Flow Hedging and Mutual Fund Performance[*]

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Abstract

This paper studies hedging behavior of active mutual funds against flow volatility and its implications for fund performance. Recent evidence suggests that shocks to the common component of fund flows are a priced risk factor in expected stock returns. I find that nearly half of U.S. active equity funds tilt their portfolios toward stocks with higher exposure to common flows, suggesting that many funds do not hedge against flow risk. A model in which informed managers receive more precise private signals about common flows provides an explanation for this behavior. Using managers' portfolio tilt as a proxy for ability, I confirm the model's main prediction that funds having higher exposure to common flows generate better risk-adjusted performance. These funds also attract higher future flows.

Keywords: Mutual Fund Performance, Flow Risk, Common Flows, Agency Issues, Risk Taking

JEL classification: G11, G23, G32

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1 Introduction

A vast literature in mutual fund research studies whether portfolio managers engage in risk-taking to improve performance and attract flows.[1] Recent studies shift to examine whether funds strategically adjust risk to avoid flow volatility. Fund managers might want to avoid flow risk because volatile flows can impair fund performance (e.g., Rakowski, 2010), or outflows induced by extreme performance of portfolio holdings can reduce fee revenue (e.g., Di Maggio, Franzoni, Kogan, and Xing, 2023). Notably, Dou, Kogan, and Wu (2023) show that equity funds hedge against flow risk by tilting away from stocks that are more likely to have poor performance during systematic outflows. This flow-hedging behavior predicts (i) stocks with high flow risk have higher expected return, and (ii) funds have lower expected return relative to the market.[2] While Dou et al. (2023) provide extensive empirical evidence to support the first prediction, this paper examines the empirical evidence of the second.

The latter remains puzzling for two reasons. First, it challenges prior evidence that there are active equity funds that outperform the market (Pástor and Vorsatz, 2020, Bessembinder, Cooper, and Zhang, 2023).[3] Second, it remains unclear why all funds do not exploit the risk premium associated with stocks that have higher exposure to common flow risk. In my sample period, the annual average return of high-flow-risk stocks is 3% more than that of low-flow-risk stocks. Foregoing this opportunity does not appear to align with active funds' objective to add value over their clients' alternative investment opportunity set. Thus, this paper seeks to provide insights about the flow-hedging behavior and its performance consequences in the cross-section of active funds.

I first document a significant variation in the flow-hedging behavior among U.S. domestic active equity funds. Figure 1 shows the distribution of the tilting coefficient from the regression of the deviation of a fund' portfolio weights from their market weights on underlying stocks' exposure to flow risk, or stocks' flow beta. Flow beta capture stocks' exposure to common flows, which are the

[1]See Brown, Harlow, and Starks, 1996, Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Huang, Wei, and Yan, 2007, Chen and Pennacchi, 2009, Huang, Sialm, and Zhang, 2011, Lee, Trzcinka, and Venkatesan, 2019.

[2]The first prediction arises because a common component of fund flows acts as a state variable that prices the cross-section of stocks. For the second prediction, I use a simple example for illustration. Suppose that the market portfolio contains only two stocks A and B, and stock A hedges against flow risk while stock B does not. Thus, stock A has lower expected return compared to stock B. If a fund overweights stock A relative to its optimal market weight due to flow hedging, we expect the fund to underperform the market.

[3]While on average active mutual funds deliver negative risk-adjusted net returns (see, e.g., Fama and French, 2010), not all funds underperform the market. For example, Bessembinder et al. (2023) show that almost a third of U.S. domestic equity mutual funds outperform the S&P500 market benchmark after fees over their lifetime.

first principal component of flows across all active funds (Dou et al., 2023). The red line illustrates the estimated coefficient obtained using the aggregate mutual fund portfolio. Consistent with Dou et al. (2023), the aggregate mutual fund hedges against flow risk by tilting toward stocks with low flow beta. However, the distribution shows that there is a wide heterogeneity in the flow-hedging behavior across funds. The almost symmetrical distribution and zero mean suggest that half of the active funds tilt their portfolio toward stocks with high flow beta, and thus do not appear to hedge against flow risk.

I rationalize this empirical finding in an extended model of Kacperczyk and Seru (2007), which features informed and uninformed investors who differ in the precision of private information they receive about future flows. The model's main prediction is that a fund can increase its holdings of high-flow-beta stocks relative to other funds if it has more accurate private information on the common fund flows. Since flows in this model come from common sources (Dou et al., 2023), private signals about flows can be thought of as information on market-wide shocks that drive flows in and out of the equity market.[4] Such information can come from funds' ability to predict the market's demand for equity assets, which stems from changing investment opportunities and macroeconomic fundamentals. This conjecture further implies that funds who deviate away from their benchmark in a positive relation with flow beta are more likely to be skilled funds. Subsequently, the empirical prediction that I seek to verify in the data is that these funds should outperform funds that deviate less with respect to flow beta.

To capture the extent to which active equity funds manage flow betas, I use fund holdings data and construct an empirical measure AFB (Active Flow Beta), defined as the covariance between deviations of a fund's portfolio weights from the market portfolio and its holdings' flow betas. The interaction between deviations in portfolio weights and flow betas is an important feature of the measure because the model's main prediction is that the higher a stock's flow beta is, the larger the tilt is if the manager is skillful. From this perspective, AFB not only captures the response of a portfolio's holdings to flow risk but also measures the extent to which the fund manager actively manages exposure to common flow risk.

Using the holdings data for a sample of U.S. domestic active equity funds, I estimate AFB for each fund and quarter. Because differences in funds' active flow beta may arise from differences in

[4] Dou et al. (2023) model endogenous common flows, driven by exogenous macroeconomic shocks such as uncertainty. Since this paper's focus is on the flow-hedging behavior, I assume common flows are exogenous.

funds' compensation structure, I complement the sample with information on portfolio managers' pay from funds' Statement of Additional Information (Ma, Tang, & Gomez, 2019). I then perform a determinant analysis to examine whether different compensation structure drives the variation in the hedging magnitude among funds. First, I find that compensation structure (i.e., whether portfolio managers' compensation is performance- and/or assets under management-based) does not determine the hedging status of lowest AFB funds. Only activeness and size appear to be strong determinants of these funds' hedging magnitude. This is consistent with Dou et al.'s (2023) argument that more active and smaller funds hedge more. Second, I find that funds that do not hedge (i.e., funds in the top quintile of AFB) are less likely to be compensated based on assets under management (AUM). Particularly, funds in the top quintile of AFB are 20% less likely to give bonus to their managers based on AUM. This suggests that not having compensation tied to AUM can serve as a mechanism to mitigate the flow-hedging behavior. Overall, the determinant analysis suggests that variation in compensation structure can affect the hedging against flows among funds to certain extent, beyond activeness and size.

Next, I assess the performance of different AFB funds. I find that AFB strongly predicts fund performance in subsequent quarters. In a univariate portfolio sort, I document that funds in the top quintile of the AFB outperform those in the bottom quintile by 0.28% monthly (or 3.36% annually) in net return, even after adjusting for risk exposure to Fama and French's (2015) five-factor model augmented with Carhart's (1997) momentum factor. This difference is statistically significant at the 5% level. Controlling for Pástor and Stambaugh's (2003) liquidity risk factor does not affect the outperformance of high AFB funds. More importantly, AFB is a persistent predictor as top quintile funds continue to outperform for up to more than two years after portfolio formation.

The predictive power of AFB is over and above other fund characteristics that have been shown to predict subsequent fund performance in the literature. In a series of double sorts on AFB and other fund performance predictors, including *Return gap* (Kacperczyk, Sialm, & Zheng, 2008), *Reliance on public information* (Kacperczyk & Seru, 2007), *Active share* (Cremers & Petajisto, 2009), *Risk shifting* (Huang et al., 2011), and *Active fund overpricing* (Avramov, Cheng, & Hameed, 2020), the alphas that AFB-based strategy deliver are substantial and statistically significant.

If AFB captures the ability of fund managers to add value, we should expect higher AFB to be associated with higher future flows. In a panel regression, I confirm that this is the case. Moreover, I rule out several explanations that might drive the results. First, funds whose clients are institutions might be more likely to be high AFB funds as they can take more risk due to longer-term goals. Controlling for the institutional status of funds does not crowd out the predictive ability of AFB funds for future flows. Second, high AFB funds can have a different compensation structure that incentivize them to take additional risk; thus, explain the better performance and higher future flows. However, including both performance- and AUM-based compensation status into the analysis does not affect the main result significantly. Third, Evans, Gómez, Ma, and Tang (2020) show that funds whose portfolio managers are compensated based on their performance relative to peers tend to generate higher alphas and flows, and it is possible that high AFB funds are more likely to be compensated in this way. Adding the variable that indicates whether or not funds' performance benchmark is peer-based into the analysis, I still find the predictive ability of AFB remains strong, ruling out the performance benchmark explanation.

In the last empirical tests, I verify an important prediction from the model to gain more insights about funds' hedging behavior. The model predicts that while the skilled funds deviate from the benchmark positively in the direction of flow beta, they do less so for stocks whose public information is more noisy. In other words, conditional on a stock's flow beta, the more imprecise the public information is, the less a skilled fund tilts away from the benchmark. To test this hypothesis, I construct two measures of public information precision based on the prior literature. Particularly, I use the dispersion in analysts' earnings forecasts and stocks' idiosyncratic volatility to proxy for the volatility of public information. Consistent with the model's prediction, the coefficient on the interaction between flow beta and both disagreement measures is significantly smaller among the high-flow-beta funds. The difference is economically large and statistically significant at the 5% level. This result supports the notion that high AFB funds deviate less from the benchmark when the public information on the stock is less precise. Finally, I find that the ability of funds to actively manage flow betas is more valuable during times of high public disagreement. I construct the aggregate version of the two public disagreement measures following Huang, Li, and Wang (2021), and document that funds with high AFB perform significantly better during periods of high public disagreement.

