), the fund's realized CAPM alpha $\hat{\alpha}_q$ will be overstated from the manager's perspective. If investors incorporate the manager's information into their allocation decisions, flows should be lower than what the fund's historical alpha alone suggests. Thus, in the flow-performance regression above, we should observe $\kappa_2 < 0$. Instead, if $\kappa_2 = 0$, then the manager's (valuable) information has no explanatory power for investor behavior, consistent with asymmetric information.

For the average fund, we estimate moderately negative values for κ_2, but this average effect masks significant heterogeneity in investor behavior. Guided by agency theory, we split funds on three dimensions: the degree to which fund managers have skin in the game, the beta gap (which captures managerial incentives to reveal their information), and whether the fund's reported risk exposures are option-like (i.e., nonlinear).[3]

Across these three splits, we consistently find evidence that contracting and reputation do not fully overcome the informational asymmetry between fund managers and investors. For instance, investors respond strongly to manager information when the beta gap is

[3] Lo (2001) and Jurek and Stafford (2015) suggest that managers of funds with nonlinear exposures have incentives to keep their information private since the compensation for exposure to tail events may appear to investors as alpha in normal times (see Section 4.4.3).

negative, but not for funds with positive beta gaps. In other words, when a fund's historical alpha exceeds the manager's perceived alpha, the manager's information appears to remain private and does not influence investor flows. Similarly, investors do not respond to manager information in funds with low insider ownership or option-like equity exposure.

We show these results are robust in a variety of ways. First, we control for detailed fund-level controls, including liquidity terms and strategy-by-time fixed effects, ensuring we are comparing funds to which investors likely apply similar risk adjustments. Second, we show that our results are robust to the possibility that investors and fund managers use multifactor models of risk. Third, we provide corroborating evidence from fees. Like flows, fees are related to the beta gap for negative beta-gap funds, but not positive beta-gap funds. In other words, when a fund's historical alpha exceeds the manager's perceived alpha, the manager's information appears to remain private and does not influence fees paid by investors. Similarly, fees appear to incorporate managers' information for funds with linear risk exposures but not for funds with option-like exposures.

These results suggest that contracting and reputation do not overcome the informational asymmetry between investors and fund managers. Managers with positive beta gaps perceive lower risk-adjusted performance than implied by their returns. If the private information of these managers were revealed to investors, it would reduce flows and hence assets under management, making the managers worse off. Conversely, managers with negative beta gaps perceive higher risk-adjusted performance than implied by their returns. It is beneficial for these managers to reveal their private information to investors, as it increases flows and assets under management. We provide formal conditions under which this interpretation is valid in Section 4.2.

An alternative interpretation is that investors are aware of managers' information for all funds but choose to ignore it for funds with positive beta gaps and option-like equity exposures. To examine this alternative, we analyze flows during the first quarter of 2020, when public equity markets fell by almost 20% in response to the outbreak of the Covid-19 pandemic. Market drawdowns of this kind are useful because they magnify the divergence

between historical and manager-perceived betas. Consider a fund with a positive beta gap and assume investors are unaware of the manager's private information. After a sharp market decline, such a fund is more likely to significantly underperform expectations based on its historical beta, triggering abnormally large outflows.

This is precisely what we find. In 2020Q1, outflows from funds with a positive beta gap were strongly increasing in the size of their beta gap. Importantly, our tests study abnormal flows, defined as actual flows minus predicted flows based on a pre-2020 flow–performance relationship. This implies that investors were not simply reacting to weak performance but instead revised their views of fund risk. This pattern, which contrasts sharply with behavior in normal times, suggests investors were caught off guard by the poor performance of these funds. If investors were aware of managers' information but had good reasons to ignore it, they should have continued to ignore it in 2020Q1.

Overall, our findings indicate that hedge fund managers have valuable information about fund risk that is not reflected in past returns. Moreover, investors do not always respond to this private information, suggesting that contracting and reputation do not fully mitigate the informational asymmetry. A back-of-envelope calculation implies that this agency distortion is economically meaningful in aggregate: according to our estimates, roughly 10-20% of flows into the hedge fund sector since 2015 may have been allocated differently if investors had access to managers' private risk assessments.

Our paper belongs to the broad literature on agency problems in asset management. Following Jensen and Meckling (1976) and Holmström (1979), the key underlying friction in much of this literature is moral hazard—investors cannot observe the manager's actions. Makarov and Plantin (2015) and Acharya et al. (2016) are recent examples that apply this idea specifically to models of manager risk taking. A related theoretical literature studies the optimal contract between investors and fund managers in the face of such information frictions, including Bhattacharya and Pfleiderer (1985), Stein (2005), Panageas and Westerfield (2009), He and Xiong (2013) and Buffa et al. (2022).

Although agency problems in asset management are relatively well-understood in theory,

they are challenging to measure because researchers seldom observe the distinct information sets of managers and investors. Past studies have therefore relied on indirect approaches. For instance, Brown et al. (1996), Chevalier and Ellison (1997), Huang et al. (2011), and Han et al. (2021) show that the observed risk of mutual funds is positively correlated with variables that proxy for the personal incentives of managers. Similarly, Lo (2001), Agarwal and Naik (2004), and Jurek and Stafford (2015) argue that hedge funds with positive realized CAPM alpha may simply be taking option-like risks that are hard to detect in normal times. Relative to previous work, the unique nature of Form PF allows us to more directly observe the agency problem because it contains assessments of fund risk that are made privately by hedge fund managers. Our key finding is that investors frequently behave as though they are unaware of this information, resulting in economically meaningful distortions to the allocation of capital.

The idea that asset managers may hide risk also features prominently in policy discussions (e.g., Rajan, 2005; Acharya et al., 2009). In a narrow sense, our results suggest these concerns may be warranted for some hedge funds. More broadly, if agency concerns are detectable even among hedge funds that largely invest in publicly traded securities, then they are likely more severe in settings where risk is harder to observe from past returns, including structured products (Coval et al., 2009), private equity and credit (Stafford, 2021; Erel et al., 2024), and real estate (Garmaise and Moskowitz, 2004; Couts et al., 2024). This observation is especially relevant given the expansion of alternative asset classes over the past decade (Ivashina and Lerner, 2018; Greenwood et al., 2024; Begenau et al., 2025).

The remainder of the paper proceeds as follows. Section 2 provides background on Form PF and describes our analysis sample. Section 3 analyzes managers' private risk assessments and shows they provide valuable information that is not captured by past returns. Section 4 documents that investor flows respond to this information in some funds but not others. Section 5 shows that investors revise their views on fund risk following extreme market returns. Finally, Section 6 evaluates the aggregate size of this agency distortion and concludes.

2 Background and Data

In this section, we outline our data sources, describe our analysis samples, define key variables, and present basic summary statistics.

2.1 Form PF

Our data on hedge funds primarily come from Securities and Exchange Commission (SEC) Form PF, which was adopted in 2011 to implement parts of Title IV of the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010.[4] Investment advisers registered with the SEC that advise one or more private funds and have at least $150 million in gross assets under management in private funds must periodically file Form PF. Investment advisers registered with the SEC generally meet one of two criteria: they either operate in the United States or have U.S. investors. As such, many funds that file Form PF are legally incorporated outside the United States, including for instance in the Cayman Islands. The information contained in Form PF is confidential and is intended to assist regulators in their assessment of systemic risk in the U.S. financial system. Managers have strong incentives to report truthfully: willful misstatements or omissions of material facts in a Form PF filing are unlawful under Section 207 of the Investment Advisers Act of 1940 and may result in the adviser's registration being revoked or criminal prosecution.

Hedge fund advisers file Form PF at least annually and report items such as gross and net asset values, returns, borrowings, and strategies. Advisers with at least $1.5 billion in gross assets managed in hedge funds are required to file Form PF quarterly and additionally report more detailed information about their asset class exposures, risk metrics, asset and funding liquidity, and counterparties for each of their large ("qualifying") hedge funds.[5] We restrict our sample to qualifying hedge funds, as only these are required to provide

[4] Form PF has been amended. The version of Form PF used in the paper can be found here: https://www.sec.gov/files/formpf-legacy.pdf

[5] A qualifying hedge fund has a net asset value of at least $500 million as of the last day in any month in the fiscal quarter preceding the adviser's most recently completed fiscal quarter. Kruttli et al. (2022) and Kruttli et al. (2025) also base their studies on qualifying hedge funds filing Form PF and use similar variable and sample construction procedures. For aggregate statistics from Form PF data, see the SEC's Private Fund Statistics: https://www.sec.gov/divisions/investment/private-funds-statistics

information about their sensitivities to the equity market factor in Question 42, which we use to infer their managers' risk perceptions. As of 2023Q3, qualifying hedge funds managed 80% (86%) of the net (gross) assets of all hedge funds filing Form PF. We start the analysis in January 2013 because 2013 was the first full year in which hedge funds were required to report. The sample ends in July 2023.

2.2 Variable Construction and Analysis Sample

We next define several key variables for our analysis. The unit of observation in our primary analysis sample is fund-quarter. Assets under management (AUM) is defined based on each fund's net asset value as reported in Question 9. Net quarterly flows into each fund are constructed using observed AUMs and quarterly net-of-fee returns. Following standard practice in the literature, we trim the top and bottom 1% of the flow distribution.

Several different measures of leverage can be extracted from the PF data. We focus on gross-to-net asset value, which is akin to the ratio of assets to equity for nonfinancial firms. As with flows, we trim the top and bottom 1% of the leverage distribution.

Question 50 of Form PF asks for the fraction of each fund's capital base that can be withdrawn over one of the following fixed windows: 1 day or less, 2-7 days, 8-30 days, 31-90 days, 91-180 days, 181-365 days, and more than 365 days. We define the length l of each window using its midpoint. For example, we set the length of the 8-30 day window to be $l = 19$ days. The window exceeding 365 days is given a length of $l = 365$ days. We define the liquidity of the fund to be a weighted average of these window lengths, with weights based on the fraction of capital $f(l)$ that can be withdrawn over the window.

Inside ownership is taken from Form ADV, which is used by hedge fund managers to register with the SEC.[6] Form ADV is updated annually, and we match fund-quarter observations in Form PF to the most recent annual Form ADV filing.

Fund strategy is inferred based on Question 20, which asks the percentage of assets managed in each of 22 possible strategies. For example, one strategy is "Equity, Market

[6]Question 14 of Form ADV, Part 1A, Schedule D, Section 7.B.(1).A asks for the fraction of the fund owned by insiders.

Neutral." We collapse these detailed strategies into one of the following nine high-level strategies: (i) equity; (ii) macro; (iii) relative value; (iv) event-driven; (v) credit; (vi) managed futures; (vii) investments in other funds; (viii) multi-strategy; and (ix) other. Funds are assigned to a particular strategy if at least 70% of their assets are in associated detailed granular strategies. Funds that do not meet this criterion are labeled multi-strategy.

Table 1a summarizes quarterly variables for funds that report enough information to compute the manager's perceived equity risk exposure. Funds also report on Form PF their gross- and net-of-fee returns on a monthly basis. We use monthly gross returns to construct rolling 36-month estimates of beta and alpha with respect to the CRSP Value-Weighted index, requiring at least 24 months of valid return observations.[7] Table 1b shows summary statistics for these monthly variables. Realized fees are the difference between gross- and net-of-fee returns.

3 Manager Risk Perceptions

In this section, we describe our approach to inferring managers' perceptions about the risk of their funds using the Form PF data. We define risk in the classic CAPM sense, based on the beta of the fund with respect to the aggregate stock market (i.e., equity market beta). We compare perceived CAPM betas with the beta implied by historical returns, finding that this "beta gap" is economically meaningful. Most importantly, we show that manager beliefs contain valuable information about a fund's subsequent equity market exposure that is not embedded in past returns. This result is essential. It is a necessary condition for agency problems to arise between managers and investors. Whether managers are reporting CAPM betas or some other notion of risk—and regardless of the underlying source of the beta gap (e.g., estimation error)—the key point is that managers have information that would be useful to investors assessing future fund risk.[8]

[7] As discussed below, we use gross returns because they correspond to the manager's perceived exposure.

[8] None of our analysis requires managers or investors to believe that the CAPM holds as a description of equilibrium asset returns. The only requirement is that some investors reward managers for market-adjusted returns. See Section 4.2.

3.1 Basic Properties

We infer manager perceptions about risk based on their response to Question 42 in Form PF, which is stated as follows:

> For each of the market factors identified below, determine the effect of the specified changes on the reporting fund's portfolio and provide the results.

There are eight market factors that each fund is asked to consider: (i) equity prices; (ii) risk-free interest rates (parallel shifts in the yield curve); (iii) credit spreads; (iv) currency rates; (v) commodity prices; (vi) option-implied volatilities; (vii) default rates on asset-backed securities (ABS); and (viii) default rates on corporate bonds and credit default swaps (CDS). For each factor, the question specifies what it means by a change in the factor. For example, for equity prices, it says:

> A change in "equity prices" means that the prices of all equities move up or down by the specified amount, without regard to whether the equities are listed on any exchange or included in any index.

The fund is then asked to separately report the instantaneous response of the long and short components of the portfolio, as a percent of NAV, conditional on a pre-specified change in the market factor. For the equity-market factor, these shock scenarios are: (i) an increase of 5%; (ii) an increase of 20%; (iii) a decrease of 5%; and (iv) a decrease of 20%.

Table 2a shows response rates for each of the eight market factors for each fund-quarter observation. R-T stands for "relevant and tested"—these are cases where the fund manager provided a complete response for the factor. "R-NT" refers to instances where the manager indicated that the factor is relevant but not tested by their risk-management protocols. "NR" denotes cases where the manager reported that the factor was not relevant for the fund's portfolio.

The equity market factor is the most frequently reported, with 75% of respondents reporting it as relevant and 47% reporting it as both relevant and tested. The funds that

report equities as relevant but not tested tend to invest more heavily in non-listed equities. After equity market exposure, the two most relevant factors are currencies and risk-fee rates.

For the remainder of the paper, we focus exclusively on equity-market exposure, as it is the factor that is relevant and tested for the largest number of funds. The concept of equity-market risk we consider is CAPM beta. Agarwal et al. (2018) show that CAPM alpha—constructed using CAPM beta—is the measure that best explains flows into hedge funds. Consistent with this interpretation, when fund managers include clarifying notes about their answers on Form PF, they typically write that their answer to Question 42 is based on a CAPM beta.

To compute betas from Form PF, we proceed as follows. Let $\beta(x)$ be a function that yields a manager's perceived beta given an aggregate market return of x. For $x \in \{-20\%, -5\%, 5\%, 20\%\}$, we set $\beta(x) = R(x)/x$, where $R(x)$ is how the manager expects the fund to perform given a market return of x.[9] For instance, if a manager reports that the fund's net position will fall by 10% when the market falls by 20%, then $R(-20\%) = -10\%$ and $\beta(-20\%) = 0.5$. For values of x not in the reported scenarios, we use linear interpolation to determine beta when $|x| \leq 20\%$. For example, if $x = -10\%$, then $\beta(-10\%) = (1/3) * \beta(-20\%) + (2/3) * \beta(-5\%)$. For $x < -20\%$ or $x > 20\%$, we assume $\beta(x)$ equals the nearest boundary value.

Our definition of $\beta(x)$ assumes that managers do not embed perceived alpha in their reported values of $R(x)$, since Question 42 asks about *instantaneous* changes in the equity market. This interpretation is consistent with the clarifying notes managers sometimes provide.[10] Our results are also robust to defining betas using changes in expected returns across scenarios, which would difference out any constant alpha.[11]

In each month t in quarter $q(t)$, we then use each fund's lagged $\beta(x)$ function to define

[9] We trim outliers of $\beta(x)$ separately for each value of $x \in \{-20\%, -5\%, 5\%, 20\%\}$ at the 1% level.

[10] It also accords with international regulatory reporting practices. In other jurisdictions such as the UK and EU, the analogue to Form PF asks managers to report their equity market "delta," which equivalent to a portfolio's beta with respect to equity markets and does not reflect any alpha. See, for instance, Question 179 on Form AIF002, as collected by the U.K. Financial Conduct Authority.