My contribution to the literature on mutual funds is two-fold. First, I show that there exists a significant heterogeneity of flow hedging across U.S. active equity funds. Almost half of active funds appears to tilt toward high-flow-beta stocks, an empirical finding that is not explicit from Dou et al.'s (2023) theoretical model and empirical findings. I provide both theoretical arguments and empirical results to rationalize this finding by showing that skilled funds who might have private information about future flows may not engage in flow hedging. Second, the paper adds to the broad literature on the mutual fund performance by establishing a measure that is informative about fund performance. I show that active management of flow betas strongly predict subsequent fund performance and its predictive ability cannot be subsumed by other persistent fund predictors.

The remainder of the paper is organized as follows. Section 2 describes the model and generates testable predictions. Section 3 describes the data, and the empirical construction of AFB. Section 4 examines the predictive ability of AFB for fund performance, and Section 5 concludes.

2 The Model

In this section, I extend Kacperczyk and Seru's (2007) model to show that the precision of the private signal about asset flows that an informed investor receives can explain her higher holdings of assets with high flow beta relative to an uninformed investor. The key intuition is that an asset' future flows are correlated positively with its future payoffs, making an informed investor who has more precise information about future flows to invest more in assets with high flow beta.

2.1 Simple Model of Flows and Payoffs

The standard model is an information economy with two periods in which investors make asset allocation decisions today, and receive payoffs from these assets tomorrow. Investors also receive an exogenous flow tomorrow.[5] In the model of Dou et al. (2023), flows are endogenously driven by aggregate exogenous shocks (e.g., economic uncertainty). However, the model presented here is agnostic about the sources of flows by assuming that flows are exogenously determined. It is important to note that flows in the model implicitly come from common sources; therefore, all investors receive either inflows or outflows when flows occur, but the magnitude of flows can be different across investors.

[5] In the mutual fund literature, flows are generally determined by funds' past performance (e.g., Berk and Green, 2004).

The investors' investment opportunity set includes one risk-free asset with a constant price normalized to one, and one risky asset. The future value (u) and future flow (F) of the risky asset have the following bivariate normal distribution

$$u, F \sim N\left(\begin{bmatrix} \bar{u} \\ \bar{F} \end{bmatrix}, \begin{bmatrix} \rho_u & \psi \\ \psi & \rho_F \end{bmatrix}\right) \tag{1}$$

where $\bar{u}$ (ρ_u) and $\bar{F}$ (ρ_F) are the mean and the variance of u and F, respectively. The parameter ψ is the covariance between future payoff and future flow. I assume that ψ is strictly positive. This assumption is motivated from profound empirical evidence that flows are positively correlated with contemporaneous returns (e.g., Warther, 1999, Edelen and Warner, 2001, Ben-Rephael, Kandel, and Wohl, 2012).[6] ψ captures the economic channel that underlies the decision of informed investors to invest more in assets whose payoffs co-move more with flows. Following Kacperczyk and Seru (2007), the per capita stock of the risky asset follows an independent normal distribution with mean $\bar{t}$ and variance η. The price, p, of the risky asset is endogenously determined today under the market clearing condition.

Investors obtain signals today for the future value and future flow of the risky asset. I assume that a public signal s_1 for the future payoff is observed by both informed and uninformed investors, and a private signal s_2 for the future flow is observed only by informed investors. In empirical settings, examples of public signals are analysts' forecasts for firms' future earnings or analysts' stock recommendation as in Kacperczyk and Seru (2007). Generally, public signals contain information about assets' fundamentals. Since flows in this model come from common sources, private signals about flows can be thought of as information on market-wide, non-fundamental shocks that drives flows in and out of the equity market. Such information can come from funds' ability to predict market demand for equity assets in response to variations in investment opportunities. It is worth to emphasize that these private signals are not about firm-specific private information that can

[6] The assumption that ψ is positive implies that flow beta is always positive in this economy. However, empirical flow betas can be negative. Relaxing this assumption does not change the main conclusion that an informed investor's demand for the risky asset relative to an uninformed investor is positively correlated with flow beta. That is, if flow beta is negative, an informed investor would underweight the asset more relative to an uninformed.

motivate informed trading. The public and private signals have the following bivariate normal conditional distribution

$$s_1, s_2 | u, F \sim N \left(\begin{bmatrix} u \\ F \end{bmatrix}, \begin{bmatrix} \rho_1 & 0 \\ 0 & \rho_2 \end{bmatrix} \right) \tag{2}$$

where ρ_1 and ρ_2 are the variance of s_1 and s_2, respectively. Conditional on the value and flow of the risky asset, the public and private signals are independent. I assume that an α $(0 < \alpha < 1)$ fraction of investors are informed (I), and $1 - \alpha$ fraction are uninformed (U). There are J investors in the economy $(j = 1, 2, \ldots, J)$ in which each investor has CARA utility and their coefficient of risk aversion γ is strictly positive. The equilibrium price is obtained by imposing the market clearing condition that the investors' demand of the risky asset is equal to the available supply.

Each investor in the economy faces the following budget constraint

$$c^j + px^j = e^j, \tag{3}$$

where x^j is the amount of risky assets the investor j purchases in the first period, c^j is the amount of cash she holds, and e^j is the initial wealth. The terminal wealth, ω^j, in the second period is

$$\omega^j = c^j + ux^j + F^j. \tag{4}$$

Using Equation 3 to rewrite Equation 4 in terms the investor's initial wealth, her subsequent capital gains and additional flow

$$\omega^j = e^j + (u - p)x^j + F^j. \tag{5}$$

The investor chooses her demand for the risky asset that maximizes her expected utility. She uses the signals to update her beliefs about the payoff and flow $(u^j, F^j | \mathbf{s} = \{s_1, s_2\})$, which follows a conditional bivariate normal distribution.[7] The CARA utility implies that the investor's asset allocation decision is to choose x^j that maximizes

$$E_{\mathbf{s}}[\omega^j] - \frac{\gamma}{2}\mathrm{Var}_{\mathbf{s}}[\omega^j]. \tag{6}$$

[7] Uninformed investors do not observe private signals s_2 directly. Instead they learn only noisy estimates θ; therefore, the set of signals for uninformed investors is $\mathbf{s} = \{s_1, \theta\}$.

Follwing Kacperczyk and Seru (2007), I solve for the equilibrium price p by conjecturing its form as a linear combination of the variables in the model. The partially revealing price for the risky asset in this economy has the following solution

$$p = a_1\bar{u} - a_2\bar{F} + bs_1 + cs_2 - dt + e\bar{t} + g, \tag{7}$$

where $a_1 = \frac{(\rho_\theta+\rho_F)\kappa_1+\alpha(\rho_\theta-\rho_2)\kappa_2}{\kappa}\rho_1$, $a_2 = \frac{\rho_2(\rho_\theta-\rho_2)\kappa_1}{\kappa}\rho_1$, $b = \frac{\kappa_2}{\kappa}$, $c = \frac{\psi\kappa_1+\alpha\rho_u(\rho_\theta-\rho_2)}{\kappa}\rho_1$, $d = \frac{\kappa_1\kappa_2\rho_1\gamma}{\kappa(\psi\kappa_2+\alpha\psi\rho_u(\rho_\theta-\rho_2))}$, $e = \frac{(1-\alpha)\psi\gamma\rho_1\kappa_1^2\kappa_2}{(\psi\kappa_2+\alpha\psi\rho_u(\rho_\theta-\rho_2))+(1-\alpha)\kappa_1)\kappa}$, $g = \frac{\rho_1\psi[\alpha(\rho_u\rho_F-\psi^2)(\rho_2-\rho_\theta)+\rho_\theta\kappa_1]}{\kappa}$, where $\kappa_1 = \rho_u\rho_2 + \rho_u\rho_F - \psi^2$, $\kappa_2 = \rho_u\rho_\theta + \rho_u\rho_F - \psi^2$, and $\kappa = \alpha(\rho_\theta-\rho_2)\rho_1\psi^2 + (\rho_F\rho_1 + \rho_1\rho_\theta + \kappa_2)\kappa_1$.

The optimal allocation for investor j is determined as

$$\begin{aligned} x^{j*} &= \frac{1}{\gamma}\frac{E_{\mathbf{s}}(u^j - p)}{\mathrm{Var}_{\mathbf{s}}(u^j)} - \frac{\mathrm{Cov}_{\mathbf{s}}(u^j, F^j)}{\mathrm{Var}_{\mathbf{s}}(u^j)} \\ &= \frac{1}{\gamma}\frac{E_{\mathbf{s}}(u^j - p)}{\mathrm{Var}_{\mathbf{s}}(u^j)} - \frac{\mathrm{Cov}_{\mathbf{s}}(u^j, F^j)}{\mathrm{Var}_{\mathbf{s}}(F^j)}\frac{\mathrm{Var}_{\mathbf{s}}(F^j)}{\mathrm{Var}_{\mathbf{s}}(u^j)} \\ &= \underbrace{\frac{1}{\gamma}\frac{E_{\mathbf{s}}(u^j - p)}{\mathrm{Var}_{\mathbf{s}}(u^j)}}_{\text{mean-variance tradeoff}} - \underbrace{\beta^j_{\text{flow}}\frac{\mathrm{Var}_{\mathbf{s}}(F^j)}{\mathrm{Var}_{\mathbf{s}}(u^j)}}_{\text{hedging component}}. \end{aligned} \tag{8}$$

Additional details of the optimal demands and equilibrium price can be found in Section B.1 of the Appendices. Since the main interest is in the relative holdings of an informed investor to an uninformed investor in terms of the private signal s_2 and the flow risk β_{flow}, I analyze the difference in the holdings between the two groups of investors ignoring irrelevant terms in the standard mean-variance tradeoff. Because $\beta^I_{\text{flow}} = \beta^U_{\text{flow}} = \frac{\rho_1\psi}{\rho_F\rho_1+(\rho_u\rho_F-\psi^2)}$, the difference in the holdings can be rewritten in terms of the model's parameters

$$\Delta \propto \underbrace{\left[\frac{\psi}{\gamma}\frac{(\rho_\theta-\rho_2)(\rho_u+\rho_1)}{\kappa}\right]}_{\text{private signal coefficient}} s_2 + \underbrace{\left[\frac{(\rho_F\rho_1+\rho_u\rho_F-\psi^2)(\rho_u\rho_F-\psi^2)(\rho_\theta-\rho_2)}{\rho_1\kappa_1\kappa_2}\right]}_{\text{flow risk coefficient}} \beta_{\text{flow}}. \tag{9}$$

The terms on the numerators are non-negative because $\rho_u\rho_F - \psi^2 \geq 0$, $\rho_\theta - \rho_2 > 0$, and all the terms under the denominators are strictly positive. For assets that the flow risk coefficient is strictly positive (i.e., $\rho_u\rho_F - \psi^2 > 0$), Equation 9 implies that informed investors have higher holdings of the risky asset relative to those of the uninformed investors given the asset's flow risk.