[11] Specifically, we set $\tilde{\beta}(x_1, x_2) = (R(x_2) - R(x_1))/(x_2 - x_1)$.

the manager's perceived beta based on the realized market return in t. Extending our notation above, let $\beta_{i,q}(x)$ be the beta function reported by fund i's manager at the end of quarter q. Then, for month t, if the realized market is $R_{m,t}$, we define the manager's perceived beta as $\beta^R_{i,t} = \beta_{i,q(t)-1}(R_{m,t})$. That is, in each month, we evaluate the beta function submitted in the previous quarter using the current market return. This construction means that $\beta^R_{i,t}$ is forward-looking in the sense that it reflects the manager's ex-ante risk assessment prior to the realization of returns in month t.

The remaining issue is how to compute $\beta^R_{i,t}$ for funds that report that the equity-market factor is either not relevant (NR) or relevant but not tested (R-NT). We think it is most natural to assume that $\beta^R_{i,t} = 0$ for those that say the factor is not relevant. For the remaining funds, we treat $\beta^R_{i,t}$ as missing.

Table 2b provides summary statistics on the reported beta function $\beta_{i,q}(x)$ across fund-quarter observations for the values of x directly reported on Form PF, i.e., $x \in \{-20\%, -5\%, 5\%, 20\%\}$. The average $\beta_{i,q}(x)$ in the sample is around 0.2, similar to the unconditional average CAPM beta for hedge funds of 0.37 reported by Barth et al. (2023). There is also substantial heterogeneity in betas: for example, at $x = -5\%$, the 5th percentile fund reports zero beta whereas the 95th percentile fund reports a beta of one. The fifth row of the table reports the ratio $\beta_{i,q}(-20\%)/\beta_{i,q}(-5\%)$, which captures nonlinearity in betas during market downturns. A meaningful fraction of funds exhibit ratios not equal to one, indicating nonlinear risk exposure in declining markets.[12] In Appendix B.1, we further describe the manager-reported beta using a series of fixed effects regressions.

3.2 The Unconditional Beta Gap

In this subsection, we compare the CAPM beta perceived by fund managers, β^R, to the one implied by historical fund returns, $\hat{\beta}$. This difference is defined as the beta gap, $g = \beta^R - \widehat{\beta}$. To start, we estimate each fund i's CAPM beta, $\widehat{\beta}_i$, by regressing its full history of monthly excess returns on the excess return of the CRSP value-weighted (VW) index. Excess returns

[12] When the ratio is 0/0, we set it to 1.

are computed relative to the one-month Treasury bill rate, and gross returns are used to ensure comparability with manager-perceived exposures reported on Form PF. Estimating $\widehat{\beta}_i$ using the full sample maximizes precision but ignores potential time-variation in market exposures. In later sections, we allow $\widehat{\beta}_i$ to vary over time using rolling regressions.

We then compare each fund's estimated $\widehat{\beta}_i$ to its average manager-perceived beta, $\bar{\beta}_i^R$, computed using all available Form PF filings. Figure 1 displays the cross-sectional distribution of beta gaps, $g_i = \bar{\beta}_i^R - \widehat{\beta}_i$. Outliers of g_i are removed by trimming its 1% tails. The distribution has a mean of -0.06, suggesting that on average, fund managers' perceptions of risk align with historical returns.

However, the figure also reveals significant dispersion in the beta gap, g_i: many managers perceive their funds to have significantly more or less market exposure than what is implied by past returns. The standard deviation of the beta gap is 0.33.

Beta gaps of this size significantly impact perceived alphas. For example, suppose that the equity market is the only priced factor. From the manager's perspective, the fund's alpha is $\alpha_i^R = \mu_i - \beta_i^R \mu^M$, where μ_i and μ^M are the average excess returns of the fund and market, respectively. The alpha of the fund based on historical returns is $\widehat{\alpha}_i = \mu_i - \widehat{\beta}_i \mu^M$. The difference between the two alphas is $\alpha_i^R - \widehat{\alpha}_i = -(\beta_i^R - \widehat{\beta}_i)\mu^M = -g_i \mu^M$. Intuitively, a positive beta gap $g_i > 0$ means the manager believes the fund's beta is relatively high and thus attributes more of the fund's average return to market exposure, not alpha. For a market risk premium of $\mu^M = 5\%$, a beta gap of $g_i = 0.3$ indicates the manager's perceived alpha is 1.5% per year lower than historical returns imply. This difference is economically significant, comparable to the cross-sectional standard deviation of historical CAPM alphas in Table 1b. The realized market risk premium over our sample is 11.5% per year, implying that the gap between the two alphas is even larger in sample at nearly 3.5% per year.

3.3 Sources of the Beta Gap

There are several reasons a fund may have a non-zero beta gap ($g_i \neq 0$). One possibility is that managers report CAPM betas from multifactor models, while we estimate historical

betas based on a single-factor model.[13] Appendix A.3 suggests this is not the case, reporting robustness tests controlling for additional factors—both those reported on Form PF and those commonly used in the academic literature (e.g., size, value, momentum).

Other potential sources of a non-zero beta gap include: (i) estimation error in historical CAPM betas, which is more likely when return histories are short or noisy; (ii) time-series variation in the true beta that is not fully captured by our regressions; (iii) nonlinearity in market exposure, which can be generated by strategies with option-like payoffs; and (iv) return smoothing or asset illiquidity, both of which can mechanically dampen the observed correlation between fund returns and the market.

As a first step toward understanding drivers of the beta gap, we examine its time-series persistence. If the gap were purely driven by estimation error in $\widehat{\beta}_i$, it should be uncorrelated across non-overlapping return windows. To test this idea, we divide each fund i's monthly history into up to three non-overlapping 36-month periods, indexed by $\tau_i = \{1, 2, 3\}$, and compute beta gaps within each period.[14]

Figure 2 shows a binscatter plot of the estimated beta gap from period τ_i against its value from the preceding period, $\tau_i - 1$. The plot reveals meaningful persistence. The slope of the regression line is 0.56, with a standard error of 0.03 based on clustering by fund.

To interpret the magnitudes, suppose that each fund's true beta gap is a permanent characteristic and drawn from a distribution with variance σ_g^2. In addition, assume that in each non-overlapping period a fund's observed beta gap $\hat{g}_{i,\tau}$ is measured with independent noise $\varepsilon_{i,\tau}$ with variance σ_ε^2. Then the regression coefficient in Figure 2 is given by $Cov(\hat{g}_{i,\tau}, \hat{g}_{i,\tau-1})/Var(\hat{g}_{i,\tau-1}) = \sigma_g^2/(\sigma_g^2 + \sigma_\varepsilon^2)$, the fraction of variation in the observed beta gap attributable to persistent differences in the true beta gap. Thus, the figure suggests that roughly half of the beta gap is persistent and half is transitory.

Taking a step back, it is important to emphasize that our analysis of agency problems

[13] We formally derive the omitted variable bias for this case in Appendix A. If the beta gap were driven by omitted factor exposure, it should not forecast realized market exposure, as we show it does in Section 3.4.

[14] The maximum number of non-overlapping periods is determined by the fact that our sample contains at most 132 months of returns per fund.

does *not* require us to identify the specific source of the beta gap. What matters is that the manager's information is useful for predicting the fund's future risk. For example, suppose managers know their fund's future CAPM beta exactly, while investors must rely on a short history of returns. In that case, the beta gap would be entirely driven by estimation error, yet an informational asymmetry would still exist. More generally, agency frictions can arise whenever managers possess risk-relevant information that is not easily inferred from historical performance.

3.4 Are Manager Perceptions Informative?

We now establish a key necessary (but not sufficient) condition for asymmetric information: that manager beliefs contain information about fund risk that is not embedded in historical returns. To examine whether a manager's perceived beta $\beta^R_{i,t}$ helps predict the fund's equity market exposure, after controlling for the information in past realized returns, we estimate the regression:

$$\tilde{R}_{i,t+1} = \gamma_0 + \gamma_1(\beta^R_{i,t+1}\tilde{R}_{M,t+1}) + \gamma_2(\widehat{\beta}_{i,t}\tilde{R}_{M,t+1}) + \varepsilon_{i,t+1}, \tag{1}$$

where $\tilde{R}_{i,t+1}$ is fund i's realized excess return in month $t+1$. The manager-perceived beta, $\beta^R_{i,t+1}$, is constructed using the beta function reported on Form PF from the quarter prior to month $t+1$, evaluated at the realized market return in $t+1$ (see Section 3.1). For example, to forecast returns in March 2025, we use the Form PF filing from 2024Q4 and plug in the March 2025 market return. This is the precise sense in which $\beta^R_{i,t+1}$ is forward looking: it reflects risk assessments that were submitted before $\tilde{R}_{i,t+1}$ is realized. Similarly, $\widehat{\beta}_{i,t}$ is fund i's estimated CAPM beta based on realized returns between month $t-35$ and t, and $\tilde{R}_{M,t+1}$ is the realized excess return of the CRSP VW index in month $t+1$. If $\gamma_1 > 0$, the manager's beta contains information that is not in past returns.

Figure 4 reports the results graphically. It shows a binscatter of $\tilde{R}_{i,t+1}$ against $\beta^R_{i,t+1}\tilde{R}_{M,t+1}$, after controlling for $\widehat{\beta}_{i,t}\tilde{R}_{M,t+1}$.[15] The figure reveals a strong positive rela-

[15] Throughout the paper, we construct binned scatter plots following Cattaneo et al. (2024).

tionship: manager risk perceptions contain significant information about fund risk. The slope of the relationship is $\gamma_1 = 0.29$, and it is strongly statistically significant with a standard error of 0.02.[16] For comparison, the coefficient on the fund's historical CAPM beta scaled by the realized market excess return is $\gamma_2 = 0.61$ (not depicted in the figure), and a perfect measure of the fund's equity exposure would recover a slope of 1. The upshot of Figure 4 is that manager perceptions offer economically meaningful incremental information about future fund risk beyond what is contained in historical returns. This simple fact opens the door for potential agency frictions between managers and investors.

4 How Do Investors Respond?

We now ask whether contracting and reputation overcome the information asymmetry documented above in equilibrium. We start with a simple framework to motivate our empirical tests. The key idea is that fund flows help reveal whether investors are using managers' information in their asset allocation decisions. This revealed-preference approach is related to those taken by Berk and van Binsbergen (2016), Barber et al. (2016), and Agarwal et al. (2018). The crucial difference is that we ask whether investor flows take into account fund managers' private information, whereas past research has studied which factors investors consider when risk-adjusting returns (e.g., market risk, value, or momentum).

4.1 Illustrative Conceptual Framework

To fix ideas, suppose that investors form beliefs about fund i's CAPM beta by taking a weighted average of its historical beta and the manager's perceived beta:

$$\beta_i^I = \omega \beta_i^R + (1 - \omega)\hat{\beta}_i \tag{2}$$

The parameter $\omega \in [0, 1]$ reflects how much weight investors put on the manager's beliefs when forming their own views. For simplicity, we assume that investors define the alpha

[16] Based on Driscoll and Kraay (1998) standard errors with fourteen lags, chosen according to Lazarus et al. (2018). Similar standard errors obtain when clustering by fund and time.

of the fund from the perspective of the CAPM:

$$\alpha_i^I = \bar{r}_i - \beta_i^I \mu_m, \tag{3}$$

where $\bar{r}_i$ and μ_m are the average excess return of the fund and the aggregate market, respectively. We discuss how multifactor pricing affects the interpretation of our tests in Section 4.2 and in Appendix A. Similarly, the historical alpha of the fund equals $\hat{\alpha}_i = \bar{r}_i - \hat{\beta}_i \mu_m$. The two alphas are related as follows:

$$\alpha_i^I = \hat{\alpha}_i - \omega \underbrace{(\beta_i^R - \hat{\beta}_i)}_{g_i} \mu_m. \tag{4}$$

If the beta gap g_i is positive, investors perceive the fund's alpha to be lower than what historical returns alone suggest. The amount they adjust the measured alpha when forming their own beliefs depends on the beta gap (g_i), the realized market excess return (μ_m), and the weight they put on the manager's beliefs (ω).

Further, assume that investor allocate fund flows according to:

$$flow_i = \theta \alpha_i^I + \nu_i = \theta \widehat{\alpha}_i - \theta \omega (\beta_i^R - \widehat{\beta}_i) \mu_m + \nu_i, \tag{5}$$

where ν_i is i.i.d and $\theta > 0$. This equilibrium condition could be microfounded in a number of ways, for instance following Berk and Green (2004). The coefficient θ on $\widehat{\alpha}_i$ captures the response of flows to fund outperformance when it is measured using only historical alpha. However, if investors also consider fund managers' information, their risk adjustment differs from that used to compute $\widehat{\alpha}_i$. The difference is captured by the term $(\beta_i^R - \widehat{\beta}_i)\mu_m$. When the beta gap is positive, the manager perceives higher risk than implied by historical returns. Following positive market returns ($\mu_m > 0$), the manager's estimated alpha would then be lower than the one implied by returns ($\widehat{\alpha}_i$). Thus, if investors consider the manager's information ($\omega > 0$), fund flows would be lower than those predicted solely by $\widehat{\alpha}_i$.

Finally, consider a standard flow-performance regression that is augmented by the beta

gap times the realized market risk premium:

$$flow_i = \kappa_0 + \kappa_1 \widehat{\alpha}_i + \kappa_2 (\beta_i^R - \widehat{\beta}_i)\mu_m + \epsilon_i. \tag{6}$$

If $\kappa_2 \neq 0$, then investors incorporate managers' information β_i^R into their asset allocation decision. If we take the conceptual framework literally, equation (5) implies that the ratio $-\kappa_2/\kappa_1$ recovers the weight ω that investors put on managers' information. In our subsequent regression analysis, we report this ratio to help interpret the magnitude of the estimated coefficients.

4.2 Interpreting the Augmented Flow-Performance Regression

Looking ahead, our main results will split funds on three dimensions guided by agency theory: the degree to which fund managers have skin in the game, the beta gap (which captures whether managers' private information is beneficial or detrimental to them), and whether the fund's reported risk exposures are nonlinear. In each case, we will find $\kappa_2 < 0$ for one set of funds and $\kappa_2 \approx 0$ for the other.

We can interpret these results as evidence that contracting and reputation do not overcome the information asymmetry between fund managers and their investors under three conditions. We derive these conditions more formally in Appendix A and discuss here the key intuitions. To make the discussion concrete, consider splitting funds based on the sign of their beta gap. Similar conditions apply for the other splits.

The first condition is that the managers' information must be useful for assessing fund risk in both subgroups. Figure 4 in Section 3.4 confirms this is true on average for all funds, while Figure A2 confirms it specifically for funds with a positive beta gap.

Second, flows must be increasing in perceived alpha, as in Equation (5) and confirmed by a large literature studying flows. Note that this assumption does not require that investors believe that the CAPM holds for equilibrium asset returns. It only requires that investors reward funds with flows for market-adjusted performance.[17]

[17]For instance, suppose investors do not think the CAPM holds but knows that market exposures can

The third condition is the most substantive: investors must apply similar risk-adjustments when evaluating funds in different groups, e.g., positive and negative beta gap funds. This condition is satisfied by equation (3) in the illustration above, but the required condition is looser. It holds, for instance, if investors consistently use the same multifactor model for all funds. The key intuition is that $\kappa_2 < 0$ means investors find managers' information useful for evaluating one group of funds. If investors apply risk adjustments consistently across funds, they should also find managers' information useful when evaluating the other group. Thus, if we observe $\kappa_2 = 0$ for the second group, it must be that investors in those funds did not have access to the managers' information.[18]

We take several steps to ensure that this third condition holds (see also Appendix A.3). First, we include strategy-by-time fixed effects in our baseline regressions, which ensure we are comparing similar funds, where investors are likely applying similar risk adjustments. Second, in untabulated results, we confirm that the distribution of investor types (e.g., endowments, pensions, etc.) is balanced across the fund splits we consider, reducing concerns about differential investor preferences. Finally, we show that our results are robust to estimating alphas and betas using multifactor models and directly controlling for loadings on additional factors in the flow–performance regressions. These results suggest that agency frictions between fund managers and investors are the most likely explanation for the difference in κ_2 we document between positive and negative beta gap funds.

More broadly, our performance-flow regression can be interpreted in terms of conditional expectations. Flows into fund i reflect investors' expectations of its alpha: $\mathbb{E}[\alpha_i|\Omega_i]$, where Ω_i is investors' information set. Our empirical results imply that this conditional expectation depends on manager information for one group of funds but not the other. Given that managers have valuable information, investors in both groups should want to use it

be cheaply obtained from low-cost index funds. Such investors would only want to pay fund managers for market-adjusted returns and would have fund flows described by Equation (5).

[18] Appendix A analyzes the multifactor case in detail. Under certain conditons, the beta gap could reflect loadings on factors other than market risk, and our estimated κ_2 coefficients could capture investor responses to those exposures. In other words, omitted variables bias could impact both the beta gap and regression (6). Crucially however, under the third condition, this omitted variable bias should affect all funds uniformly and cannot by itself generate the kind of asymmetry in κ_2 that we observe across groups.

so long as they apply the same risk model. If they do, then the asymmetry in behavior between groups implies an information asymmetry.

4.3 Full-Sample Results

We start by estimating our augmented flow-performance regression on all funds:

$$flow_{i,q+1} = \kappa_0 + \kappa_1 \hat{\alpha}_{i,q} + \kappa_2 \left(\beta^R_{i,q} - \hat{\beta}_{i,q}\right) \times \mu^M_{i,q} + \Gamma X_{i,q} + \varepsilon_{i,q+1}, \tag{7}$$

where $flow_{i,q+1}$ is the flow into fund i in quarter $q+1$, $\hat{\alpha}_{i,q}$ is the fund's realized CAPM alpha, measured from a 36-month rolling regression using monthly returns through the end of quarter q. $\beta^R_{i,q}$ is the manager's reported beta for the last month of quarter q. $\mu^M_{i,q}$ is the average market excess return measured over the same 36-month window as $\hat{\alpha}_{i,q}$ and $\hat{\beta}_{i,q}$.[19] $X_{i,q}$ is a vector of controls, including lagged quarterly flows and log AUM, along with liquidity and strategy-by-time fixed effects, consistent with the standard approach in the literature.[20] We report Driscoll and Kraay (1998) standard errors with eight lags. The choice of lag length is based on Lazarus et al. (2018).

Table 3 presents the results. In column 1, the coefficient on $\hat{\alpha}_{i,q}$ is $\kappa_1 = 1.80$ and is strongly statistically significant (s.e. $= 0.24$). Since the $\hat{\alpha}_{i,q}$ is in monthly units and $flow_{i,q+1}$ is quarterly, this implies that outperformance of one percent translates into monthly flows of roughly $\kappa_1/3 = 0.60\%$ of assets. These magnitudes are consistent with the literature and imply that investors respond to CAPM alpha when allocating capital (e.g., Fung et al., 2008; Getmansky, 2012; Barth et al., 2023; Kruttli et al., 2025).

The coefficient on $(\beta^R_{i,q} - \hat{\beta}_{i,q}) \times \mu_{m,q}$ is $\kappa_2 = -0.66$. As predicted, the coefficient is negative, suggesting that on average investors do take managers' information into account. The coefficient is also statistically significant with a standard error of 0.26. The row labeled ω in Table 3 interprets the estimates of κ_1 and κ_2 through the lens of the framework laid

[19] The sample is restricted to funds with a minimum of 24 monthly returns over the 36-month window. The i subscript on $\mu^M_{i,q}$ reflects the fact that we measure the average market excess return only for months where the fund reports returns.

[20] See Sirri and Tufano (1998), Agarwal et al. (2018), and Barber et al. (2016) as just a few examples.

out in Section 4.1. In that framework, ω reflects the weight investors put on managers' information, which our estimates imply is $\omega = 0.37$ with a standard error of 0.14.

The remaining columns of Table 3 illustrate the robustness of these results. In column (2), we add controls for lagged size, the log of each fund's net asset value (NAV) last quarter, and lagged flows. Column (3) controls for fixed effects capturing fund liquidity terms.[21] Column (4) controls for strategy-by-time fixed effects, which absorb any time-series variation in fund flows or alternative factor returns that is common across funds with the same strategy.[22] The last column adds all fixed effects and controls. Reassuringly, the results are very similar across all columns.

In sum, we find that for the average fund, investors' flows appear to moderately respond to managers' information. Next, we explore variation across different types of funds.

4.4 Heterogeneity Consistent with Agency Problems

We now characterize the types of funds for which investors respond more strongly to managers' information. Guided by agency theory, we split funds on three dimensions: the degree to which fund managers have skin in the game, the beta gap (which captures managerial incentives to reveal their information), and whether the fund's reported risk exposures are nonlinear. These three tests are largely independent: the pairwise correlations between dummy variables for low inside ownership, positive beta gap, and nonlinear risk exposure are all small.

4.4.1 Low vs. High Inside Ownership

We start with a simple, direct implication of agency theory: that agency frictions can often be mitigated by skin in the game, i.e., having managers invest a meaningful fraction of their wealth in the fund (Jensen and Meckling, 1976). We now investigate this idea by testing

[21] We divide funds into deciles in each quarter based on the weighted average number of days needed for investors to redeem capital and include fixed effects for each decile.

[22] As discussed in Section 2.2, strategy definitions are based on Question 20 of Form PF and can be one of nine types, for instance equity or credit. In untabulated results, we find similar results if we define strategy-by-time fixed effects using the full set of more detailed strategies defined in Form PF, rather than the nine high-level types.

whether ω varies with the amount of inside ownership across funds. Inside ownership is measured based on Form ADV (see Section 2.2). To the extent that low values of ω reflect an agency problem between investors and fund managers, we expect ω to be higher in high-inside ownership funds, where incentives are better aligned.

Columns (1)-(2) of Table 4 run regression (7) for funds with below-median inside ownership as of the end of quarter q. The first column shows results when no other controls are added, and the second adds the controls, strategy-by-time fixed effects, and liquidity term fixed effects used in Table 3. Both columns indicate that investor flows are not sensitive to managers' information in funds with low inside ownership. The estimated loading κ_2 on the beta gap is near zero. Thus, the implied weight ω that investors place on manager information when risk-adjusting the fund's returns is less than 0.15 and not statistically significant.

Columns (3)-(4) rerun the regression for funds with above-median inside ownership. Focusing on column (4), which includes the whole suite of controls and fixed effects, the coefficient κ_2 on the beta gap is now negative and statistically significant. This suggests investors in above-median funds inside ownership account for manager information. Indeed, the implied ω for this subset of funds is around 0.7 and statistically different from zero at conventional levels.

Overall, the results in Table 4 are consistent with the idea that high inside ownership aligns incentives between fund managers and investors. When inside ownership is high, investor flows appear to incorporate managers' private information. When inside ownership is low, however, investors do not seem to incorporate managers' private information, consistent with the idea that contracting and reputation do not overcome the informational asymmetry between managers and investors. Formally, we can reject the null that the estimated κ_2s are equal across the two groups. Additionally, the fact that the implied ω is large for funds with high inside ownership lends further support to our interpretation of the augmented flow–performance regression: in the extreme case of a fund with no outside

investors, the implied ω should converge to one.[23]

4.4.2 Positive vs. Negative Beta Gap

We next turn to a sample split based on the sign of the beta gap. The idea is to partition funds according to the incentives created by managers' private information. Funds with a positive beta gap are those for which the manager perceives higher market risk than is implied by the fund's historical returns. In turn, managers in these funds have an incentive to withhold their private information from investors, since their perceived alpha is lower than the fund's measured alpha, $\hat{\alpha}_{i,q}$. The implication of this logic is that ω should be lower for funds with a positive beta gap.

Table 5 explores this hypothesis by estimating equation (7) for funds with a positive or negative beta gap. We define positive or negative beta gap funds using the same beta gap $g_{i,q} = \beta^R_{i,q} - \hat{\beta}_{i,q}$ that appears in equation (7), allowing for time-series variation in both historical and perceived beta. The first column examines funds with positive beta gaps. To reiterate, these are funds whose managers perceive more risk than implied by recent realized returns. The coefficient κ_2 on $(\beta^R_{i,q} - \hat{\beta}_{i,q}) \times \mu_{m,q}$ is close to zero and insignificant, implying that flows into these funds are not sensitive to the lagged beta gap. Thus, the implied weight ω that investors place on manager information when risk-adjusting the fund's returns is also close to zero. The second column of Table 5 shows that the estimates for positive beta-gap funds are robust to adding controls for size, lagged flows, and investor redemption restrictions, as well as strategy-by-time fixed effects.

Column (3) of Table 5 examines funds with negative beta gaps—that is, funds whose managers perceive less risk than what is implied by recent returns. In contrast to positive beta gap funds, the coefficient κ_2 for these funds is -1.38 and strongly statistically significant (s.e. = 0.34). We can easily reject the null hypothesis that κ_2 is equal across the positive and negative beta-gap groups. Combined with κ_1, the estimate of κ_2 in column (3) implies

[23] Internet Appendix B.3 also shows that the results in Table 4 are not mechanically driven by the inclusion of insider flows. When we exclude insider flows, the findings remain robust, reinforcing the interpretation that skin in the game helps mitigate the agency frictions associated with hidden risk.

that investors put a weight ω of 0.69 (s.e. = 0.23) on managers' information when risk-adjusting the returns of negative beta gap funds. Similar estimates obtain in column (4), when controlling for size, lagged flows, liquidity terms, and strategy-by-time fixed effects. Across specifications, investors place significantly more weight on manager information for negative beta-gap funds than for positive beta-gap ones.

Appendices A.3 and B.4 probe the robustness of our results to a range of modeling and measurement choices. First, we estimate historical alphas and CAPM betas using a variety of multi-factor models, including those that incorporate the additional risk factors listed on Form PF. We then re-run regression (7) using these alternative alphas and CAPM betas in regression, and include the additional factor loadings as controls. Second, we define strategy-by-time fixed effects using more granular strategy classifications (e.g., Event Driven, Distressed/Restructuring). Third, we replace strategy-by-time fixed effects with fund and time fixed effects. Fourth, we cluster standard errors by fund and time, as opposed to using Driscoll and Kraay (1998). Finally, we define the beta gap using rolling averages of perceived beta, $\beta^R_{i,q}$. Across all specifications, we continue to find strong asymmetry in the flow–performance relationship between positive and negative beta-gap funds.

These results suggest that contracting and reputation do not fully resolve the informational asymmetry between investors and fund managers. Managers with positive beta gaps perceive lower risk-adjusted performance than implied by their returns. These managers have little incentive to reveal their private information, as doing so would likely reduce investor flows. In contrast, managers with negative beta gaps perceive higher risk-adjusted performance than implied by their returns, giving them a clear incentive to reveal this information to investors.

4.4.3 Non-Linear vs. Linear Beta

Finally, we study funds with nonlinear reported betas. Lo (2001) and Jurek and Stafford (2015) suggest that managers of funds with nonlinear exposures have incentives to keep their information private since the compensation for exposure to tail events may appear to

investors as alpha in normal times.

For each fund i and quarter q, we define:

$$D_{i,q} = \frac{\beta_{i,q}(-20\%)}{\beta_{i,q}(-5\%)}, \qquad U_{i,q} = \frac{\beta_{i,q}(20\%)}{\beta_{i,q}(5\%)}, \tag{8}$$

where $\beta_{i,q}(x)$ is the beta function that i reports in its Form PF response at the end of q (see Section 3.1). $D_{i,q}$ is simply the ratio of the fund manager's perceived beta conditional on a 20% market fall relative to its perceived beta under a 5% fall. $U_{i,t}$ is defined similarly, but for market booms.

We then define a variable, $O_{i,q}$, that equals one if either $D_{i,q}$ or $U_{i,q}$ exceeds one. $O_{i,q}$ indicates whether the manager perceives the fund's market exposure to increase with the absolute size of the market return. Such an exposure could arise, for instance, if the fund writes out-of-the-money put options or purchases out-of-the-money call options. We refer to funds for which $O_{i,q} = 1$ as nonlinear beta funds.

Table 6 tests whether investors in nonlinear beta funds respond to the beta gap by estimating regression (7) based on whether $O_{i,q} = 1$. Column (1) show estimates for nonlinear beta funds ($O_{i,q} = 1$). The coefficient κ_2 on the lagged beta gap interacted with the market return is positive and statistically insignificant. We obtain similar results in column (2), when adding controls and fixed effects for strategy and liquidity terms. The implied ω in both specifications is around -0.2, and we cannot reject the null hypothesis that it is zero. Thus, in nonlinear beta funds, there is little evidence to suggest that investor flows account for manager perceptions of risk.

Column (3) instead estimates regression (7) for funds where the manager reports betas that are linear in market returns ($O_{i,q} = 0$). For these funds, κ_2 is negative and statistically significant. This remains true when we add controls and fixed effects in column (4). In contrast to nonlinear beta funds, the estimated ω in column (4) implies that investors assign a weight of 0.53 (s.e. = 0.11) to the manager's information when risk-adjusting returns.[24]

[24]The difference in κ_2 between high and low inside ownership funds, as well as between positive and negative beta-gap funds, is strongly statistically significant. The difference in κ_2 between funds with linear

Overall, Table 6 is consistent with the idea contracting and reputation do not overcome the informational asymmetry between managers of nonlinear beta funds and their investors.

4.5 Fees

Fees offer a complementary way to test whether agency frictions between investors and fund managers are overcome in equilibrium. To see why, consider two funds, i and j, with the same return history and hence same measured gross beta ($\widehat{\beta}_i = \widehat{\beta}_j = \widehat{\beta}$) and alpha ($\widehat{\alpha}_i = \widehat{\alpha}_j = \widehat{\alpha}$). Suppose the manager-perceived betas of the two funds are such that $\beta_i^R > \widehat{\beta} > \beta_j^R$. This means i has a positive beta gap and j has a negative one. So long as investors in both funds put non-negative weights on manager risk perceptions, equation (4) implies that investors in fund i will perceive its alpha to be lower than in fund j. Consequently, their willingness to pay for fund i should be lower.

We test this logic by regressing realized fees on measured alpha and the beta gap interacted with the market return. We first compute the average realized fee, fee_i, for each fund i based on the difference between its monthly gross-of-fee and net-of-fee returns. We also compute the unconditional beta gap $g_i = \bar{\beta}_i^R - \widehat{\beta}_i$ using each fund's full history of returns, as in Section 3.2. We then run the following cross-sectional regression for different subsamples of funds:

$$fee_i = \lambda_0 + \lambda_1 \widehat{\alpha}_i + \lambda_2 (\bar{\beta}_i^R - \widehat{\beta}_i)\mu_i^m + \varepsilon_i, \tag{9}$$

where $\widehat{\alpha}_i$ is each fund's unconditional measured alpha and μ_i^m is the average excess return of the CRSP VW index over the fund's lifetime. Standard errors are clustered by adviser. All regressions include fixed effects for strategy, deciles based on each fund's average share liquidity, and deciles based on each fund's average NAV. Funds must have at least one year of data to be included in the analysis. If investors adjust fees for managers' information, we should find $\lambda_2 < 0$ for all funds, regardless of the sign of their beta gap. If not, this is

versus nonlinear beta functions is only marginally significant, likely due to the relatively small number of nonlinear beta funds.

an indication that investors do not account for managers' information when determining fund fees.

Column (1) of Table 7 shows estimates of equation (9) for funds with a positive average beta gap. Unsurprisingly, the estimated λ_1 is positive and statistically significant, suggesting average fees are increasing in measured alpha. However, while λ_2 is negative, it is not statistically different from zero, implying that fees in positive beta-gap funds are not sensitive to the size of the beta gap. In contrast, column (2) shows that λ_2 is negative and statistically significant for funds with a negative beta gap, though the estimates are too imprecise to reject the null that λ_2 is equal across the two subsamples.

In columns (3)-(4), we run the test for nonlinear beta funds, which we define unconditionally based on whether i's manager reports a nonlinear beta $O_{i,q}$ for at least half of its sample. Column (3) shows that fees are not sensitive to the beta gap within funds with a nonlinear beta, whereas column (4) shows that they are for funds with a linear beta. Overall, our analysis of fees reinforces our previous findings that flows into positive beta-gap and nonlinear beta funds are not sensitive to managers' information (Section 4.4.2). These results are consistent with the idea that agency frictions between investors and fund managers are not overcome in equilibrium.