More importantly, this difference increases in the flow beta: informed investors boost their holdings of the risky asset the higher its flow risk is.

The intuition behind this relation is that an informed investor can bet on high-flow-beta assets to take advantage of the positive correlation between future flows and payoffs. If flow risk commands a premium as shown in Dou et al.'s (2023) model (or implied from the hedging component in Equation 8), it is possible that informed investors make investment decisions to capture this risk premium. It is clear that this is an optimal allocation decision if future flows are positive (i.e., inflows). In case of outflows, an informed investor who receives private signals about potential outflows (i.e., s_2 is negative) lowers her holdings by a magnitude of the private signal coefficient, offsetting the demand for high-flow-risk assets captured by the flow risk coefficient. Moreover, Equation 9 implies that the more precise the private signal is (i.e., lower ρ_2), the more weight an informed investor put to the private signal and flow beta.

Based on the analyses so far, I conjecture that more skilled investors receive more accurate private information about potential flows (s_2 with lower σ_2), and their portfolios have higher exposure to flow risk. To gauge the relation between a portfolio's holdings and underlying stock flow betas in the cross section, I rewrite the flow risk coefficient from Equation 9 in terms of the covariance between the difference in risky holdings and β_{flow}

$$\begin{aligned} \text{Flow risk coefficient} &\propto \text{Cov}(x^I - x^U, \beta_{\text{flow}}) \\ &= \text{Cov}(x^I, \beta_{\text{flow}}) - \text{Cov}(x^U, \beta_{\text{flow}}) \geq 0. \end{aligned} \tag{10}$$

I use this covariance representation to later motivate an empirical measure that captures the heterogeneous skill in managing the flow betas among US active mutual fund managers. It is important to discuss what β_{flow} captures. To be precise, β_{flow} captures the co-movement between an asset's payoff and its future flows. If we extend an asset to a portfolio with N stocks in the context of an equity fund, $\beta_{\text{flow,i}}$ captures the co-movement between stock i's payoff and the future flows into the fund's portfolio. Since Dou et al. (2023) show that flows in and out of mutual funds share a common structure, I use the common flows to proxy for all funds' flows. That is, the empirical measure $\beta_{\text{flow,i}}$ captures the co-movement between stock i's payoff and the common fund flows.

2.2 Empirical Predictions

Following the analyses from Section 2.1, in this section I formally state the testable predictions.

Since I conjecture that more skilled investors have higher exposure to flow risk, the underlying hypothesis is that funds who deviate more from the benchmark in a positive direction with flow beta are skilled funds. This hypothesis directly leads to the first empirical prediction: a fund whose covariance between its holdings' deviation from a benchmark and underlying stock flow beta has higher subsequent performance.

A second testable prediction is related to how the fund deviates from the benchmark with respect to the precision of public information. The model predicts that while the skilled funds deviate from the benchmark positively in the direction of flow beta, they do less so when the public information on the stock is more volatile. In other words, the more imprecise the public information on the stocks, the less the funds deviate from the benchmark. The formal prediction is that funds deviate less from the benchmark for stocks that has volatile public information, conditional on stocks' flow beta.

3 Data

Section 3.1 provides construction details of the mutual fund sample. Section 3.2 describes construction details of common flow shocks and stock flow beta, and Section 3.3 provides construction details of the AFB measure.

3.1 Mutual Fund Sample

I obtain data on monthly fund returns and total net assets (TNA) from Center for Research in Security Prices Survivor-Bias-Free U.S. Mutual Fund (CRSP MF). The fund returns are net of fees, expenses, and brokerage commissions, but before any loads. I convert the net returns to excess returns by subtracting the risk-free rate.[8]. I obtain quarterly fund equity holdings data from the Thomson Reuters Mutual Fund Holdings Database (S12) for the sample period before the third quarter of 2008, and the CRSP mutual fund holdings data for the rest of the sample. The use

[8]I obtain data on the monthly factor returns (i.e., the market, size, value, momentum, and liquidity factors) and the risk-free rate from Kenneth French's and Robert Stambaugh's website at http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/ and https://finance.wharton.upenn.edu/~stambaug/. I thank Kenneth French and Robert Stambaugh for making these data available.

of CRSP data on portfolio holdings is to minimize concerns related to data quality of Thomson Reuters holdings data before 2008 (Zhu, 2020).

I use the CRSP MF database to collect information on fund characteristics such as expenses, fund portfolio turnovers, and percentage of portfolio invested in common stocks and other asset classes. Since a mutual fund can have multiple share classes, I use the MFLINKS database to identify such funds and combine different share classes into fund-level portfolios. For each period, I use the most recent TNA to construct fund-level TNA, returns, and characteristics. In particular, I take the sum of TNA across all share classes of a fund to construct the fund's TNA. The fund's returns and other characteristics are TNA-weighted averages. Similar to prior studies (e.g., Kacperczyk et al., 2008, Jiang and Zheng, 2018), I estimate monthly gross returns by dividing the annual expense ratio by 12 and adding that to the monthly net returns. I also use the MFLINKS database to merge the holdings data with the CRSP MF data.

I follow Dou et al. (2023) and restrict the sample to domestic actively managed U.S. equity funds. In particular, I eliminate index funds, balanced funds, sector funds, international funds, bond funds, money market funds, and exchange-traded funds.[9] I also remove funds for which fund names are missing. To address concerns related to omission bias (Elton, Gruber, & Blake, 2001) and incubation bias (Evans, 2010), I perform additional screens on the sample. In particular, I delete any fund-month observations prior to the first offer dates of funds, and exclude observations if the fund's TNA in the previous month is below $15 million. Finally, I include only funds that have more than 80% of their holdings on average in common stocks. I also identify the family associated with each fund following Dannhauser and Spilker III's (2023) procedure and keep only funds that are in a fund family.[10]

I supplement this sample with information on portfolio managers' compensation structure hand collected from funds' Statement of Additional Information (SAI). Following Ma et al. (2019), I construct two indicator variables to identify whether the variable component in managers' pay

[9]To exclude index and exchange-traded funds, I use both CRSP index fund flag and check for funds' name with the following key words: 'index', 'inde', 'indx', 'inx', 'idx', 'dow jones', 'ishare', 's&p', 's &p', 's& p', 's & p', '500', 'wilshire', 'russell', 'msci', 'etf', 'exchange-traded', 'exchange traded'. I identify balanced, sector, international, bond, and money market funds by using the following CRSP policy code: 'C & I', 'Bal', 'Bonds', 'Pfd', 'B & P', 'GS', 'MM', 'TFM'. U.S. equity funds are further selected by using the following policy code: Lipper classes and objective codes 'EIEI', 'G', 'LCCE', 'LCGE', 'LCVE', 'MCCE', 'MCGE', 'MCVE', 'MLCE', 'MLGE', 'MLVE', 'SCCE', 'SCGE', 'SCVE', 'CA', 'EI', 'GI', 'MC', 'MR', 'SG'; Strategic Insight objective codes 'AGG', 'GMC', 'GRI', 'GRO', 'ING', 'SCG'; Wiesenberger objective codes 'G', 'GCI', 'IEQ', 'LTG', 'MCG', 'SCG'.

[10]I thank Caitlin Dannhauser for making the fund-family cleaning code available.

depends on performance (*Performance pay*) and/or assets under management (*AUM pay*). If a fund's manager is compensated based on performance, the fund generally states which benchmarks are used for comparison. Similar to Evans et al. (2020), I construct two indicator variables to capture whether funds use pure (*Pure benchmark*) and/or peer (*Peer benchmark*) indices to assess managers' performance. The variable *Both benchmark* indicates whether funds use both types of indices for performance assessment.

The final mutual fund sample contains 2,179 unique funds from 2006 to 2021.[11] Panel A of Table 1 shows the summary statistics for mutual funds in my sample. The average fund manages \$2.19 billion of assets. On average, a fund exists for over 7 years during the sample period. The quarterly mean return is 2.72% and its distribution appears symmetric since the median is close to the mean. Consistent with prior studies (e.g., Jiang and Zheng, 2018), fund flow is positively skewed as the mean of quarterly flow (-1.33%) is significantly higher than the median (-2.06%). The average annual expense ratio is 1.03% in my sample and the turnover ratio is 67.48% annually. Consistent with Ma et al. (2019), about 70% of funds have performance-based pay, while less than 20% include AUM-based pay. When funds use performance-based compensation, 18.8% use only pure benchmarks (e.g. S&P500), and only 10.8% use only peer benchmarks (e.g., Morningstar or Lipper style indices). About 40% of funds in the sample use both pure and peer indices as benchmarks when they have performance-based compensation.

3.2 Construction of Common Flows and Stock Flow Beta

Common Flow Shocks. I follow Dou et al. (2023) to estimate the time-series common fund flows. Since I use these estimates later to evaluate future mutual fund performance, it is important to avoid look-ahead biases. As a result, my estimation procedure adopts an expanding-window design in which I re-estimate all the parameters to construct the common fund flows at month t using data only up to month t.[12] The detailed process is as follows.