5 Are investors surprised by fund performance?

The previous section provided evidence that asymmetric information problems between fund managers and investors are not solved by contracting and reputation. In other words, the first best is not achieved in equilibrium. An alternative interpretation is that the third condition in Section 4.2 is violated: investors are aware of managers' private information for all funds but choose to ignore it for funds with low inside ownership, positive beta gaps, and option-like equity exposures because they use different risk adjustments for those funds.

In this section, we provide evidence against this alternative explanation. We show that investors tend to reallocate away from positive beta-gap funds after extreme market returns, suggesting that investors regret their allocations to these funds ex post. In other

words, extreme market events help investors recognize the actual risk levels of different funds, leading them to withdraw their capital.

This type of investor updating is most likely during periods of high market volatility, such as the onset of the Covid-19 pandemic in the first quarter of 2020. During this period, the CRSP VW index fell by over 20%, and the VIX index, a measure of stock market volatility, exceeded 50%. We therefore use this event to study investor updating.

The logic of our test can be readily understood through a simple example. Consider a fund with a positive beta gap on the eve of the pandemic. If investors had been aware of the manager's information and chosen to ignore it, then they would not be surprised by the fund's performance when the stock market fell sharply in 2020Q1. In this case, there would be little reason for investors to withdraw more capital than a standard performance-flow regression would predict. In contrast, if investors were not aware of the manager's information, the fund's performance was likely worse than investors expected in 2020Q1. Consequently, flows out of the fund would be abnormally high relative to other funds. This argument of course assumes the manager has relevant information about the fund's risk, which we confirmed in Section 3.4.

Testing this hypothesis empirically requires a measure of abnormal fund flows. Following the literature (e.g., Guercio and Tkac, 2008), we first construct several measures using variants of the following flow-performance regression:

$$flow_{i,q+1} = \lambda_{s,l,h} + \sum_{s=0}^{3} c_s^r R_{i,q-s} + \sum_{s=0}^{3} c_s^f flow_{i,q-s} + \varepsilon_{i,q+1}, \tag{10}$$

where $R_{i,q}$ is the return of fund i in quarter q. Our baseline specification pools all funds together and includes strategy-by-liquidity-by-size fixed effects.[25]

In all cases, we estimate regression (10) using data only through 2019Q4, ensuring the estimated parameters only reflect investor behavior *before* the pandemic. Using the fitted

[25]These fixed effects are constructed by first sorting funds into deciles based on their liquidity terms in each quarter. We also sort funds into deciles based on their NAV. The fixed effect $\lambda_{s,l,h}$ is then based on the interaction of strategy (s) and indicators for the liquidity (l) and size (h) decile assignments.

coefficients, we then construct a predicted flow $\widehat{flow}_{i,2020Q1}$ for each fund in 2020Q1. The abnormal flow in the quarter is then defined as $\varepsilon_{i,2020Q1} = flow_{i,2020Q1} - \widehat{flow}_{i,2020Q1}$.

Armed with a measure of abnormal flows, we then run the following regression:

$$\varepsilon_{i,2020Q1} = a + b_1 1(g_i > 0) + b_2 g_i + b_3 1(g_i > 0) g_i + \nu_i \tag{11}$$

where $g_i = \bar{\beta}_{i,R} - \widehat{\beta}_i$ is the beta gap of fund i, also measured using all data through 2019Q4.[26] By the logic outlined above, we should observe $b_1 < 0$ if investors were on average surprised by the poor performance of positive beta-gap funds during 2020Q1. Moreover, the size of the surprise for funds with a positive beta gap should be increasing in the beta gap, meaning we should expect $b_3 < 0$.

Column (1) of Table 8 presents regression estimates of equation (11). The coefficient on b_1 is indeed negative, though is measured imprecisely. More strikingly, $b_3 = -14.92$ and is statistically significant (s.e. $= 4.19$), indicating that outflows from positive beta-gap funds are increasing in the size of the beta gap. The magnitude of this effect is large. Within the set of positive beta-gap funds, the 10th and 90th percentiles of the beta gap are 0.02 and 0.56, respectively. The estimated b_3 therefore implies that the 90th percentile fund experienced 8.02 percentage points more abnormal outflows than the 10th percentile fund.

Interestingly, the estimated b_2 is positive and statistically significant, although it is smaller in absolute magnitude than b_3 by a factor of two. This positive coefficient implies that, within the group of funds with a negative beta gap, funds with a more negative gap faced greater abnormal outflows. One possible explanation is that funds with a more negative beta gap experienced steeper declines during the market crash in the first quarter of 2020. This relatively poor performance then prompted investors to reassess the fund's beta, shifting their view away from the manager's information towards the higher beta implied by historical returns, and thus leading to larger outflows.

The remaining columns of Table 8 probe the sensitivity of the results in column (1) to

[26] Our approach to testing equation (11) is a two-step procedure, where abnormal flows are estimated in the first step. In Appendix B.5, we show that a one-step version of the test yields similar results.

different measures of abnormal flows, $\varepsilon_{i,2020Q1}$. In column (2), we allow the flow-performance relationship in equation (10) to vary by fund strategy, share liquidity, size, and the sign of the beta gap. We specifically do so by including only one lag of returns ($R_{i,q}$) and interacting it with the fixed effect $\lambda_{s,h,l}$ and the sign of the beta gap. Column (3) goes one step further by allowing the constant and the coefficient on lagged returns to instead vary by manager. In column (4), we use the same abnormal flows from column (3) and include a fixed effect for strategy and deciles of share liquidity in regression (11). Column (5) instead uses abnormal flows based on fund-by-fund regressions and uses no fixed effect in regression (11). The estimated b_2 is somewhat lower in this case compared to the other specifications, but that is likely driven by the fact that fund-level estimates of equation (10) yield noisier estimates of abnormal flows.

6 Implications and Conclusion

6.1 Counterfactual Flows

Given our results, it is natural to ask how fund flows might differ if investors accounted for managers' information when risk-adjusting returns. In the language of the model, we seek to compute counterfactual flows—and thus fund sizes—under different weights ω. Recall from Section 4.3 that we estimate ω via the following panel regression:

$$flow_{i,q+1} = \kappa_0 + \kappa_1 \widehat{\alpha}_{i,q} + \kappa_2 \left(\beta^R_{i,q} - \hat{\beta}_{i,q}\right) \times \mu^M_{i,q} + \Gamma X_{i,q} + \varepsilon_{i,q+1}, \tag{12}$$

where $\kappa_1 = \theta$ recovers how sensitive investor flows are to their own beliefs about fund alpha and $\kappa_2 = -\theta\omega$. Next, suppose that instead of the ω embedded in κ_2, investors put a weight ω_c on managers' information. Holding all other parameters fixed, including the idiosyncratic shock to flows $\varepsilon_{i,q+1}$, flows into the fund would then be given by:

$$\begin{aligned} flows^c_{i,q+1} &= \kappa_0 + \kappa_1 \widehat{\alpha}_{i,q} - \theta\omega_c \left(\beta^R_{i,q} - \hat{\beta}_{i,q}\right) \times \mu^M_{i,q} + \Gamma X_{i,q} + \varepsilon_{i,q+1} \\ &= flow_{i,q+1} - (\theta\omega_c + \kappa_2) \left(\beta^R_{i,q} - \hat{\beta}_{i,q}\right) \times \mu^M_{i,q}. \end{aligned} \tag{13}$$

To understand the intuition of this relationship, consider positive gap funds. As we showed in Section 4.4.2, roughly speaking, these funds have an $\omega = 0$, or equivalently, $\kappa_2 = 0$. This means that, in reality, investors put zero weight on managers' information. Now suppose we want to run the counterfactual in which $\omega_c = 1$. In this case, for positive beta-gap funds, investors in the counterfactual will perceive the alpha of the fund to be lower than they do in the data. Consequently, counterfactual flows in equation (13) will be lower than actual flows by an amount $\theta \left(\beta^R_{i,q} - \hat{\beta}_{i,q} \right) \times \mu^M_{i,q}$.

Equation (13) therefore suggests a simple two-step procedure for computing counterfactual flows for different ω_c. First, estimate (12) for any subset of funds and retain the estimated $\kappa_1 = \theta$ and κ_2. Second, plug these estimates and a desired counterfactual ω_c into equation (13) to compute counterfactual flows. It is then straightforward to construct a time-series of counterfactual fund NAVs by combining observed fund returns and counterfactual flows $flows^c_{i,q+1}$.

Figure 5 displays the time series of aggregate hedge fund flows under a few different counterfactuals. For comparison, the solid blue line shows actual aggregate flows. The plot starts in January 2015, as this is the first year for which we have sufficient data to estimate (12). The dotted blue line considers a counterfactual in which we set $\omega_c = 1$ for funds with positive beta gaps. In the language of the model from Section 4.1, this means we assume investors in these funds put full weight on the manager's information, which is higher than measured beta. Flows into negative beta-gap funds are held at their true values. In this counterfactual, total flows into the hedge fund sector would have been reduced by about 8 percentage points or roughly $35 billion.

The green dotted line in the plot instead holds fixed the actual flows into positive beta-gap funds and sets $\omega_c = 0$ for negative beta-gap funds. This counterfactual therefore reflects a scenario where investors in negative beta-gap funds ignore manager information when risk-adjusting returns, since perceived risk is lower than what is implied by returns. Under this counterfactual, flows into the hedge fund sector would have been reduced by over 10 percentage points.

Finally, the maroon dotted line combines both counterfactuals. That is, we set $\omega_c = 1$ for positive beta-gap funds and $\omega_c = 0$ for negative beta-gap funds. κ_1 is also allowed to differ across both groups and is based on subsample estimates of equation (12). The idea behind this counterfactual is to simulate how the industry would have evolved if investors were both fully aware of manager information and skeptical when forming their beliefs about each fund's risk. By skeptical, we mean that investors assume the fund's risk is given the maximum of $\beta^R_{i,q}$ and $\hat{\beta}_{i,q}$. This means investors put full weight on each fund's measured beta for negative beta-gap funds and full weight on the manager's perceptions for positive beta-gap funds. In this case, flows into the hedge fund sector from January 2015 through June 2023 would have been reduced by roughly 20 percentage points ($84 billion).

This exercise is only suggestive for several reasons. First, our regressions are identified in part from cross sectional variation and the usual concerns about extrapolating to the aggregate from the cross section apply. These concerns are particularly stark in this case, as we are assuming in our counterfactual that if a particular fund does not attract flows, those flows do not enter the hedge fund sector at all. An alternative interpretation of our calculation is that approximately 10-20% of flows would have been allocated differently across funds, with a smaller effect on the aggregate assets of the hedge fund sector. Second, we do not know what the correct level of ω is; it is likely to vary across funds and over time. Thus, our counterfactuals do not clearly correspond to any notion of the first best. Third, equation (12) is not a microfounded structural equation and is unlikely to exactly capture counterfactual flows. Finally, these counterfactuals assume that managers' information is available to investors, which it may not be.

To conclude, we ask whether information available to investors can help predict the beta gap. In other words, are the counterfactuals partially achievable? We estimate regressions of the following form:

$$1(\beta^R_{i,t} - \hat{\beta}_{i,t} > 0) = a + bX_{i,t} + \varepsilon_{i,t}, \tag{14}$$

where $X_{i,t}$ is one of several different characteristics for fund i. The sample for the regression contains non-overlapping 36-month windows for each fund. All standard errors are clustered by fund. For continuous variables, we standardize $X_{i,t}$ to have a mean of zero and standard deviation of one. Indicator variables are not standardized in this fashion. We scale the outcome variable by 100 to make the regression coefficients more interpretable. Table 9 contains the results.

The first characteristic we consider in column (1) is the beta implied by the fund's returns. To minimize any mechanical relationship between this beta and the sign of the beta gap, we use lagged values of measured beta. The table shows that the level of measured beta is a strong and negative predictor of the sign of the beta gap. A one standard deviation decrease in measured beta corresponds to roughly a -10 percentage point (s.e. $= 1$) increase in the likelihood that a fund has a positive beta gap. Recall that roughly half of funds have a positive beta gap. Even if some of the relationship in column (1) is mechanical, the broader point is that investors possess some information that could allow them to discern between positive and negative beta-gap funds ex-ante.

Columns (2) and (3) explore whether a fund's balance sheet structure offers predictive power for the sign of the beta gap. Column (2) focuses on balance sheet leverage, as measured by the ratio of gross and net assets. The table shows that funds with high leverage, defined as being in the top tercile of leverage, are 6 (s.e. $= 2$) percentage points more likely to have a positive beta gap. Column (3) shows that a one standard deviation increase in derivatives usage, defined as ratio of gross notional in derivatives to NAV, corresponds to a roughly 2 (s.e. $= 1$) percentage point increase in the likelihood of having a positive beta gap.[27]

In column (4), we explore whether fund size is associated with the beta gap. Specifically, in each month, we sort funds into terciles based on their last available NAV. We then define an indicator variable for funds in the top tercile of size. Column (4) shows that large funds

[27]For both derivative usage and balance sheet leverage, we use the last available observed value for each fund-month observation. Gross notional of derivatives is based on Question 44 of Form PF. Outliers of derivative usage are trimmed at their 1% tails.

are 6 percentage points (s.e. = 2) more likely to have a positive beta gap.

The last fund characteristic we consider is past performance. Past returns are defined using the previous 36-months of gross returns and funds are considered to have high returns if they are in the top tercile. The table shows that high past returns are a statistically significant and positive predictor of the sign of the beta gap. In terms of magnitude, high performing funds are 9 percentage points more likely to have a positive beta gap.

Overall, the results in Table 9 show that the sign of the beta gap is predictable by a number of observable fund characteristics, most notably the CAPM beta based on historical returns alone. These findings suggest our counterfactuals are partially achievable: investors in hedge funds could improve their asset allocations with available information.

6.2 Conclusion

In this paper, we use novel data from SEC form PF to study how hedge fund managers perceive the risk of their funds. We show that for many funds, managers perceptions differ meaningfully from risk measured from historical returns. Consistent with the idea that contracting and reputation do not overcome this informational asymmetry, investor flows appear to take manager information into account only when doing so is beneficial to the manager. We provide evidence that investors update about fund risk after extreme market downturns and could have used available information to update earlier.

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Table 1: Summary Statistics for Analysis Sample

(a) Quarterly sample

	Mean	Stdev	p10	p25	p50	p75	p90	N
AUM ($ billion)	2.11	3.66	0.22	0.56	1.04	2.15	4.69	31,169
Inside Ownership (%)	13.68	24.82	0.00	0.00	3.00	13.00	41.00	29,983
Leverage	1.71	1.34	1.00	1.03	1.26	1.73	2.86	30,398
Share Restrictions (days)	141	125	4	19	95	247	365	31,166
Net Flows (%)	-2.45	10.96	-13.26	-5.45	-0.87	1.09	6.42	30,550
Number of advisers	620							
Number of funds	2,111							

(b) Monthly sample

	Mean	Stdev	p10	p25	p50	p75	p90	N
Gross return (%)	0.66	4.44	-3.03	-0.76	0.49	1.91	4.32	91,757
Net return (%)	0.47	4.09	-2.99	-0.80	0.38	1.68	3.95	91,670
Fee (%)	0.19	0.85	0.00	0.00	0.08	0.19	0.47	91,670
Measured CAPM β	0.33	0.35	-0.02	0.07	0.24	0.51	0.88	91,757
Measured CAPM α (%)	0.30	0.77	-0.46	-0.09	0.24	0.62	1.08	90,375

Notes: This table provides summary statistics for our main sample of funds. Panel (a) is based on the quarterly sample of funds that have a non-missing beta gap, as defined in Section 4.3. Inside ownership comes from form ADV. Leverage is defined as the ratio of gross-to-net assets. Share restrictions are a capital-weighted average of the number of days over which investors can redeem shares in each fund. Panel (b) summarizes monthly returns for the same set of funds. Measured CAPM β and α are based on rolling 36-month regressions of fund returns on the CRSP VW index, both in excess of the one-month riskless rate. See Section 2.2 for more details on data and variable construction.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 2: Response Rates and Reported Equity-Market Betas

(a) Response Rates by Risk Factor Exposures

	Equity	Rates	Currency	Credit	Vol	Def-Corp	Commodity	Def-ABS
Fraction R-T	0.47	0.39	0.41	0.35	0.28	0.15	0.25	0.13
Fraction R-NT	0.28	0.30	0.24	0.27	0.23	0.29	0.15	0.24
Fraction NR	0.25	0.31	0.36	0.37	0.49	0.56	0.60	0.64
Unique Fund Count	4,574							
Total Fund-Quarter Obs	74,523							

(b) Summary Statistics of Reported Equity-Market Betas

	Mean	p5	p25	p50	p75	p95	N
$\beta(-20)$	0.21	-0.05	0.00	0.00	0.35	1.00	56,793
$\beta(-5)$	0.22	0.00	0.00	0.00	0.40	1.00	56,926
$\beta(5)$	0.24	0.00	0.00	0.00	0.40	1.00	56,742
$\beta(20)$	0.24	0.00	0.00	0.00	0.40	1.00	56,859
$\beta(-20)/\beta(-5)$	0.96	0.50	1.00	1.00	1.00	1.25	51,778
$\beta(20)/\beta(5)$	0.99	0.75	1.00	1.00	1.00	1.25	51,310
$\beta(-20)/\beta(20)$	0.90	0.00	1.00	1.00	1.00	1.00	56,009

Notes: Table 2a shows the fraction of fund-quarter observations in which a fund reports the extent to which it is exposed to a particular risk factor. R-T means the fund reports the factor is both relevant and tested; R-NT means the fund reports it is relevant, but is not tested; and NR means the fund reports that factor is not a relevant risk factor in a given quarter. Def-ABS and Def-Corp respectively correspond changes in default rates for asset-backed securities and corporate bonds. Vol corresponds to changes in option-implied volatility. See Section 3.1 for details. Table 2b reports the distribution of equity factor betas implied by the reported equity factor exposures. The equity factor question gives four scenarios for returns to a diversified equity index: down 20%, down 5%, up 5%, and up 20%. Fund i reports the change, as a % of net assets, in response to each of these scenarios. From each scenario s, we can then construct an implied $\beta(s)$ as $\beta(s) = \%\Delta NAV/\%\Delta Market(s)$. Funds report the effect of each scenario separately for their long and short positions, and we net these effects first before calculating betas. When $\beta(s_1) = \beta(s_2) = 0$, we set $\beta(s_1)/\beta(s_2) = 1$. Data for both panels is at the fund-quarter level.

Data Sources: U.S. Securities and Exchange Commission Form PF.

Table 3: Full-Sample Flow-Performance Regression

	$Flow_{i,q+1}$				
	(1)	(2)	(3)	(4)	(5)
$\widehat{\alpha}_{i,q}$	1.80***	1.29***	1.92***	1.86***	1.44***
	(7.46)	(6.69)	(7.22)	(7.48)	(6.84)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	-0.66**	-0.60***	-0.75**	-0.65*	-0.69**
	(-2.57)	(-2.68)	(-2.64)	(-1.96)	(-2.29)
ω	0.37	0.46	0.39	0.35	0.48
$t(\omega)$	2.61	2.56	2.76	1.91	2.18
Controls	No	Yes	No	No	Yes
Liquidity FE	No	No	Yes	No	Yes
Strategy-by-Time FE	No	No	No	Yes	Yes
Adjusted R^2	0.02	0.09	0.02	0.02	0.09
N	28,905	28,572	28,902	28,905	28,569

Notes: This table reports regressions of the following form:

$$flow_{i,q+1} = \kappa_0 + \kappa_1 \hat{\alpha}_{i,q} + \kappa_2 \left(\beta^R_{i,q} - \widehat{\beta}_{i,q}\right) \times \mu^M_{i,q} + \Gamma X_{i,q} + \varepsilon_{i,q+1},$$

where $flow_{i,q+1}$ is the flow into fund i in quarter $q+1$, $\hat{\alpha}_{i,q}$ is the fund's realized CAPM alpha, measured from a 36-month rolling regression using returns through the end of quarter q. $\beta^R_{i,q}$ is the reported equity beta by fund i from the last month of quarter q and $\hat{\beta}_{i,q}$ is the estimated beta based on a 36-month rolling return regression. $\mu^M_{i,q}$ is the market return measured over the same 36-month window as $\hat{\alpha}_{i,q}$ and $\hat{\beta}_{i,q}$. $X_{i,q}$ is a vector of controls measured in quarter q that includes log net asset value and fund flows. Liquidity fixed effects are based on deciles for the weighted average number of days needed for investors to redeem capital. Within the conceptual framework in Section 4.1, $\omega = -\kappa_2/\kappa_1$ corresponds to the weight that investors place on manager beliefs. t-statistics are reported below regression estimates and are based on standard errors from Driscoll and Kraay (1998) with eight lags. The t-statistic for ω is constructed using the delta method. The unit of observation in the regression is fund and quarter. See Section 4.3 for more details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 4: Flow-Performance Regressions for Low and High Inside Ownership Funds

	$Flow_{i,q+1}$			
	(1)	(2)	(3)	(4)
$\widehat{\alpha}_{i,q}$	2.32***	1.87***	1.73***	1.29***
	(4.91)	(5.06)	(6.60)	(6.15)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	-0.34	-0.23	-1.17***	-1.04***
	(-1.06)	(-0.80)	(-3.21)	(-3.23)
ω	0.15	0.12	0.67	0.81
$t(\omega)$	1.18	0.85	2.69	2.54
Subsample	Low I-O	Low I-O	High I-O	High I-O
Controls	No	Yes	No	Yes
Liquidity FE	No	Yes	No	Yes
Strategy-by-Time FE	No	Yes	No	Yes
Adjusted R^2	0.02	0.10	0.02	0.08
N	13,871	13,698	13,967	13,823

Notes: This table reports subsample regressions of the same form contained in Table 3. Subsamples in Table 4 are determined based on whether a fund has above- or below-median inside ownership, as reported in Form ADV. t-statistics are reported below regression estimates and are based on standard errors from Driscoll and Kraay (1998) with eight lags. The unit of observation in all regressions is fund and quarter. See Table 3, Section 4.3, and Section 4.4.1 for complete details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 5: Flow-Performance Regressions for Positive and Negative Beta Gap Funds

	$Flow_{i,q+1}$			
	(1)	(2)	(3)	(4)
$\widehat{\alpha}_{i,q}$	1.57***	1.13***	2.00***	1.60***
	(6.28)	(5.60)	(5.68)	(4.80)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	0.13	0.10	-1.38***	-1.21***
	(0.26)	(0.22)	(-4.10)	(-5.06)
ω	-0.08	-0.09	0.69	0.76
$t(\omega)$	-0.26	-0.22	2.95	3.42
Subsample	β-Gap(+)	β-Gap(+)	β-Gap(−)	β-Gap(−)
Controls	No	Yes	No	Yes
Liquidity FE	No	Yes	No	Yes
Strategy-by-Time FE	No	Yes	No	Yes
Adjusted R^2	0.01	0.08	0.02	0.09
N	11,458	11,329	17,447	17,240

Notes: This table reports subsample regressions of the same form contained in Table 3. The subsamples are determined based on whether a fund has a positive or negative beta gap, $g_{i,q} = \beta^R_{i,q} - \hat{\beta}_{i,q}$, as of the end of quarter q. t-statistics are reported below regression estimates and are based on standard errors from Driscoll and Kraay (1998) with eight lags. The unit of observation in the regression is fund and quarter. See Table 3, Section 4.3, and Section 4.4.3 for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 6: Flow-Performance Regressions for Nonlinear and Linear Beta Funds

	$Flow_{i,q+1}$			
	(1)	(2)	(3)	(4)
$\widehat{\alpha}_{i,q}$	2.07***	1.46***	1.62***	1.36***
	(7.44)	(5.55)	(6.51)	(6.18)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	0.31	0.38	-0.85***	-0.87***
	(0.52)	(0.54)	(-4.41)	(-3.50)
ω	-0.15	-0.26	0.53	0.64
$t(\omega)$	-0.50	-0.51	4.59	3.21
Subsample	Non-Linear β	Non-Linear β	Linear β	Linear β
Controls	No	Yes	No	Yes
Liquidity FE	No	Yes	No	Yes
Strategy-by-Time FE	No	Yes	No	Yes
Adjusted R^2	0.03	0.09	0.01	0.08
N	5,300	5,250	19,532	19,272

Notes: This table reports subsample regressions of the same form contained in Table 3. The subsamples are determined based on whether the fund reports a non-linear beta as of the end of quarter q. t-statistics are reported below regression estimates and are based on standard errors from Driscoll and Kraay (1998) with eight lags. The unit of observation in the regression is fund and quarter. See Table 3, Section 4.3, and Section 4.4.3 for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 7: Fees and Agency Frictions

	Fee_i			
	(1)	(2)	(3)	(4)
$\widehat{\alpha}_i$	0.24***	0.35***	0.17***	0.32***
	(14.62)	(9.26)	(5.80)	(9.55)
$(\bar{\beta}_i^R - \widehat{\beta}_i) \times \mu_i^m$	-0.06	-0.32***	0.03	-0.32**
	(-0.62)	(-2.90)	(0.26)	(-2.54)
Subsample	β-Gap(+)	β-Gap(-)	Non-Linear β	Linear β
Liquidity FE	Yes	Yes	Yes	Yes
Strategy FE	Yes	Yes	Yes	Yes
Size FE	Yes	Yes	Yes	Yes
Adjusted R^2	0.79	0.87	0.70	0.84
N	827	1,206	289	1,744

Notes: This table shows subsample regressions of the average realized fee of each fund on its unconditional realized alpha and its beta gap times the average realized market risk premium. Average realized fees are computed as the difference between each fund's gross- and net-of-fee returns. Realized alpha is based on a full sample regression of gross returns on the CRSP VW index, both in excess of the riskless rate. Columns (1) and (2) are subsample regressions for funds with a positive and negative beta gap, respectively. Columns (3) and (4) are subsample regressions for funds with a non-linear or linear perceived beta, respectively. Whether a fund has a non-linear beta is defined unconditionally based on whether fund i's manager reports a non-linear beta $O_{i,q}$ for at least half of its sample. See Section 4.5 and Section 4.4.3 for details. t-statistics are reported below regression estimates and are based on standard errors clustered by adviser.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table 8: Are Investors Surprised by Fund Performance?

	Abnormal Flow$_{i,2020Q1}$				
	(1)	(2)	(3)	(4)	(5)
$1\{\beta_i - \widehat{\beta}_i > 0\}$	-0.43	-0.45	-0.49	-1.02	-1.21
	(-0.43)	(-0.45)	(-0.49)	(-1.01)	(-0.90)
$(\beta_i - \widehat{\beta}_i)$	6.83**	6.95**	7.03**	5.64**	2.22
	(2.24)	(2.28)	(2.29)	(2.04)	(0.88)
$1\{\beta_i - \widehat{\beta}_i > 0\} \times (\beta_i - \widehat{\beta}_i)$	-14.92***	-15.09***	-15.18***	-12.76***	-7.60*
	(-3.56)	(-3.59)	(-3.61)	(-2.98)	(-1.70)
Approach	Baseline	(s, l, h, g)	m	m	Fund
FE	None	None	None	(s, l)	None
R^2	0.04	0.04	0.04	0.18	0.01
N	889	889	889	887	825

Notes: This table shows regressions of the following form:

$$\varepsilon_{i,2020Q1} = a + b_1 1(g_i > 0) + b_2 g_i + b_3 1(g_i > 0) g_i + \nu_i,$$

where $\varepsilon_{i,2020Q1}$ is the abnormal flow of fund i in 2020Q1, g_i is its beta gap estimated using data up to 2020, and $1(g_i > 0)$ is an indicator for whether the beta gap is positive. Abnormal flows $\varepsilon_{i,2020Q1}$ are constructed using a two-stage procedure. In stage 1, we use data prior to 2020 to estimate a regression of flows on lagged performance. In stage 2, we take the estimated coefficients from stage 1 and use them to compute the expected flow in 2020Q1. Abnormal flows are then the difference between realized flows in 2020Q1 and the predicted flow form Stage 2. Columns (1)-(5) differ in the exact procedure used to construct abnormal flows in stage 1. Column (1) assumes the same performance-flow relationship for all funds. Column (2) lets the relationship vary by fund strategy, liquidity, size, and the sign of the beta gap. Columns (3) and (4) allow it to vary by manager. The difference between the two is that column (4) includes a strategy-by-liquidity fixed effect in the regression of abnormal flows on the beta gap. Column (5) lets the performance-flow relationship vary by fund. See Section 5 for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

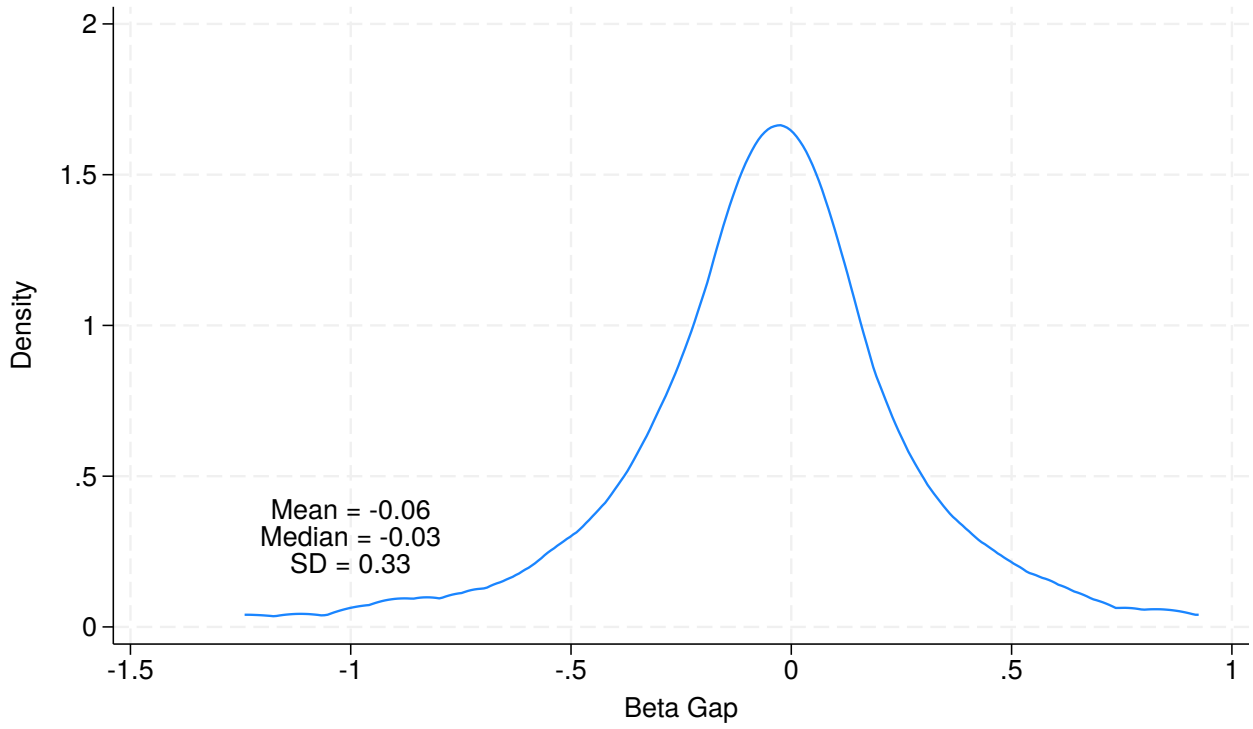
Table 9: Predictors of the β Gap

	$100 \times 1\{\beta_{i,t} - \widehat{\beta}_{i,t} > 0\}$				
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta}_{i,t-1}$	-9.98***				
	(-8.51)				
1{High Leverage}		6.24***			
		(3.38)			
Derivatives Usage			2.09**		
			(2.06)		
1{Large Fund}				5.61***	
				(2.92)	
1{High-Return Fund}					8.92***
					(4.82)
R^2	0.04	0.00	0.00	0.00	0.01
N	1,972	3,573	2,179	3,649	3,649