Starting from December 2005, I first run a pooled panel regression of fund flows on funds' current and prior performance and prior flows using data from January to December 2005

$$F_{j,t} = \beta_0 + \beta_1 R^e_{j,t} + \beta_2 R^e_{j,t-1} + \beta_3 F_{j,t-1} + \gamma_t + \varepsilon_{j,t}, \tag{11}$$

[11] The restriction on the start date of the sample is due to the availability of SAIs on SEC's EDGAR starting from 2005.

[12] This is different from Dou et al.'s (2023) main procedure in which they use the full sample for estimation.

where $F_{j,t}$ is fund j's flow at month t, $R^e_{j,t}$ is fund j's excess return relative to the market return over month t, and γ_t is the month t fixed effects.[13] The fund-flow shock for fund j at month t is estimated as

$$flow_{j,t} = \gamma_t + \varepsilon_{j,t}. \tag{12}$$

Second, I sort all funds in each month into five groups based on their TNA in the previous month, and use fund-flow shock $flow_{j,t}$ to calculate the TNA-weighted average flow shock for each group. The process produces five time-series flow shocks. Similar to Dou et al. (2023), I detrend the series of each quintile to account for the time trend in asset size of the mutual funds. Finally, I obtain the common fund flows ($flow_t$) by extracting the first principal component of the fund flow shocks across the quintiles using principal component analysis. I repeat the procedure for each month until December 2021 to obtain the monthly time-series of common fund flows from 2006 to 2021. Panel A of Figure 3 plots the time-series of the common fund flow shocks during my sample.

Stock Flow Beta. I estimate the exposure of stock i to the common fund flows in month t using 36-month rolling regressions, controlling for the market exposure

$$r_{i,t-\tau} = \alpha_{i,t} + \beta_{mkt,i,t} MKT_{t-\tau} + \beta_{flow,i,t} flow_{t-\tau} + \varepsilon_{i,t-\tau}, \quad \tau = 0, 1, \ldots, 35, \tag{13}$$

where $r_{i,t-\tau}$ is stock i's monthly excess returns, $MKT_{t-\tau}$ is the market excess returns, and $flow_{t-\tau}$ is the common fund flow shocks.[14] I require at least 12 months of observations for each regression to ensure reliable estimation for $\beta_{flow,i,t}$.

I construct the stock sample using the universe of firms covered by the Center for Research in Security Prices (CRSP) and the Compustat Fundamentals Annual (Compustat). Similar to Dou et al. (2023), I include only U.S. common stocks that are listed on NYSE, NASDAQ, and Amex. To ensure sufficient data for estimation, I require a stock to have at least 2 years of data on Compustat. Panel B of Table 1 shows the summary statistics of the stock sample. The mean of flow beta is -0.09, and the distribution appears symmetric as the median is close to the mean. The average firm in my sample has a market capitalization of \$553 million. On average, the book-to-market ratio

[13] Flow $F_{j,t}$ is defined as $[A_{j,t} - A_{j,t-1}(1 + R_{j,t})]/[A_{j,t-1}(1 + R_{j,t})]$, where $A_{j,t}$ is fund j's TNA at month t. The return adjustment in the denominator is to minimize large distortions in flows due to intermediate contemporaneous flows and returns within month t (e.g., Berk, Van Binsbergen, and Liu, 2017, Sialm and Zhang, 2020).

[14] Dou et al. (2023) do not control for the market exposure. I include the market factor because the asset pricing model in Dou et al. (2023) represents an ICAPM model in which the market risk is priced.

is -0.67. Both liquidity and uncertainty betas appear symmetric with mean of 0.005 and -0.012, respectively. The average firm has an Amihud's illiquidity measure of 2.13.

Table A1 in the Appendix provides the summary statistics for quintile portfolios of stocks sorted on their flow beta. Consistent with main findings in Dou et al. (2023), high-flow-beta stocks has higher monthly returns on average because of the flow risk premium associated with the common fund flows. The average monthly return for the top quintile portfolio from 2006 to 2021 is 1.15% compared to 0.89% of the bottom quintile portfolio.[15] High-flow-beta stocks are smaller and less liquid. They are more likely to be value stocks. Stocks with high flow risk also have higher exposure to aggregate liquidity risk and uncertainty risk.

3.3 Construction of Active Flow Beta

In this section I describe the construction of an empirical measure that captures a fund manager's portfolio exposure to common fund flows. Equation 10 suggests that one can capture the portfolio exposure to flow risk by estimating the covariance between the portfolio weights and underlying stock flow betas. This type of performance measure has been analyzed and adopted in the literature on fund manager skills (e.g., Grinblatt and Titman, 1993, Jiang and Zheng, 2018). Grinblatt and Titman (1993) show that the covariance between a fund's portfolio weights and its underlying asset returns is a reasonable proxy for active management. Jiang and Zheng (2018) improve the measure by changing the assets' returns to their abnormal returns around earnings announcements to better capture fundamental values of the assets. Moreover, because mutual fund managers evaluate their performance relative a benchmark (Cremers & Petajisto, 2009), Jiang and Zheng (2018) use the relative portfolio weights instead of absolute holdings.

I adopt the covariance logic and empirically measure the active management of fund j's flow betas across its holdings as follows

$$AFB_{j,q} = \sum_{i=1}^{N_j} \mathrm{Cov}(\omega_{j,i,q} - \omega_{bm,i,q}, \beta_{flow,i,q}) \approx \sum_{i=1}^{N_j} (\omega_{j,i,q} - \omega_{bm,i,q})\beta_{flow,i,q}, \tag{14}$$

where $AFB_{j,q}$ is the active flow beta of fund j in quarter q, $\omega_{j,i,q}$ and $\omega_{bm,i,q}$ are the portfolio weights of asset i in fund j's portfolio and its benchmark portfolio, respectively. Equation 14 requires

[15] In untabulated results, I confirm that CAPM risk-adjusted return of the top quintile portfolio is higher and the difference is statistically significant (diff = 4.12% annually; t-stat = 2.16).

identifying the benchmark portfolio for each fund j. I discuss two potential concerns relating to the empirical benchmark identification.

First, the theoretical relation from Equation 10 is silent on benchmark identification. Nevertheless, the model implies that the investment opportunity set, or the benchmark, of all fund managers is the same. Motivated by this observation, I use all available stocks in the stock market as the benchmark for main analyses. This benchmark choice is also consistent with the empirical choice in Dou et al. (2023). However, mutual funds differ in their benchmark empirically (e.g., Cremers and Petajisto, 2009), motivating the use of fund-specific benchmarks for performance evaluation. I show in the robustness section that the main results do not change significantly when fund-specific benchmarks, constructed following Cremers and Petajisto's (2009), are used to measure AFB.

Second, a same market benchmark for all fund managers requires assigning zero weights to stocks that are in the benchmark but not in the funds' portfolio. In other words, since funds only report the stocks with non-negative holdings, the absence of other stocks in their portfolios implies that funds completely deviate from the benchmark. According to the model, this is an ideal empirical assumption. However, the assumption requires the stacking of large holdings data, and thus limits deeper empirical analyses. Therefore, I restrict the estimation of AFB to only those stocks that funds report. In untabulated results, I find that the stacking design does not affect the main results significantly.

Table 2 shows the mean of fund characteristics for portfolios sorted by AFB. I provide construction details of the fund predictors in Section B.2 in the Appendices. For each quarter from 2006 to 2021, I calculate the AFB for each fund and sort the funds into five quintile portfolios based on their lagged AFB. The high (low) quintile portfolio contains funds with the highest (lowest) AFB. In each quarter, I calculate the cross-sectional mean for each characteristic and portfolio, and report the time-series average of these cross-sectional means. The last column reports the mean difference of the characteristics between the top and bottom quintiles. Consistent with Dou et al. (2023), funds with higher AFB appear to be larger and older. However, only size difference is statistically significant at the 1% level. These funds have significantly higher returns and flows. On average high-AFB funds have lower expense ratios and higher turnover ratios, but the differences are not statistically significant.

There are no significant differences between high- and low-AFB funds in the characteristics that have been shown to predict cross-sectional fund performance. These results suggest that other prominent fund performance predictors are less likely to be correlated with the flow hedging behavior. There is only one exception with Cremers and Petajisto's (2009) *Active share*, in which low-AFB funds appear to be more active and the difference is statistically significant at the 10% level. This is consistent with Dou et al.'s (2023) main argument that more active funds hedge against flow risk more.

4 Active Flow Beta and Mutual Fund Performance

4.1 Determinants of Flow Hedging

Dou et al. (2023) argue for several fund characteristics that are more likely to explain the magnitude at which funds hedge against flow risk, including activeness, size, and age. These are based on a central assumption that fund flows drive fund size, which plays a significant role in determining portfolio managers' compensation. Since there exists variation in the compensation structure among U.S. portfolio managers (Ma et al., 2019), it is natural to test whether different compensation structures affect the extent to which managers hedge against flow risk. In this section, I perform a determinant analysis to examine which factors affect the magnitude of flow hedging.

Table 3 reports the results from the linear probability regressions of funds' hedging status on several variables that capture funds' compensation structure and characteristics. At the beginning of each calendar quarter from 2006Q1 to 2021Q4, I sort all funds into quintile portfolios according to AFB. The high (low) quintile portfolio includes funds with the highest (lowest) activeness with regard to flow beta. In Panel A (B), the dependent variable is an indicator variable that is equal to 1 if funds belong to the top (bottom) quintile of AFB (*High AFB Fund*) (*Low AFB Fund*). All independent variables are lagged by one quarter. I find that *AUM pay* appears to be a strong determinant of the hedging behavior for high-AFB funds. Across specifications, high AFB funds are less likely to have AUM-based compensation by about 3.5% percentage points compared to the rest of funds, and the coefficient estimate is statistically significant at the 1% level. Since the sample unconditional mean of *AUM pay* is 19%, the estimate is equivalent to about 20% less likely to be paid based on AUM for high-AFB funds.