Notes: This table shows regressions of an indicator for whether a fund has a positive beta gap on the beta implied by returns, an indicator variable for whether the fund is in the top tercile of gross-to-net assets (leverage), the ratio of gross notional in derivatives to NAV, an indicator variable for whether the fund is in the top tercile of size, and an indicator variable for whether the fund is in the top tercile of trailing 36-month returns. The dependent variable in this regression is multiplied by 100. Standard errors in panel are clustered by fund and all continuous variables are standardized to have mean zero. The sample for all subtables is the same as in Figure 2 and ensures that each fund has non-overlapping samples.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

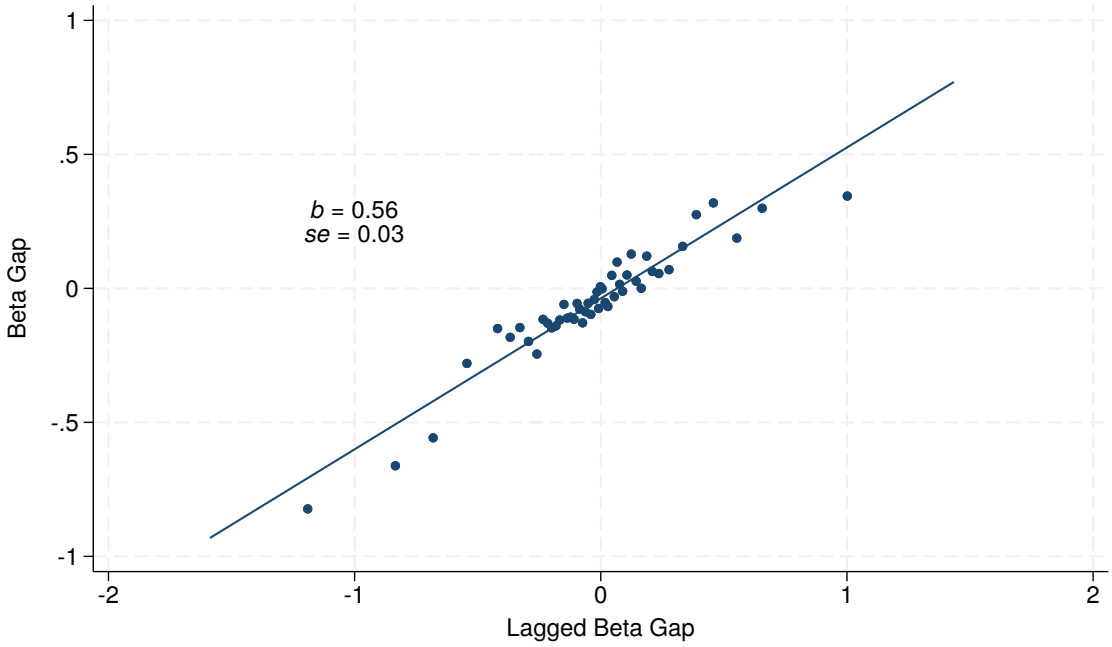
Figure 1: The Distribution of the Beta Gap



Notes: This figure shows a kernel density plot of the unconditional beta gap, $\bar{\beta}_i^R - \widehat{\beta}_i$. $\bar{\beta}_i^R$ is defined as the average monthly perceived beta over each fund's full sample. $\widehat{\beta}_i$ is estimated using a full-sample regression of each fund's monthly returns on the CRSP VW index, both in excess of the riskless rate. See Section **??** for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Figure 2: Is the Beta Gap Persistent?



Notes: This plot shows a binned scatter plot of each fund's beta gap on its lagged value, using non-overlapping windows. For each fund, we construct 36-month non-overlapping windows and compute the beta gap based on data in each window. The binscatter then shows each fund's beta gap in a given window on its beta gap from the previous window. An OLS regression line is also included in the plot with standard errors based on clustering at the fund level.
Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Figure 3: Are Manager Perceptions Informative?

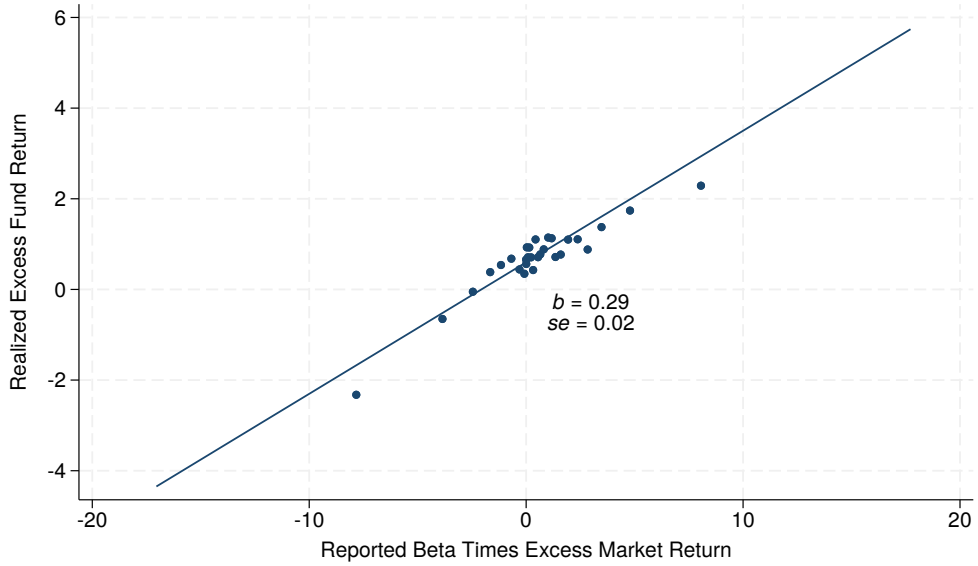
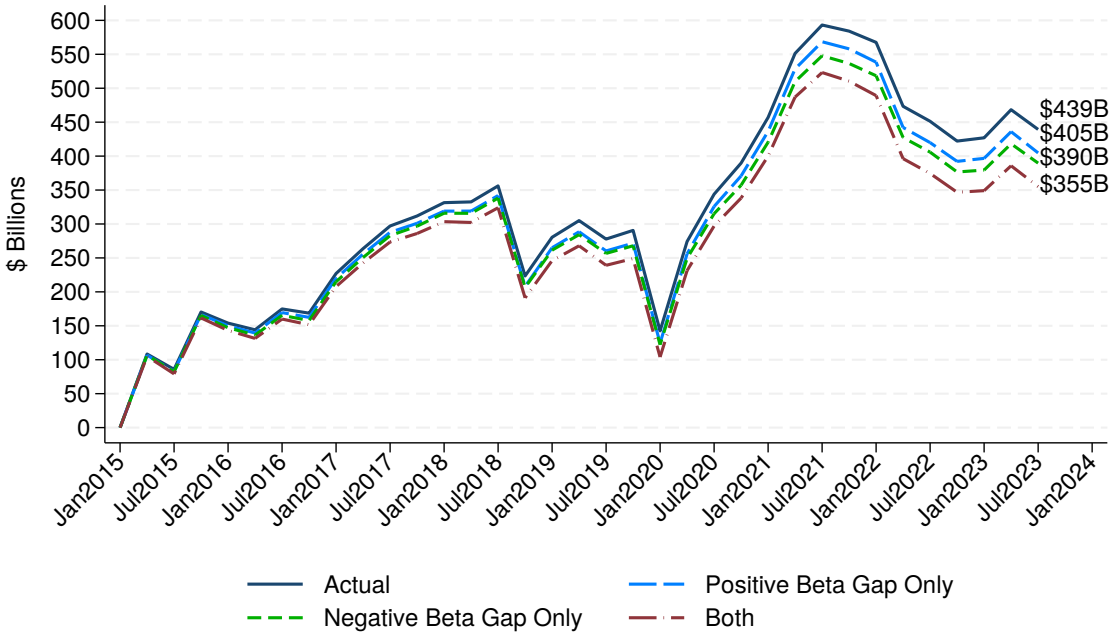


Figure 4: Predictive Power of Manager-Perceived Beta

Notes: This figure shows a binned scatter plot of each fund's excess return $\tilde{R}_{i,t+1}$ in month $t+1$ on its manager's expected beta for the same month times the realized excess return of the CRSP-VW index, $\beta^R_{i,t+1}\tilde{R}_{M,t+1}$. The binned scatter plot controls for the measured beta using a 36-month rolling window through month t times the realized excess market return in month $t+1$, denoted by $\widehat{\beta}_{i,t}\tilde{R}_{M,t+1}$. The slope in the plot is based on an OLS regression with standard errors clustered by fund and month.
Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Figure 5: AUM under Counterfactual Flows



Notes: This figure shows actual aggregate flows into the sample of hedge funds for which we observe a beta gap from 2015 to 2023 (dark solid blue line). In addition, it shows three counterfactual sets of aggregate flows. In the first counterfactual (light blue dashed line), we construct flows into positive beta-gap funds under the assumption that investors put a weight of one on the manager's perceived risk when risk-adjusting returns. Flows into negative beta-gap funds are held constant at their true value. In the second counterfactual, we construct flows into negative beta-gap funds under the assumption that, when risk-adjusting returns, investors put the zero weight on the manager's perceived risk. Flows into positive-beta gap funds are held at their true value. In the last counterfactual, we assume investors in positive beta gap funds put full weight on manager risk perceptions and investors in negative beta-gap funds put zero weight on manager risk perceptions. See Section 6.1.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

A Multifactor Risk Adjustments

In Section 4.4, we show that investor flows are unresponsive to manager information in funds with low inside ownership, a positive beta gap, and a non-linear reported beta function. The opposite is true for funds with high inside ownership, a negative beta gap, and a linear beta function. We interpret these patterns as evidence that contracting and reputational concerns do not fully resolve the agency frictions associated with hidden risk. This interpretation is grounded in the conceptual framework from Section 4.1, which for simplicity assumes that investors care only about market exposure.

In this appendix, we argue that our interpretation of the data—specifically, that there is asymmetric information between managers and investors for a subset of funds—remains valid even when alpha depends on multiple risk factors. While the inclusion of additional factors introduces omitted variable bias into our performance–flow regressions, there is no reason to expect this bias to vary systematically with the sign of the beta gap, the level of inside ownership, or the linearity of reported betas. We illustrate this broader point through several concrete examples.

A.1 Misspecification by the Econometrician

We start by considering a model in which there is *no private information*: managers and investors fully agree on the fund's beta exposures, which are inferred from only from historical returns. Both groups evaluate performance using a correctly specified multi-factor model, while the econometrician estimates alphas and betas using a misspecified single-factor model. This setup serves three purposes:

1. Showing that the beta gap will capture loadings on factors used by investors and managers but not the econometrician.

2. Demonstrating that, despite this omitted variables bias, the results of our performance–flow regressions cannot be generated in the absence of private information.

3. To highlight that the purpose of control variables in our performance–flow regressions is to ensure comparisons between funds where investors use the same factor model.

The basic building blocks of this model are as follows. Ignore time for notational simplicity. The are k priced factors F_k in the economy each with constant mean μ_k. The first factor F_1 should be interpreted as the aggregate stock market. The return average return of fund i is $\bar{r}_i$ and its true data-generating process is:

$$r_i = \alpha_i + \sum_k \beta_{i,k} F_k + \nu_i.$$

As mentioned above, there is no information asymmetry: managers and investors agree that the beta of the fund with respect to factor k equals $\beta_{i,k}$. This means their perceived alpha is $\alpha_i = \bar{r}_i - \sum_k \beta_{i,k}\mu_k$.

Now suppose that the econometrician estimates alpha and beta using a misspecified one-factor model:

$$r_i = \alpha_i^e + \beta_{i,1}^e F_1 + e_i.$$

so that:

$$\begin{aligned}\beta^e_{i,1} &= \beta_{i,1} + \overbrace{\beta_{i,2}\frac{\mathbb{C}(F_1, F_2)}{\mathbb{V}(F_1)}}^{\equiv\rho} \\ &= \beta_{i,1} + \beta_{i,2}\rho. \end{aligned} \tag{15}$$

Even though the true beta gap is zero by assumption, we define it:

$$g_i = \beta_{i,1} - \beta^e_{i,1} = -\beta_{i,2}\rho \tag{16}$$

Thus, if $\rho \neq 0$, any cross-sectional variation in $\beta_{i,2}$ leads to spurious variation in what we call the beta gap g_i. In principle, this could explain heterogeneity in g_i documented in Section 3.2. However, for this explanation to hold, the distribution of $\beta_{i,2}$ would need to be centered around zero—consistent with the fact that g_i is approximately mean-zero in the data. More importantly, we can directly test whether omitted factor exposure drives variation in the beta gap using several approaches. First, we re-estimate market betas after controlling for two sets of additional risk factors: (i) those reported on Form PF, and (ii) standard factors from the asset pricing literature. Details of these exercises are provided in Section A.3. Second, we project the beta gap on strategy fixed effects, which should absorb persistent cross-strategy differences in $\beta_{i,2}$. In both cases, we continue to observe substantial variation in the beta gap and find that our flow–performance regressions yield similar results. These findings suggest that omitted factor exposure is unlikely to be the primary driver of our results.

Next consider the differential flow sensitivity we find to managers' information on Form PF. In this symmetric information model, the flow-performance regression should yield a common slope on the beta gap term across all funds. That is, any omitted variable bias from misspecifying the historical model would be identical across subgroups, assuming investor preferences and pricing rules do not vary across subgroups.

To see this formally, first note that the econometrician's estimated alpha equals:

$$\alpha^e_i = \bar{r}_i - \beta^e_{i,1}\mu_1 \tag{17}$$

$$\begin{aligned} &= \bar{r}_i - (\beta_{i,1} + \beta_{i,2}\rho) = \bar{r}_i - \beta_{i,1} - \beta_{i,2}\mu_2 + \beta_{i,2}\mu_2 - \beta_{i,2}\rho \\ &= \alpha_i + \beta_{i,2}(\mu_2 - \rho) \\ &= \alpha_i + \beta_{i,2}\delta, \end{aligned} \tag{18}$$

where δ is the risk-adjusted return of F_2 with respect to F_1. As in the main text, we assume true flows into the fund depend on investor perceptions about alpha:

$$\begin{aligned} Flow_i &= \theta\alpha_i + \varepsilon_i \\ &= \theta\alpha^e_i - \theta\beta_{i,2}\delta + \varepsilon_i \end{aligned} \tag{19}$$

where the last line comes from plugging in Equation (18).

Running our performance-flow regression:

$$Flow_i = \kappa_1\alpha^e_i + \kappa_2 g_i\mu_1 + \xi_i$$

yields:

$$\begin{aligned}\kappa_1 &= \theta \\ \kappa_2 &= \frac{\mathbb{C}(-\theta\beta_{i,2}\delta, g_i\mu_1)}{\mathbb{V}(g_i\mu_1)} = \frac{\mathbb{C}(-\theta\beta_{i,2}\delta, -\beta_{i,2}\rho\mu_1)}{\mathbb{V}(-\beta_{i,2}\rho\mu_1)} \\ &= \frac{\theta\delta}{\rho\mu_1}\end{aligned} \tag{20}$$

Equation (20) shows that κ_2 in the symmetric information model is driven by the omission of additional factors in the econometrician's model of historical returns. Critically, the sign and magnitude of this omitted variable bias depends on the properties of the omitted risk factors (δ, ρ, and μ_1), as well as the sensitivity of flows to perceived alpha (θ). In the simplest version of the model, these parameters are constant across funds. As a result, the model implies a common κ_2 across the cross-section, which is inconsistent with the heterogeneity we observe empirically.

There are two related ways to break this result and generate the exact heterogeneity in κ_2 we observe across funds. The first is to allow θ—the sensitivity of flows to perceived alpha—to vary across funds. In particular, θ would need to be zero for a subset of funds (e.g., those with high inside ownership), implying that flows for these funds are entirely unresponsive to alpha. We view this explanation as unlikely, given that investor composition appears balanced across subgroups, and we consistently estimate κ_1 to be significantly different from zero across all subsamples (see Tables 4–6).