Performance-based contract can lead to excessive risk-taking behavior (e.g., Lee et al. (2019)). The tilt toward high flow-beta stocks of high-AFB funds can be a consequence of these funds having performance-based compensation. However, I find that the estimated coefficient on *Performance pay* is not statistically significant, suggesting that high-AFB funds are not simply associated with excessive risk-taking induced by performance-based contract. Moreover, being compensated based on peer benchmarks also does not appear to impact the hedging behavior, suggesting that the performance of high-AFB funds is less likely to be associated with extra efforts stemmed from peer competition (Evans et al., 2020).

Turning to low-AFB funds, I find that the characteristics that Dou et al. (2023) identify as the key determinants of the hedging behavior (i.e., size and activeness) are strong determinants of the hedging behavior for low-AFB funds. However, there is lack of evidence that their compensation structure determines their behavior. While there is evidence that these funds are less likely to be compensated based on performance, the statistical significance disappears when I control for other fund characteristics. Both *AUM pay* and *Peer benchmark* also do not appear to impact managers' tilt toward low-beta stocks. The overall result suggests that compensation structure of low-AFB funds is less likely to be helpful in explaining their hedging behavior relative to the rest of funds.

4.2 Portfolio Sorts

In this section, I evaluate the performance of a strategy that invests in mutual funds based on their AFB. I compute the equal-weighted returns for the quintile portfolios sorted on AFB in the first month of each quarter and track their excess returns over the next two months. I rebalance the portfolios quarterly. To account for the portfolios' exposures to risk factors, I compute the risk-adjusted returns on the portfolios as the intercept from the time-series regressions based on Fama and French's (2015) five-factor model, augmented with Carhart's (1997) momentum factor (i.e., the six-factor model)

$$\begin{aligned} r_{p,t} - r_f = \alpha_p + \beta_{MKTRF} MKTRF_t + \beta_{SMB} SMB_t + \beta_{HML} HML_t + \\ \beta_{CMA} CMA_t + \beta_{RMW} RMW_t + \beta_{UMD} UMD_t + \varepsilon_{p,t}, \end{aligned} \tag{15}$$

where $r_{p,t} - r_f$ is portfolio p's monthly excess returns. $MKTRF_t$, SMB_t, HML_t, UMD_t are the excess returns on the market, size, value, investment, profitability and momentum factors, respectively.[16]

Table 4 summarizes the results from these portfolio tests. Panel A (B) reports the results on the portfolios' alpha using funds' gross (net) returns. Panel A shows that the difference in gross alpha of low- and high-AFB funds is about 0.28% per month, or 3.36% per year.[17] This difference is economically large and statistically significant at the 5% level. After adjusting for expense ratios, the net alpha difference remains economically and statistically significant. The panels also report the exposure of each quintile portfolio and the long-short portfolios to the risk factors. The long-short portfolio does not appear to load statistically significant on any common risk factors, suggesting that the difference in performance between low- and high-AFB funds is less likely to be attributed to common risk exposures.

A common issue with identifying mutual fund skill is that the documented performance might not be persistent (Carhart, 1997). If AFB captures the skill of fund managers to manage their exposure to common flow risks, it is important to examine whether this skill is persistent. Similar to prior studies (e.g., Kacperczyk et al., 2008), I establish the persistence of the mutual fund skill with regard to active flow beta by tracking the funds over time based on their portfolio rank and active flow beta. Specifically, at the beginning of each calendar quarter from 2006Q1 to 2021Q4, I sort all funds into quintile portfolios according to AFB as the investment strategy above. Then I track the portfolio rank and AFB of each fund for the subsequent 10 quarters. For each quarter, I compute the equally-weighted average of the portfolio rank and AFB. Finally, I compute the time-series average of these values for each quarter series in the full sample to obtain the trajectory of the portfolio ranks and active flow betas.

Figure 2 plots the trajectory of the portfolio rank (Panel A) and the active flow beta (Panel B). Both panels suggest that there exists a persistence in the performance of funds in both top and bottom quintiles. For example, Panel A shows that funds in the high-flow-beta portfolio continue to stay on top in the ranking for up to more than 10 quarters, or more than two years. On the

[16] The Appendix provides results when I add the Pástor and Stambaugh's (2003) liquidity factor to the six-factor model to account for the portfolios' exposure to aggregate liquidity risk.

[17] Since mutual funds cannot be shorted, this strategy is not implementable in real life. Therefore, the difference should be interpreted as the gross return that an investor would earn on average by buying the high-flow-beta funds than the low-flow-beta funds.

other hand, funds in the low-flow-beta portfolio continue to stay at the bottom for a similar period. Panel B shows that the persistence in the portfolio ranking comes from the persistence in AFB. The top quintile funds maintain high flow beta throughout and their AFB is positive for more than two years.

4.3 Double Sorts

The evidence so far suggests that AFB is a strong predictor of mutual fund performance. However, the literature has documented a number of fund characteristics that also have strong predictive power for funds' future returns. In this section, I test whether the AFB can provide incremental information for fund performance above and beyond what other characteristics have provided.

The five characteristics I consider include Kacperczyk et al.'s (2008) *Return gap*, Huang et al.'s (2011) *Risk shifting*, Cremers and Petajisto's (2009) *Active share*, Kacperczyk and Seru's (2007) *Reliance on public information* (RPI), and Avramov et al.'s (2020) *Active fund overpricing* (AFO). I adopt portfolio double sorts to examine the interaction between AFB and these fund characteristics in predicting fund performance. Specifically, at the beginning of each calendar quarter from 2006Q1 to 2021Q4, I independently sort all funds into quartile portfolios according to AFB. The high (low) quintile portfolio includes funds with the highest (lowest) activeness with regard to flow beta. Simultaneously, I independently sort all funds into quartile portfolios according to one of the five characteristics. The high (low) quintile portfolio includes funds with the highest (lowest) values of the characteristic. I compute the equal-weighted returns for the portfolios in the first month of each quarter and track their excess returns over the next two months. The rebalancing frequency is quarterly. I report the risk-adjusted returns according to the six-factor model for the portfolios.

Table 5 summarizes the results from these double sorts. Panel A reports the results for Kacperczyk et al.'s (2008) *Return gap*. Consistent with the findings from Kacperczyk et al. (2008), *Return gap* positively predict fund performance.[18] Nevertheless, AFB remains a strong predictor of future fund returns controlling for different *Return gap* levels. The alpha is consistently large and statistically significant in all quartiles of *Return gap*. Panel B shows that *AFB* is also less likely to capture risk-shifting as the alpha remains across portfolios sorted on *Risk shifting*. Panel C shows that AFB still predicts future fund returns after controlling for *Active share*. Panel D shows that AFB

[18]The lack of statistical significance is more likely due to performance decay documented in Jones and Mo (2021), combined with a stronger benchmark model (i.e. the six-factor model).

remains a strong predictor after controlling for *Reliance on public information*. Recent studies on skills of mutual funds argue that funds differ in their ability to identify mispriced stocks (Avramov et al., 2020). Panel E shows that Avramov et al.'s (2020) AFO predict fund future performance as found in the original study. However, they cannot subsume the predictive power of AFB. The alpha is economically large and statistically significant across all subgroups of AFO.

4.4 Active Flow Beta and Fund Flows

A large literature on mutual funds suggests that investors allocate their wealth based on past fund performance (see, for example, Chevalier and Ellison, 1997 and Sirri and Tufano, 1998). If the AFB measure captures fund managers' skill and affects fund performance, we should expect a positive relationship between a fund's AFB and its subsequent fund flows.

I test this conjecture by running the following panel regression

$$F_{j,t} = \beta_0 + \beta_1 AFB_{j,t-1} + \gamma Controls_{j,t-1} + \theta_t + \varepsilon_{j,t}, \tag{16}$$

where $F_{j,t}$ is the quarterly net flow of fund j at quarter t. *Controls* are fund-specific characteristics, including contemporaneous fund excess returns, past fund size, age, expense ratios, turnover ratios, flow and risk-adjusted performance. θ_t captures the time fixed effects. Table 6 reports the results. Column (1) shows the univariate regression in which *AFB* is the only independent variable. The estimated coefficient is positive and statistically significant at the 1% level. This effect remains strong when I add control variables in Column (2). This result suggests that high-AFB funds are associated with larger future flows and provides further evidence that high AFB is more likely to capture a skillful portfolio manager.

In Columns (3) to (5), I perform several tests to examine whether other fund characteristics that are associated with future fund flows may explain the AFB effect. First, funds whose clients are institutions might be high AFB funds. This is because institutional funds are less myoptic and more oriented to long-term goals, allowing them to tilt toward riskier assets. To test if institutional status of a fund affects the AFB effect on future flows, I follow Chen, Goldstein, and Jiang (2010) to construct an indicator equal to 1 if a fund has only institutional share classes, and 0 otherwise. Column (3) reports the results when I include this variable and its interaction with *AFB* in the regression model. The interaction term is insignificant, suggesting that institutional status does not crowd out the effect of AFB.

In Column (4), I include variables that captures funds' compensation structure and performance benchmarks, including *Performance pay*, and *AUM pay*. Lee et al. (2019) suggest that performance-based benchmark can entice higher risk-taking, which might attract larger flows. If AFB captures only risk-taking behavior, we should expect different compensation structure would mitigate the impact of AFB effect on future flows. The regression results do not suggest that this is the case as the interaction term between AFB and both compensation variables is statistically insignificant.

In Column (5), I examine whether managers whose performance-based compensation is based only on peer benchmarks are a potential explanation for the higher future flows of high-AFB funds. Evans et al. (2020) show that peer-benchmarked managers generate better alphas, which might imply higher future flows. If high-AFB funds are more likely to be these managers, one should expect being peer-benchmark reduces the impact of high-AFB status. I find that although the interaction term between *Peer benchmark* and AFB is negative, it is not statistically significant. This suggests that the better performance of higher AFB funds less likely stems from extra efforts generated by peer competition.

4.5 Active Flow Beta and Precision of Public Information

The analyses so far provide strong evidence to support the main hypothesis from the model in Section 2 that funds with higher flow beta exposure have better performance. In this section, I test the model's predictions relating to how the fund deviates from the benchmark with respect to the precision of public information. The model predicts that while the skilled funds deviate from the benchmark positively in the direction of flow beta, they do less so when public information on underlying stocks is more volatile. In other words, the more imprecise the public information on the stocks, the less the funds deviate from the benchmark. Intuitively, since the funds' expectation of stock payoff and flow is positively related to the precision of public information, skilled funds should bet less on the high-flow-beta stock if the public information is more noisy.

To test this hypothesis, I construct two measures of public information precision based on the prior literature. Particularly, I use the dispersion in analysts' earnings forecasts and stocks' idiosyncratic volatility to proxy for the volatility of public information. These two variables have been used extensively in the literature to examine the relation between disagreement and asset prices (e.g., Yu, 2011, Huang et al., 2021). I follow Huang et al. (2021) to construct the stock-level analysts' forecast dispersion and idiosyncratic volatility. To construct the aggregate holdings for each quintile portfolio sorted on AFB, I aggregate fund-level holdings and compute the portfolio-level holdings for each stock. I perform the following Fama-MacBeth regressions for each portfolio

$$\omega^j_{i,q+1} - \omega^m_{i,q+1} = \gamma_{0,q} + \gamma_{1,q}\beta_{\text{flow},i,q} + \gamma_{2,q}\beta_{\text{market},i,q} + \gamma_{3,q}\sigma_{i,q} + \gamma_{4,q}\beta_{\text{flow},i,q}\sigma_{i,q} + \varepsilon_{i,q+1}, \tag{17}$$

where $\omega^j_i - \omega^m_i$ is the deviation of stock i in portfolio's j from the market allocation and σ_i is a measure of precision of public information for stock i. The prediction is that the coefficient estimate γ_4 is significantly lower for high-flow-beta funds.

Table 7 reports the coefficient estimates and their statistical significance from Equation 17 for the high- and low-flow-beta portfolios. Panels A and B use analysts' disagreement and stocks' idiosyncratic volatility as the proxy for the imprecision of public information, respectively. The last row reports the difference in the coefficients between the two portfolios. First, the difference in the coefficient β_{flow} between the high- and low-flow-beta funds is positive and statistically significant. This is consistent with the main prediction that skilled funds who have more accurate private signals should deviate more with respect to flow beta. Second, the coefficient $\beta_{\text{flow}} \times \sigma$ is smaller in the high-flow-beta portfolio by a large magnitude compared to that of the low-flow-beta portfolio. Their difference is -0.052 and statistically significant at the 1% level. Consistent with the prediction from the model, high AFB funds deviate less from the market benchmark when the public information on the stocks is less precise.

Finally, I test if the ability of funds to actively manage flow beta is more valuable during times of high public disagreement. I construct the aggregate version of the two public disagreement measures following Huang et al. (2021) using the stocks' market capitalization as the weights. Over the sample period from 2006 to 2021, I construct an indicator variable equal to 1 if a month belongs to the top quintile of the aggregate measure, and 0 otherwise. For each quintile portfolio sorted on AFB, I perform the time-series regression that adjusts for risk exposure to six-factor model

$$\begin{aligned} r_{p,t} - r_f =& \alpha_p + \beta_{vol}\text{Volatility Indicator} + \beta_{MKTRF}MKTRF_t \\ &+ \beta_{SMB}SMB_t + \beta_{HML}HML_t + \beta_{CMA}CMA_t + \beta_{RMW}RMW_t + \beta_{UMD}UMD_t + \varepsilon_{p,t}, \end{aligned} \tag{18}$$

I conjecture that β_{vol} is positive and statistically significant if the funds' ability to manage flow beta is more profound during periods of high public disagreement.

Table 8 summarizes the results from Equation 18 for the high- and low-flow-beta fund portfolios. Panels A and B use analysts' disagreement and stocks' idiosyncratic volatility, respectively. The last row reports the results for the high-minus-low portfolio. Consistent with the conjecture, funds with high AFB perform significantly better during periods of high public disagreement. The difference between the high- and low-flow-beta portfolios is economically large and statistically significant during periods of high disagreement. On average, high AFB funds earn 0.98% more than low AFB funds on months when analysts has the most diverse opinions. The number is 0.62% when idiosyncratic volatility is used as the proxy for the imprecision of public information.

4.6 Robustness Tests

In this section, I examine the robustness of the main results to the choice of factor model used for performance evaluation and funds' benchmark.

Alternative factor model. The main analysis uses the six-factor model that includes Fama and French's (2015) five-factor model augmented with Carhart's (1997) momentum factor. One might be concerned that exposure to liquidity risk can explain the difference in hedging behavior among active funds, and consequently the return differences between high and low AFB funds. To address this concern, I add Pástor and Stambaugh's (2003) liquidity factor to the six-factor model and repeat the portfolio test from Regression 15. Table A2 reports the results and the alphas of the long-short portfolio remain robust.

Alternative fund benchmark. I construct the AFB under the assumption that all funds use the market benchmark. Since funds differ in the benchmark, I adopt the benchmark selection criteria as in Cremers and Petajisto (2009) to examine the robustness of the main results. Particularly, I use the active share data obtained from Martijn Cremers' website to identify the benchmark for each fund.[19] Similar to Jiang and Zheng (2018), I obtain the holdings of the benchmarks using the holdings of index funds that closely resemble the underlying indices. I then use these holdings to compute the benchmark weights and the deviation of funds' holdings from their benchmark, and repeat the portfolio test from Regression 15. Table A3 in the Appendix reports the results from this test. While the economic magnitude in the return differential between the high- and low-flow-beta portfolio is smaller, the net alpha remains statistically significant.

5 Conclusion

Dou et al. (2023) show that active equity funds tilt their portfolios toward low-flow-beta stocks to hedge against common flows. This flow-hedging behavior rationally explains a flow risk premium in the cross section of expected stock returns, but also predicts lower expected return for active funds. However, it is still not clear why all active mutual funds forgo the premium associated with high-flow-beta stocks.

Using a sample of U.S. domestic active equity mutual funds from 2006 to 2021, I first document that there is a significant heterogeneity in the flow-hedging behavior: almost half of active equity funds do not appear to hedge against flow shocks but rather tilt toward high-flow-beta stocks. I rationalize this finding in an extended model of Kacperczyk and Seru (2007) that features informed and uninformed investors who differ in the precision of private information they receive about future flows. The main intuition is that an informed investor that receives private signals about future flows allocate more to the high-flow-beta asset because such assets' future payoff are strongly and positively correlated with the future flow. In the mutual fund context, the main empirical prediction from the model is that funds who deviate more from the benchmark in a positive direction with flow beta are skilled funds and should have higher subsequent performance.

To test the model's prediction, I construct an empirical measure that captures the active management of mutual funds with respect to flow beta (AFB). I find that funds in the top quintile of the measure outperform those in the bottom quintile. The performance differential is economically large and statistically significant, even after adjusting for exposure to risk factors. The predictive ability of AFB is above and beyond other established fund predictors in the literature. Thus, I

[19]The benchmark is defined as the one among a set of 21 indices that funds have the lowest active share.

show that the cross-sectional difference in flow hedging among active funds can be informative about managerial skill, and provide a new insight into the management of flow risk in the mutual fund industry.

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Figure 1. Distribution of funds tilting away from stocks with high flow beta

This figure shows the distribution of the tilt away from stocks with high flow beta among U.S. domestic active equity mutual funds. Fund-level tilt for fund j is the time-series average of the tilting coefficients $\gamma_{1,j,q}$ estimated for each fund j and quarter q from the following the Fama-MacBeth regression

$$\omega_{j,i,q+1} - \omega_{m,i,q+1} = \gamma_{0,j,q} + \gamma_{1,j,q}\beta_{\text{flow},i,q} + \gamma_{2,j,q}\beta_{\text{market},i,q} + \varepsilon_{i,q+1},$$

where $\omega_{j,i,q+1} - \omega_{j,i,q+1}$ is the deviation of stock i in fund j from the market allocations in quarter $q+1$. β_{flow} is estimated following Dou et al. (2023) and described in details in Section 3.2, and β_{market} is estimated using a 60-month rolling regression of stock i's monthly excess returns on the market excess returns. Each variable is standardized to have a mean of 0 and standard deviation of 1. The red line illustrates the estimated coefficient obtained from the aggregate mutual fund portfolio as in Dou et al. (2023). The sample period is from 2006Q1 to 2021Q4.