A second possibility is that investors in different subgroups apply different risk adjustments. For example, suppose that funds with positive beta gaps are exposed only to the first factor (the market), while funds with negative beta gaps are exposed to both factors. If $\rho < 0$ and $\delta, \mu_1 > 0$, then we would expect $\kappa_2 = 0$ for positive beta gap funds—since there is no omitted variable bias—and $\kappa_2 < 0$ for negative beta gap funds, consistent with what we observe empirically. However, this asymmetry should disappear once we control for exposure to the second factor (i.e., $\beta_{i,2}$) in the flow regression (see Equation (19)). In our baseline empirical tests, we address this by including strategy-by-time fixed effects. Moreover, in Section A.3, we show that the heterogeneity in κ_2 persists even when alphas and betas are estimated using multi-factor models.

Taking a step back, this simple symmetric-information model highlights the importance of including appropriate controls in our performance–flow regressions. Implicitly, those tests assume that investors across subgroups apply similar risk adjustments when allocating flows. The inclusion of controls (e.g., strategy-by-time fixed effects) helps account for differences in omitted factor exposures, ensuring that our estimates of investor sensitivity to manager-reported risk are not confounded by systematic variation in risk adjustment across funds.

A.2 Model Misspecification with Manager Disagreement

One limitation of the symmetric information model discussed above is that it cannot account for our first key empirical fact: managers have information about fund risk (specifically, market exposure) that is not embedded in historical returns. In this subsection, we extend the symmetric model to accommodate this fact. We allow managers to hold different views about market risk relative to historical estimates, but continue to assume

that there is symmetric information between managers and investors. We also maintain the assumption that the econometrician estimates historical alpha and beta using a misspecified, single-factor model. This analysis reinforces the importance of including appropriate controls in our performance–flow regressions to account for omitted factor exposures.

Beliefs in this extension are as follows. Managers beliefs about exposure to the first factor $\beta^m_{i,1}$ can differ from what is implied by historical returns, but do not for factor 2. Investors are fully aware of manager beliefs and form their own views as:

$$\begin{aligned}\beta^I_{i,1} &= \omega\beta^m_{i,1} + (1-\omega)\beta_{i,1}\\ \beta^I_{i,2} &= \beta^m_{i,2} = \beta_{i,2},\end{aligned}$$

for some $\omega > 0$. The investor's perceived alpha is then:

$$\begin{aligned}\alpha^I_i &= \bar{r}_i - \sum_k \beta^I_k\mu_k = \bar{r}_i - \sum_k \left[\omega\beta^m_{i,k} + (1-\omega)\beta_{i,k}\right]\mu_k\\ &= \left(\bar{r}_i - \sum_k \beta^I_k\mu_k\right) - \omega\sum_k(\beta^m_{i,k} - \beta_{i,k})\mu_k\\ &= \alpha_i - \omega\sum_k(\beta^m_{i,k} - \beta_{i,k})\mu_k\\ &= \alpha_i - \omega(\beta^m_{i,1} - \beta_{i,1})\mu_1, \qquad (21)\end{aligned}$$

Recall from Equations (15) and (18) that the econometrician's estimates of alpha and the first factor beta are:

$$\begin{aligned}\alpha^e_i &= \alpha_i + \beta_{i,2}\delta\\ \beta^e_i &= \beta_{i,1} + \beta_{i,2}\rho.\end{aligned}$$

The beta gap in this model is given by:

$$g_i = \beta^m_{i,1} - \beta^e_i = \underbrace{(\beta^m_{i,1} - \beta_{i,1})}_{\text{True beta gap}} - \beta_{i,2}\rho.$$

So, once again, the beta gap is contaminated by exposure to the omitted risk factor. Heterogeneity in the true beta gap can be studied by conditioning on proxies for $\beta_{i,2}$.

To understand the impact on our performance-flow regression, plug the expressions for the econometrician's alpha and beta into the investor's perceived alpha in Equation (21):

$$\begin{aligned}\alpha^I_i &= \alpha_i - \omega(\beta^m_{i,1} - \beta_{i,1})\mu_1\\ &= (\alpha^e_i - \beta_{i,2}\delta) - \omega(\beta^m_{i,1} - (\beta^e_i - \beta_{i,2}\rho))\mu_1\\ &= \alpha^e_i - \omega(\beta^m_{i,1} - \beta^e_i)\mu_1 - \omega\beta_{i,2}\rho\mu_1 - \beta_{i,2}\delta\\ &= \alpha^e_i - \omega g_{i,1}\mu_1 - \omega\beta_{i,2}\rho\mu_1 - \beta_{i,2}\delta\end{aligned}$$

True flows into the fund continue to depend on the investor's perceived alpha:

$$\begin{aligned}Flow_i &= \theta\alpha^I_i + \varepsilon_i\\ &= \theta\alpha^e_i - \theta\omega g_{i,1}\mu_1 - \theta\beta_{i,2}[\omega\rho\mu_1 + \delta] + \varepsilon_i\end{aligned}$$

Thus, running our performance-flow regression:

$$Flow_i = \kappa_1 \alpha_i^e + \kappa_2 g_{i,1} \mu_1 + \xi_i$$

yields:

$$\begin{aligned}
\kappa_1 &= \theta \\
\kappa_2 &= -\theta\omega - \frac{\mathbb{C}(\theta\beta_{i,2}[\omega\rho\mu_1 + \delta], g_i\mu_1)}{\mathbb{V}(g_i\mu_1)} \\
&= -\theta\omega - \frac{\mathbb{C}(\theta\beta_{i,2}[\omega\rho\mu_1 + \delta], -\beta_{i,2}\rho\mu_1)}{\mathbb{V}(-\beta_{i,2}\rho)} \\
&= -\theta\omega + \frac{\theta[\omega\rho\mu_1 + \delta]\mu_1}{\rho} \\
&= -\theta\omega + \theta\omega\mu_1^2 + \frac{\theta\delta\mu_1}{\rho}
\end{aligned}$$

For a more structural interpretation, note that we infer $\hat{\omega}$ from the ratio of $-\kappa_2/\kappa_1$:

$$\begin{aligned}
\hat{\omega} &= -\frac{\kappa_2}{\kappa_1} \\
&= \omega - \omega\mu_1^2 - \frac{\delta\mu_1}{\rho}
\end{aligned} \tag{22}$$

Next, consider the case where funds with a negative beta gap have no exposure to additional factors (i.e., $\beta_{i,2} = 0$). This corresponds to the setting in the main text and implies that we recover the true ω for this group. However, for funds with a positive beta gap, if omitted factor exposure is nonzero, it is possible to observe $\hat{\omega} \approx 0$ in the data. In this case, we might mistakenly interpret the difference in flow sensitivities between positive and negative beta-gap funds as evidence of information asymmetry—even though, by construction, the true $\omega > 0$ for all funds.

As before, the core confounding issue arises because investors in different subgroups apply different factor models. The natural way to address this concern is to control for $\beta_{i,2}$ in the performance–flow regression, which we do through several empirical strategies, including the use of strategy-by-time fixed effects and multi-factor alpha estimates.

A.2.1 Correctly Specified Model with Unobserved Manager Disagreement

The final model we consider assumes that the econometrician uses the correct factor model when estimating historical alphas and betas. However, we now allow managers to disagree with investors about their exposure to non-market risk factors, and we assume that this disagreement is not observed by the econometrician. This setup introduces a new form of an omitted variable bias—arising not from omitted factors, but from unobserved disagreement about known factors—and helps us understand how such belief divergence can influence the interpretation of performance–flow regressions.

Let $\beta_{i,k}^m$ be the manager's belief about the factor loading k of each fund i . Investors place the same weight ω on manager beliefs when forming their own view:

$$\beta_{i,k}^I = \omega\beta_{i,k}^m + (1-\omega)\beta_{i,k},$$

where $\beta_{i,k}$ is the historical beta. The investor's perceived alpha is:

$$\begin{aligned}
\alpha_i^I &= \bar{r}_i - \sum_k \beta_k^I \mu_k = \bar{r}_i - \sum_k \left[\omega \beta_{i,k}^m + (1-\omega)\beta_{i,k}\right] \mu_k \\
&= \left(\bar{r}_i - \sum_k \beta_k^I \mu_k\right) - \omega \sum_k (\beta_{i,k}^m - \beta_{i,k})\mu_k \\
&= \alpha_i - \omega \sum_k (\beta_{i,k}^m - \beta_{i,k})\mu_k \\
&= \alpha_i - \omega \sum_k g_{i,k}\mu_k,
\end{aligned}$$

where $g_{i,k} = \beta_{i,k}^m - \beta_{i,k}$ is the beta gap for factor k. As in the single factor case, investors adjust the historical alpha by the size of the beta gap, with the amount dependent on ω.

As before, investor flows are given by:

$$\begin{aligned}
Flows_i &= \theta \alpha_i^I + \varepsilon_i \\
&= \theta \alpha_i - \omega\theta \sum_k g_{i,k}\mu_k + \varepsilon_i
\end{aligned}$$

For simplicity, once again assume $k = 2$. The estimated κ_1 and κ_2 in our performance-flow regression are then given by:

$$\begin{aligned}
\kappa_1 &= \theta \\
\kappa_2 &= -\omega\theta - \omega\theta \frac{\mathbb{C}(g_{i,1}\mu_1, g_{i,2}\mu_2)}{\mathbb{V}(g_{i,1}\mu_1)} \\
&= -\omega\theta \left[1 + \frac{\mu_2}{\mu_1} \frac{\mathbb{C}(g_{i,1}, g_{i,2})}{\mathbb{V}(g_{i,1})}\right] \\
&= -\omega\theta \left[1 + \rho_g \frac{\mu_2}{\mu_1}\right],
\end{aligned}$$

where ρ_g is slope from a regression of the second beta gap on the first. Thus, even without no information asymmetry (i.e., $\omega > 0$), we could observe $\kappa_2 < 0$ if $\rho_g < 0$.[28] This would require that managers who believe their market beta is relatively high also believe their non-market beta is relatively low, so that the net alpha impact is negligible. While logically possible, such negative correlation in manager beliefs would need to arise only for specific subsamples—like funds with low-inside-ownership funds or those with a positive beta-gap—to explain the heterogeneity in κ_2 we observe empirically. We see no compelling reason to expect this.

A.3 Empirical Tests

In this subsection, we summarize three complementary robustness checks of two key results: (i) there is meaningful variation in the beta gap; and (ii) investor flows respond negatively to the beta gap for funds with high inside ownership, linear beta functions, and positive beta gaps. These robustness tests are designed to address concerns that our estimates of

[28] Here, we are assuming all factor risk premia are positive, $\mu_k > 0$.

historical betas—and thus the beta gap—may be biased due to our reliance on a single-factor model rather than a multi-factor specification.

As we show in Appendix A, if we estimate CAPM betas using a misspecified single factor model, variation in the beta gap can reflect unobserved factor exposures, even if the true CAPM beta gap is zero. In turn, this introduces an omitted variable bias into our flow-performance regressions. The first way we address this concern is to estimate our flow-performance regressions using more granular strategy-by-time fixed effects. In our main analysis, we use a strategy classification that takes nine possible values (see Section 2.2). In this robustness check, we develop an alternative strategy classification that takes one of the 22 strategy values listed in Form PF Question 20 if the fund allocates at least 70% of its assets to it, and takes the value "multi-strategy" if none of the 22 strategy categories meets this criterion. This strategy classification is more granular than the one used in the main analysis of the paper. For example, one fund could be classified as following a "Equity, Market Neutral" strategy, while another fund could be classified as "Equity, Long/Short." These two funds would be classified as "Equity" funds according to the original strategy algorithm.

The second way we address concerns about misspecification is to estimate historical alphas and market betas, *after* conditioning on the other risk factors listed on Form PF. As mentioned in Section 3.1, Form PF Question 42 asks managers to consider seven market factors other than the one on equity prices that we use in the main analysis. In Table A5 we list proxies for these seven other factors (see Monin et al. (2018) for additional details). We include these factor proxies along with the equity factor to estimate historical alphas and market betas. The equity market betas from this procedure are then used to construct the beta gap, and the alphas are used in the flow-performance regressions. When doing so, we continue to find meaningful heterogeneity in the beta gap, and our conclusions from the flow-performance regressions are unchanged.

Finally, we estimate alphas and market betas conditioning on factors that are popular in the literature. We focus on two different models. The first model is the seven-factor model of Fung and Hsieh (2004), and the second model is the seven-factor model developed by Joenväärä et al. (2019) consisting of the three Fama and French (1993) factors, the cross-sectional momentum factor of Carhart (1997), the time-series momentum factor of Moskowitz et al. (2012), the betting against beta factor from Frazzini and Pedersen (2014), and the traded liquidity factor from Pástor and Stambaugh (2003). Once again, our conclusions are robust to this alternative estimation procedure.

B Additional Robustness Checks

B.1 Variance Decomposition of Reported Beta

Figure A1 reports a variance decomposition of $\beta^R_{i,t}$. The variance decomposition in the figure reflects the adjusted R^2 from a regression of $\beta^R_{i,t}$ on one of several fixed effects. The plot shows that fund fixed effects explain over 80% of the variation in $\beta^R_{i,t}$, suggesting that perceptions of beta are relatively stable within each fund. Adviser fixed effects explain around 60% of the variation in $\beta^R_{i,t}$, consistent with the idea that advisers use the same risk management and assessment tools across all of the funds they oversee. Strategy appears to explain a modest amount of variation in perceived beta. Little variation in $\beta^R_{i,t}$ is absorbed by fixed effects based on deciles of each fund's leverage, as measured by gross-to-net asset value.

B.2 Are Manager Perceptions of Positive Beta-Gap Funds Informative?

For the subsample of funds with a positive beta gap, Figure A2 shows that manager perceptions of risk are informative about future returns, even after controlling for the risk reflected in past returns.

B.3 Low vs High Inside Ownership Excluding Insider Flows

Table A1 runs our augmented performance-flow regression for funds with above or below-median inside ownership, after excluding insider flows. Focusing on outsider flows ensures the asymmetry we observe between the two groups is not mechanical. Reassuringly, outsider flows continue to be insensitive to manager' private information when inside ownership is low (and vice versa). This result reinforces the idea that contracting and reputation do not overcome the informational asymmetry between managers and investors.

B.4 Flow-Performance in Positive and Negative Beta-Gap Funds

Table A2 shows that our main conclusions regarding positive vs negative beta-gap funds are robust to:

1. Including fund and time fixed effects
2. Clustering by fund and time, as opposed to using Driscoll and Kraay (1998) standard errors as we do in the main text.
3. Using 36-month rolling averages of manager risk perceptions to define the beta gap (and its sign). This is the same window over which CAPM betas are estimated from returns.
4. Including funds that report they have zero betas with respect to all other factors. This alleviates concerns that some of the beta gap arises because managers report multivariate CAPM betas (i.e., holding other factors fixed) whereas we estimate univariate CAPM betas.

B.5 Learning During the Pandemic

In the main text, we estimate abnormal flows during the onset of Covid-19 using a two-step procedure. Here, we instead using a single panel regression to test if outflows were more sensitive to the beta-gap during the pandemic. Specifically, we estimate:

$$\begin{aligned} flow_{i,q} = \lambda_{s,l,h} &+ \sum_{j=1}^{4} \theta_j flow_{i,q-j} + \sum_{j=1}^{4} \kappa_j R_{i,q-j} \\ &+ \zeta_1 1(g_i > 0) + \zeta_2 g_i + \zeta_3 g_i 1(g_i > 0) \\ &+ C_q \left[\rho_0 + \rho_1 1(g_i > 0) + \rho_2 g_i + \rho_3 g_i 1(g_i > 0)\right] + \varepsilon_{i,q}, \end{aligned}$$

where $flow_{i,q}$ and $R_{i,q}$ are, respectively, the flow and return of fund i in quarter q. g_i is the beta gap for fund i, estimated using data through 2019Q4. $1(g_i > 0)$ is an indicator for whether the beta gap is positive. C_q is an indicator for whether quarter q equals 2020Q1. Table A3 shows the estimated coefficients for ρ_1, ρ_2, and ρ_3. They are comparable and tell the same story as our two-step procedure in the main text.