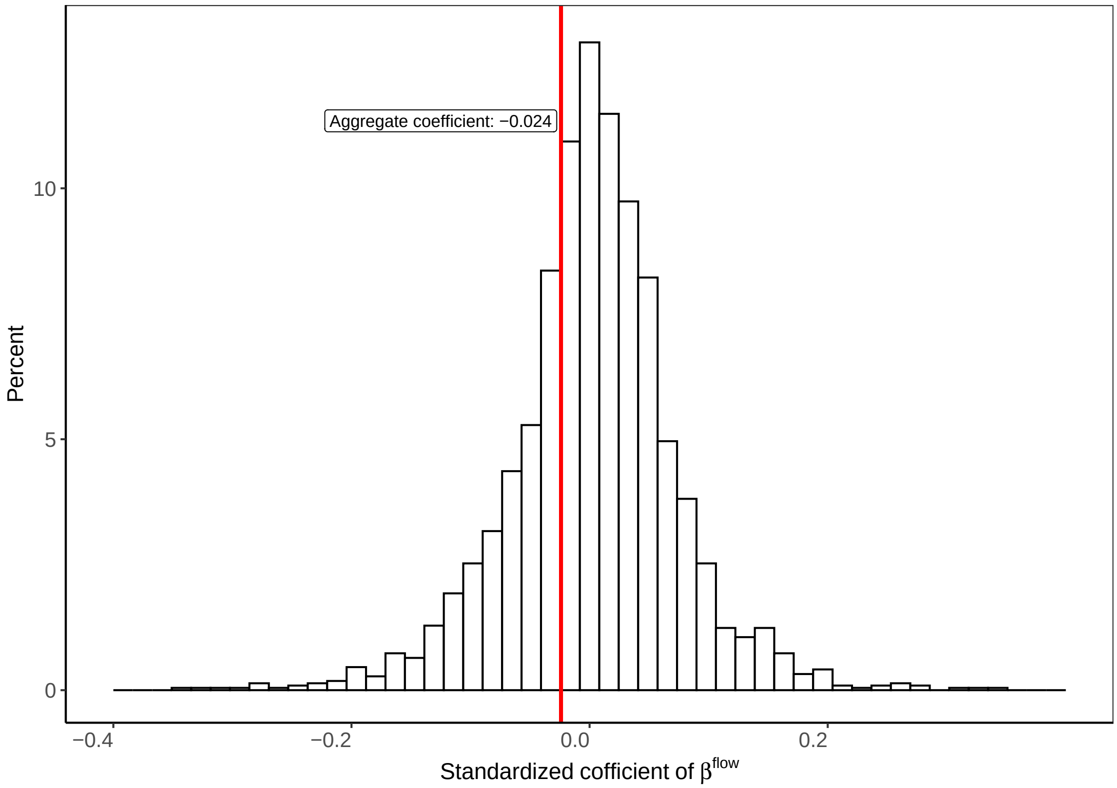


Figure 2. Persistence of active flow beta

This figure illustrates the average portfolio rank and active flow beta of mutual fund portfolios sorted on funds' active flow beta (AFB) over 10-quarter periods between 2006 and 2021. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. At the beginning of each calendar quarter, funds are sorted into quintiles according to their AFB. Each portfolio is subsequently tracked over the next 10 quarters. Panel A reports the equal-weighted average quintile rank, and Panel B reports the equal-weighted average active flow beta.

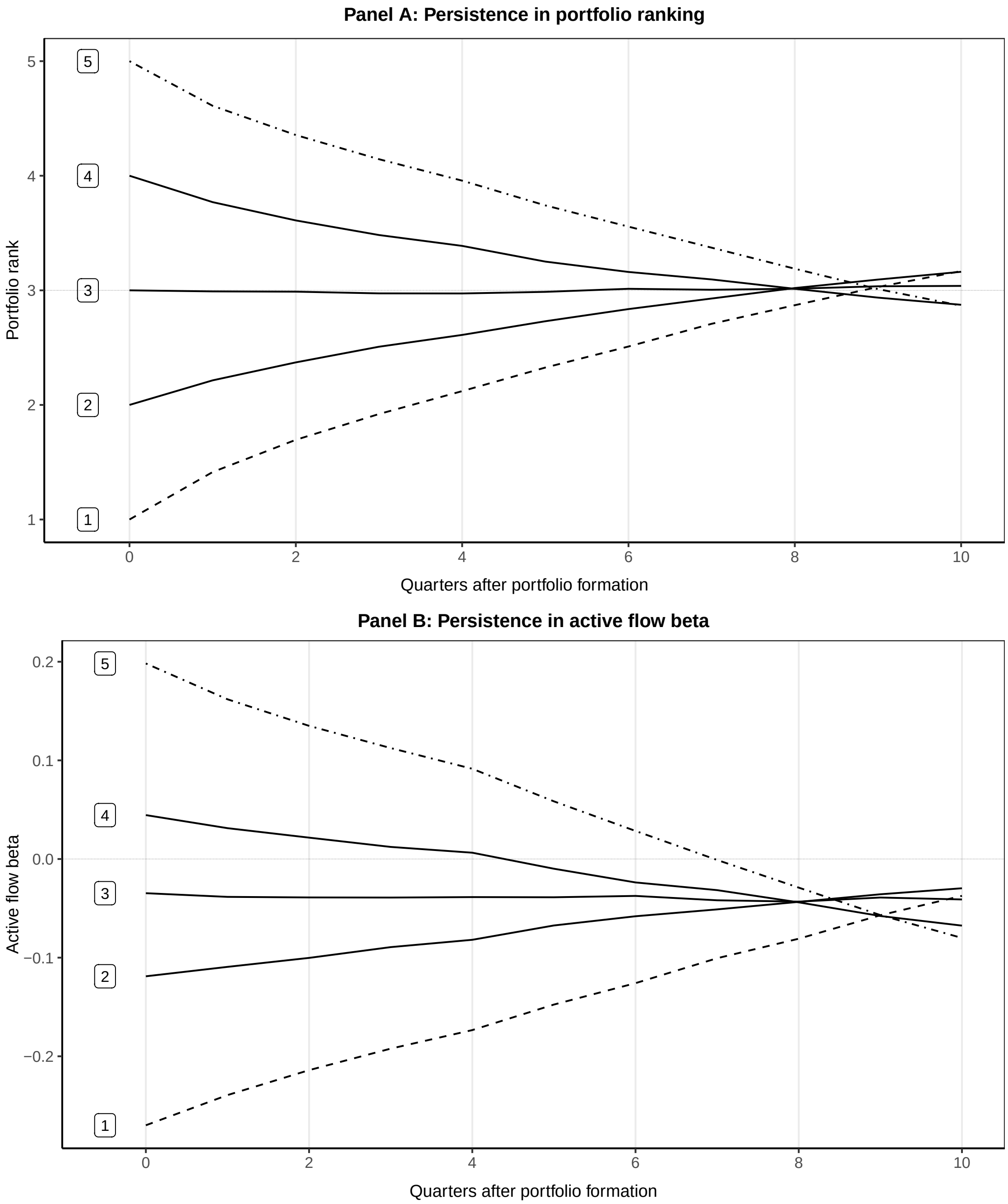
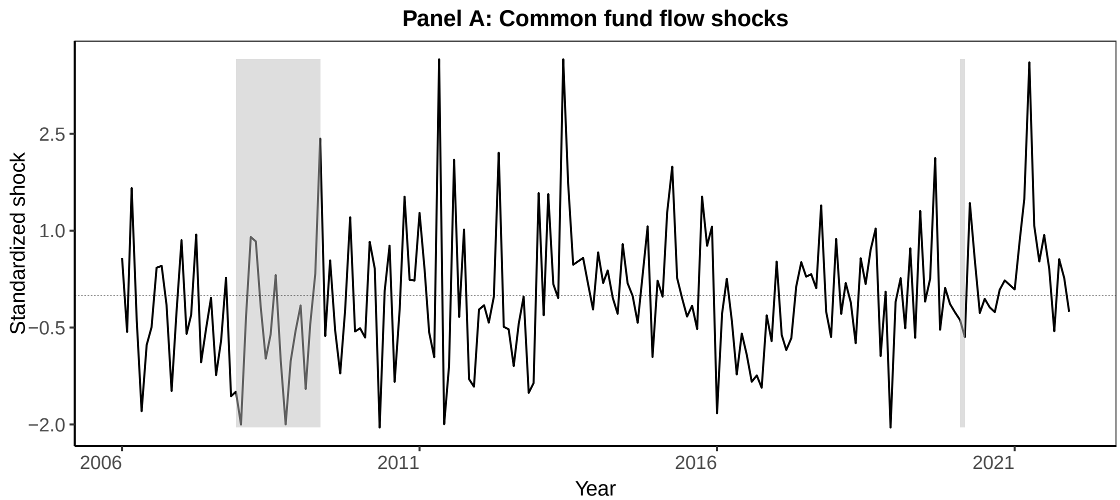


Figure 3. Common fund flows and net returns of the active flow beta strategy
This figure shows the time-series of the common fund flows and the net returns of the active flow beta (AFB) strategy for U.S. domestic active equity funds from 2006Q1 to 2021Q4. Panel A shows the time-series of the common fund flows, which are constructed following Dou et al. (2023) and described in details in Section 3.2. To construct the AFB-based strategy, at the beginning of each calendar quarter, funds are sorted into quintiles according to their AFB and their performance is tracked for the subsequent quarter. The rebalancing frequency is quarterly. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. I compute monthly equally-weighted average net returns on the portfolio that is long on the top quintile portfolio and short on the bottom quintile portfolio. Panel B shows the time-series net return of this portfolio.



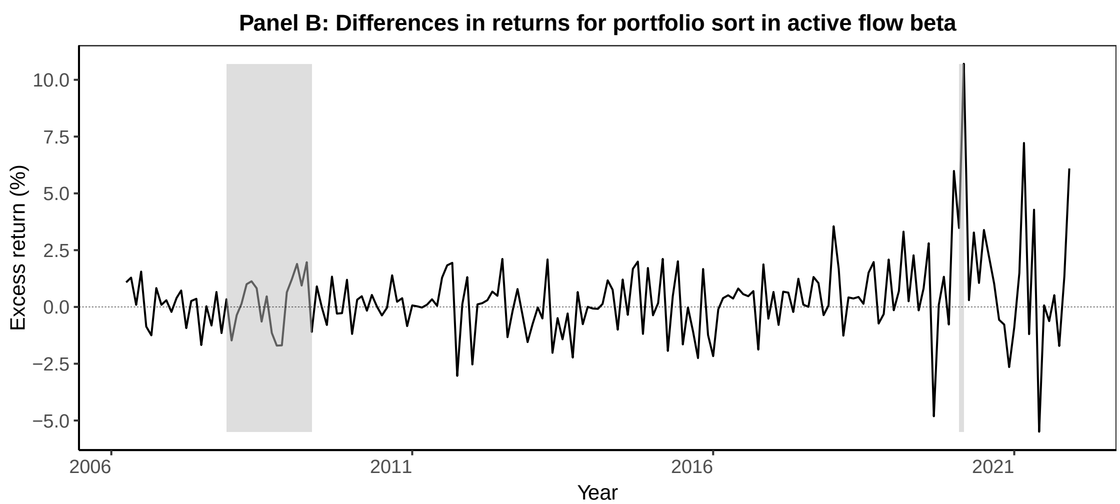


Table 1. Summary statistics

This table reports the summary statistics for the stock and the fund samples from 2006:01 to 2021:12. Panel A reports the statistics for the stock sample that includes U.S. common stocks listed on the NYSE, NASDAQ, and Amex and has at least two years of data on Compustat. β_{flow} is estimated monthly from a 36-month rolling regression of stocks' excess returns on the common flow shocks, controlling for the market factor. $\beta_{\text{liquidity}}$ is estimated monthly from a 36-month rolling regression of stocks' excess returns on the market liquidity factor, controlling for the market return, the size and value factors, the momentum factor. $\beta_{\text{uncertainty}}$ is estimated monthly from a 36-month rolling regression of stocks' excess returns on macro economic uncertainty shocks, controlling for the market return, the size and value factors, the momentum factor, the market liquidity factor, and the investment and profitability factors. *AIM* is the Amihud's illiquidity measure. Panel B reports the statistics for the fund sample that includes U.S. domestic active equity funds. *TNA* is the monthly total net fund assets. *Age* is the fund age in natural logarithm of years. *Quarterly return* is the quarterly net fund return. *Quarterly flow* is the quarterly growth rate of assets under management. *Expense ratio* is the fund expense ratio. *Turnover ratio* is the turnover ratio of the fund. Following Ma et al. (2019), *Performance pay* (*AUM pay*) is an indicator equal to 1 if the variable component in portfolio managers' compensation is based on performance (AUM) and 0 otherwise. Following Evans et al. (2020), *Pure benchmark*, *Peer benchmark*, *Both benchmarks* is an indicator equal to 1 if the performance benchmark for portfolio managers' compensation is based only on pure, peer, or both indices and 0 otherwise, respectively. Data on the compensation structure and benchmarks are from funds' statements of additional information.