B.6 Predictors of the Beta Gap

In the main text, we predict the sign of the beta gap using fund characteristics that are presumably observable to investors. For completeness, Table A4 repeats the analysis using the beta gap itself, as opposed to its sign. The main conclusions are largely unchanged.

Table A1: Flow-Performance Regressions for Low and High Inside Ownership Funds, Excluding Insider Flows

	$Flow_{i,q+1}$			
	(3)	(4)	(7)	(8)
$\widehat{\alpha}_{i,q}$	2.90***	2.34***	2.00***	1.52***
	(4.56)	(4.28)	(6.40)	(6.73)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	-0.62	-0.43	-1.09***	-1.19**
	(-0.76)	(-0.64)	(-2.98)	(-2.66)
ω	0.21	0.18	0.54	0.78
$t(\omega)$	0.86	0.71	2.81	2.52
Subsample	Low I-O	Low I-O	High I-O	High I-O
Controls	No	Yes	No	Yes
Liquidity FE	No	Yes	No	Yes
Strategy-by-Time FE	No	Yes	No	Yes
Adjusted R^2	0.01	0.05	0.01	0.05
N	13,598	13,238	13,888	13,687

Notes: This table reports subsample regressions of the same form contained in Table 3. Subsamples in Table 4 are determined based on whether a fund has above- or below-median inside ownership, as reported in Form ADV. Flows exclude insiders. t-statistics are reported below regression estimates and are based on standard errors from Driscoll and Kraay (1998) with eight lags. The unit of observation in all regressions is fund and quarter. See Table 3, Section 4.3, and Section 4.4.1 for complete details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table A2: Robustness: Flow-Performance Regressions for Positive and Negative Beta Gap

	$Flow_{i,q+1}$							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\widehat{\alpha}_{i,q}$	2.58***	1.13***	1.64***	1.19***	2.86***	1.60***	1.21***	1.74***
	(5.75)	(4.17)	(6.07)	(3.97)	(7.71)	(6.85)	(3.85)	(6.05)
$(\beta_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$	-0.08	0.10	3.14**		-1.33***	-1.21***	-1.39***	
	(-0.12)	(0.18)	(2.36)		(-2.77)	(-4.14)	(-4.98)	
$(\bar{\beta}_{i,q} - \widehat{\beta}_{i,q}) \times \mu^m_{i,q}$				-0.71				-1.68***
				(-1.02)				(-3.77)
ω	0.03	-0.09	-1.91	0.59	0.47	0.76	1.15	0.97
$t(\omega)$	0.12	-0.18	-1.88	1.00	2.54	3.83	3.30	3.83
Subsample	β-Gap(+)	β-Gap(+)	β-Gap(+)	β-Gap(+)	β-Gap(−)	β-Gap(−)	β-Gap(−)	β-Gap(−)
ZBOF only	No	No	Yes	No	No	No	Yes	No
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund-and-Time FE	Yes	No	No	No	Yes	No	No	No
Liquidity FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Strategy-by-Time FE	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Adjusted R^2	0.02	0.10	0.08	0.11	0.03	0.11	0.15	0.10
N	11,191	11,329	2,142	9,949	17,059	17,240	4,429	13,655

Notes: This table reports subsample regressions of the same form contained in Table 3. Subsamples are determined based on whether a fund has a positive or negative beta gap, $g_{i,q} = \beta^R_{i,q} - \hat{\beta}_{i,q}$, as of the end of quarter q. Columns (1)-(4) focus on funds with a positive beta gap. In column (1), we include fixed effects for fund and time. In column (2), we include fixed effects for strategy-by-time and liquidity. In column (3), we restrict the sample to funds that report zero beta on all non-equity factors (ZBOF). In column (4), we define the beta gap (and its sign), using rolling 36-month windows of each fund manager's perceived beta, $\beta^R_{i,q}$. Columns (5)-(8) repeat the specifications but for funds with a negative beta gap. t-statistics are reported below regression estimates. In columns (2) and (6), standard errors are clustered by fund and quarter. For all other columns, standard errors are based on Driscoll and Kraay (1998) with eight lags. The unit of observation in the regression is fund and quarter. See Table 3, Section 4.3, and Section 4.4.3 for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table A3: Robustness: Are investors surprised by fund performance?

	$\text{Flow}_{i,q}$			
	(1)	(2)	(3)	(4)
$1\{\beta_i - \widehat{\beta}_i > 0\}$	-0.95***	-0.46	-0.42	-0.87**
	(-4.32)	(-1.44)	(-1.23)	(-2.73)
$(\beta_i - \widehat{\beta}_i)$	6.76***	6.10***	5.53***	5.60***
	(11.65)	(10.78)	(7.45)	(6.38)
$1\{\beta_i - \widehat{\beta}_i > 0\} \times (\beta_i - \widehat{\beta}_i)$	-12.84***	-13.53***	-12.74***	-13.63***
	(-12.84)	(-11.76)	(-11.08)	(-12.86)
Approach	Baseline	(s, l, h)	(s, l, h, g)	m
R^2	0.12	0.10	0.10	0.08
N	19,412	19,412	19,369	19,422

Notes: This table shows regressions of the following form:

$$\begin{aligned} flow_{i,q} = \lambda_{s,l,h} &+ \sum_{j=1}^{4} \theta_j flow_{i,q-j} + \sum_{j=1}^{4} \kappa_j R_{i,q-j} \\ &+ \zeta_1 1(g_i > 0) + \zeta_2 g_i + \zeta_3 g_i 1(g_i > 0) \\ &+ C_q \left[\rho_0 + \rho_1 1(g_i > 0) + \rho_2 g_i + \rho_3 g_i 1(g_i > 0)\right] + \varepsilon_{i,q}, \end{aligned}$$

where $flow_{i,q}$ and $R_{i,q}$ are, respectively, the flow and return of fund i in quarter q. g_i is the beta gap for fund i, estimated using data through 2019Q4. $1(g_i > 0)$ is an indicator for whether the beta gap is positive. C_q is an indicator for whether quarter q equals 2020Q1. The table shows the estimated coefficients for ρ_1, ρ_2 and ρ_3. In column (1), the fixed effect $\lambda_{s,l,h}$ is based on the intersection of fund strategy, declines of share liquidity, and deciles of size. Column (2) retains this fixed effect, includes only one lag of returns, then allows the slope on lagged returns to vary by strategy-liquidity-size. Column (3) allows both the fixed effect and coefficient on lagged return to vary with strategy, liquidity, size, and the sign of the beta gap. Column (4) allows both to vary by adviser. The regression is estimated using all data through 2020Q1. t-statistics are listed below point estimates are based on standard errors are from Driscoll and Kraay (1998) with eight lags. See Sections 5 and B.5 for details.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Table A4: Robustness: Predictors of the β Gap

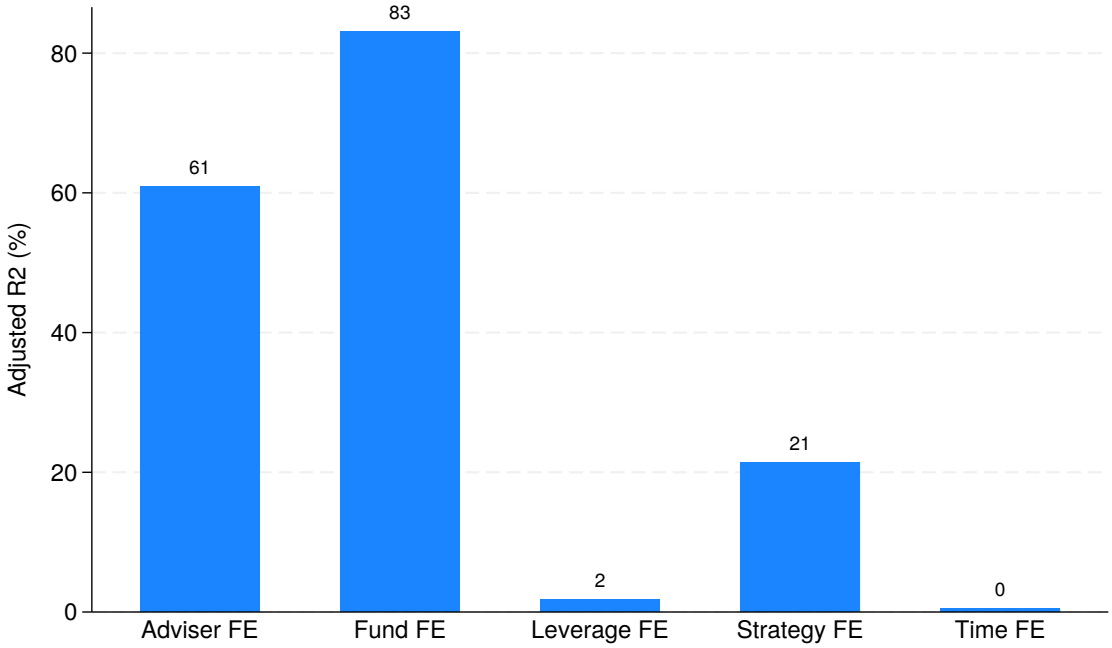
	$\beta_{i,t} - \widehat{\beta}_{i,t}$				
	(1)	(2)	(3)	(4)	(5)
$\widehat{\beta}_{i,t-1}$	-0.18***				
	(-14.79)				
1{High Leverage}		0.09***			
		(6.40)			
Derivatives Usage			0.03***		
			(4.41)		
1{Large Fund}				0.01	
				(0.48)	
1{High-Return Fund}					0.01
					(0.42)
R^2	0.22	0.01	0.01	0.00	0.00
N	1,972	3,573	2,179	3,649	3,649

Notes: This table shows regressions of the beta gap on the beta implied by returns, an indicator variable for whether the fund is in the top tercile of gross-to-net assets (leverage), the ratio of gross notional in derivatives to NAV, an indicator variable for whether the fund is in the top tercile of size, and an indicator variable for whether the fund is in the top tercile of trailing 36-month returns. Standard errors are clustered by fund and all continuous regressors are standardized to have mean zero. The sample for this table is the same as in Figure 2 and ensures that each fund has non-overlapping samples.
Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Factor from Form PF Question 42	Proxy
Risk-free interest rates	A parallel shift in the yield curve is estimated as the average monthly yield change across several points on the U.S. Treasury constant maturity yield curve, including the 1-month, 3-month, 6-month, 1-year, 2-year, 3-year, 5-year, 7-year, 10-year, 20-year, and 30-year maturities. (Source: Federal Reserve H.15, Selected Interest Rates.)
Credit spreads	Estimated as the monthly change in the Bank of America Merrill Lynch Corporate Bond BBB Effective Yield (Source: FRED) less the 10-year U.S. Treasury constant maturity yield (Source: Federal Reserve H.15, Selected Interest Rates).
Currency rates	The instructions state that a change in currency rates means that the values of all currencies move up or down by the specified amount relative to the fund's base currency, which is typically the U.S. dollar. To construct the proxy, we invert the return on the Bloomberg Dollar Spot Index (Source: Bloomberg). If r is the return on the index (expressed as a decimal), then the proxy is given by $r' = 1/(1+r) - 1$.
Commodity prices	Monthly return on the S&P GSCI, formerly the Goldman Sachs Commodity Index (Source: Bloomberg).
Option-implied volatilities	Monthly change in the CBOE Volatility Index (VIX) (Source: Bloomberg).
Default rates on asset-backed securities	We use the option-adjusted spread (OAS) on the ICE BofA Merrill Lynch Asset-Backed Master (AA-BBB Rated) Index (Source: Bloomberg) to estimate a probability of default (PD) according to a reduced-form credit risk model: $PD = 1 - \exp(-OAS \times T/(1-R))$, with an assumed recovery rate $R = 40\%$ and time to maturity $T = 5$ years. The proxy is then the monthly change in estimated default probabilities.
Default rates on corporate bonds and credit default swaps	We use the option-adjusted spread (OAS) on Markit's North American Investment Grade CDX Index (CDX.NA.IG; Source: Bloomberg) to estimate a probability of default as in the test on default rates on asset-backed securities. The proxy is then the monthly change in estimated default probabilities.

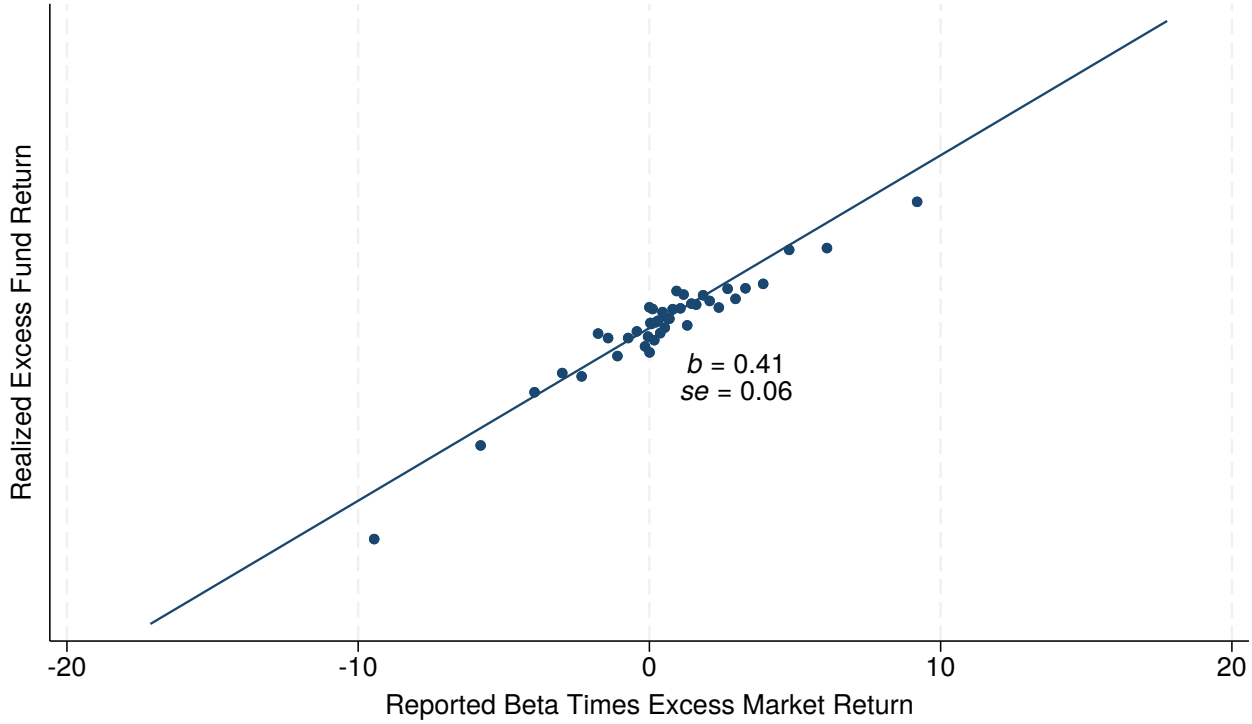
Table A5: Proxies for Non-Equity Factors in Form PF Question 42

Figure A1: Variance Decomposition of Reported β



Notes: This figure shows the adjusted R^2 from a regression of each fund's perceived beta on various fixed effects. At the end of each quarter, each fund manager reports on Form PF its exposure to movements in equity markets. In each month, we combine the realized return of the CRSP VW index and the manager's last available response to construct the fund's perceived beta. See Section 3.1 for details.
Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.

Figure A2: Are Manager Perceptions of Positive Beta-Gap Funds Informative?



Notes: This figure shows a binned scatter plot of each fund's excess return $\tilde{R}_{i,t+1}$ in month $t+1$ on its manager's expected beta for the same month times the realized excess return of the CRSP-VW index, $\beta^R_{i,t+1}\tilde{R}_{M,t+1}$. The binned scatter plot controls for the measured beta using a 36-month rolling window through month t times the realized excess market return in month $t+1$, denoted by $\widehat{\beta}_{i,t}\tilde{R}_{M,t+1}$. The slope in the plot are based on an OLS regression with standard errors clustered by fund and month. Only funds with a positive beta gap are included.

Data Sources: U.S. Securities and Exchange Commission Form PF; Center for Research in Security Prices, CRSP 1925 US Indices Database, Wharton Research Data Services, http://www.whartonwrds.com/datasets/crsp/.