	Mean	Standard deviation	p10	p25	p50	p75	p90
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Mutual fund sample							
TNA ($ million)	2190.320	7735.659	51.825	132.976	458.937	1487.777	4487.578
Age (LN(Years))	2.037	0.768	0.693	1.609	2.303	2.708	2.773
Quarterly return (%)	2.585	3.238	-1.312	0.469	2.513	4.636	6.644
Quarterly flow (%)	-1.335	9.501	-8.831	-4.710	-2.063	0.867	6.470
Expense ratio (%)	1.031	0.383	0.588	0.851	1.053	1.249	1.444
Turnover ratio (%)	67.482	59.314	17.152	30.346	53.023	86.259	130.927
Performance pay	0.713	0.452	0.000	0.000	1.000	1.000	1.000
AUM pay	0.194	0.395	0.000	0.000	0.000	0.000	1.000
Pure benchmark	0.188	0.390	0.000	0.000	0.000	0.000	1.000
Peer benchmark	0.108	0.310	0.000	0.000	0.000	0.000	0.629
Both benchmarks	0.414	0.493	0.000	0.000	0.000	1.000	1.000
Panel B: Stock sample							
β_{flow}	-0.090	2.232	-2.116	-0.977	-0.089	0.773	1.887
β_{market}	1.149	0.539	0.408	0.781	1.150	1.503	1.845
Ln(Size)	6.316	2.070	3.611	4.778	6.287	7.748	9.068
$\text{Ln(Size)}_{\text{median}}$	-0.005	0.613	-0.694	-0.268	0.003	0.307	0.671
Ln(BEME)	-0.674	0.905	-1.824	-1.191	-0.586	-0.108	0.301
$\beta_{\text{liquidity}}$	0.005	0.474	-0.519	-0.229	0.003	0.241	0.541
$\beta_{\text{uncertainty}}$	-0.012	0.559	-0.623	-0.261	-0.002	0.240	0.570
AIM	2.128	9.626	0.000	0.001	0.008	0.158	2.276

Table 2. Fund characteristics by portfolio sort

This table reports the summary statistics for fund characteristics by sorting funds' active flow beta from 2006Q1 to 2021Q4. *TNA* is the monthly total net fund assets. *Age* is the fund age in natural logarithm of years. *Quarterly return* is the quarterly net fund return. *Quarterly flow* is the quarterly growth rate of assets under management. *Expense ratio* is the fund expense ratio. *Turnover ratio* is the turnover ratio of the fund. *Performance pay* (*AUM pay*) is an indicator equal to 1 if the variable component in portfolio managers' compensation is based on performance (AUM) and 0 otherwise. *Pure benchmark*, *Peer benchmark*, *Both benchmarks* is an indicator equal to 1 if the performance benchmark for portfolio managers' compensation is based only on pure, peer, or both indices and 0 otherwise, respectively. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	P2	P3	P4	High	High-Low
TNA ($ million)	1462.445	2239.442	2519.223	2344.676	2394.392	931.947***
Age (LN(Years))	2.424	2.442	2.435	2.431	2.440	0.016
Expense ratio (%)	1.080	1.017	0.991	1.004	1.060	-0.020
Turnover ratio (%)	67.024	66.962	66.669	68.148	68.511	1.487
Quarterly return (%)	2.169	2.407	2.579	2.728	3.046	0.877**
Quarterly flow (%)	-1.480	-1.450	-1.407	-1.300	-1.033	0.448*
Active flow beta	-0.304	-0.126	-0.034	0.049	0.205	0.509***
Return gap (%)	-0.115	-0.078	-0.126	-0.121	-0.150	-0.035
Risk shifting	-0.003	-0.004	-0.003	-0.002	-0.002	0.001
Active share (%)	80.792	76.651	75.231	75.129	78.197	-2.595*
R^2 (%)	0.923	0.935	0.934	0.935	0.918	-0.005
RPI (%)	8.692	7.868	8.242	8.287	9.231	0.539
AFO	-0.076	-0.150	-0.147	-0.125	-0.031	0.045

Table 3. Determinants of flow hedging

This table reports results from panel regressions of funds' active flow beta on funds' characteristics and portfolios managers' compensation structure from 2006Q1 to 2021Q4. Panel A (B) shows the results for funds in the top (bottom) quintile of sort on active flow beta, where the dependent variable is an indicator equal to 1 if funds in the top (bottom) quintile. *Performance pay* (*AUM pay*) is an indicator equal to 1 if the variable component in portfolio managers' compensation is based on performance (AUM) and 0 otherwise. *Peer benchmark* is an indicator equal to 1 if the performance benchmark for portfolio managers' compensation is based only peer indices and 0 otherwise. *LN(TNA)* is the natural logarithm of total net fund assets. *Age* is the fund age in natural logarithm of years. *Quarterly return* is the quarterly net fund return. *Quarterly flow* is the quarterly growth rate of assets under management. *Expense ratio* is the fund expense ratio. *Turnover ratio* is the turnover ratio of the fund. *Institutional fund* is an indicator equal to 1 if the fund only has institutional share classes and 0 otherwise. The dependent variables are at quarter t and all determinant variables are at quarter $t-1$. Standard errors are clustered at the fund and time level. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: High AFB Fund				Panel B: Low AFB Fund			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Performance Pay	-0.0030		-0.0026	-0.0026	-0.0317*		-0.0353**	-0.0236
	(0.017)		(0.017)	(0.017)	(0.017)		(0.017)	(0.015)
AUM Pay	-0.0357***		-0.0357***	-0.0359***	-0.0002		0.0005	-0.0084
	(0.013)		(0.013)	(0.013)	(0.014)		(0.014)	(0.013)
Advisor-Profit Pay	0.0079		0.0080	0.0086	-0.0122		-0.0138	-0.0132
	(0.012)		(0.012)	(0.012)	(0.013)		(0.013)	(0.012)
Deferred Compensation	-0.0120		-0.0122	-0.0124	-0.0043		-0.0027	-0.0005
(0.013)		(0.013)	(0.013)	(0.013)		(0.013)	(0.012)	
Peer Benchmark		-0.0014	-0.0034	-0.0055		0.0262	0.0311	0.0175
		(0.020)	(0.020)	(0.019)		(0.019)	(0.019)	(0.017)
Ln(TNA)				0.0082**				-0.0059*
				(0.004)				(0.003)
Ln(Age)				-0.0043				0.0016
				(0.008)				(0.008)
Active Share				0.0764				0.4498***
				(0.102)				(0.077)
Expense Ratio				2.9821				7.0104***
				(2.245)				(1.840)
Turnover Ratio				-0.0081				-0.0048
				(0.010)				(0.008)
Quarterly Flow				0.0219				0.0254
				(0.032)				(0.027)
Quarterly Return				0.3368				-0.1937
				(0.474)				(0.496)
Institutional Fund				-0.0174				0.0187
				(0.015)				(0.014)
Fund Family x Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.05	0.05	0.05	0.06	0.06	0.06	0.06	0.08
# of obs.	63,355	63,355	63,355	63,355	63,355	63,355	63,355	63,355

Table 4. Active flow beta and mutual fund performance

This table reports the performance of quintile fund portfolios sorted on their active flow beta (AFB) from 2006Q1 to 2021Q4. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. Following Dou et al. (2023), each stock's flow beta is estimated at June of year t as its average flow betas from January to June of year t and remains from July of year t to June of year $t+1$. At the beginning of each calendar quarter, funds are sorted into quintiles according to their active flow beta and their performance is tracked for the subsequent three months. The rebalancing frequency is quarterly. *High* (*Low*) is the top (bottom) quintile portfolio. I report the risk-adjusted returns based on the Fama and French (2015) five-factor model that is augmented with Carhart's (1997) momentum factor. Panel A (B) reports the results using gross (net) returns, respectively. The alphas are reported in monthly percentage. Newey-West adjusted $t-$statistics are shown in square brackets. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	2	3	4	High	High-Low
	Panel A: Gross returns					
α	-0.14	-0.06	-0.02	0.05	0.14	0.28**
	[-1.78]	[-1.13]	[-0.56]	[1.07]	[1.87]	[2.11]
β_{MKTRF}	1.01	0.99	0.98	0.98	0.98	-0.03
	[43.27]	[56.19]	[69.24]	[56.69]	[40.11]	[-0.71]
β_{SMB}	0.34	0.18	0.16	0.19	0.33	-0.01
	[8.32]	[7.54]	[9.00]	[8.26]	[9.14]	[-0.18]
β_{HML}	0.05	0.06	0.04	0.02	-0.06	-0.11
	[0.59]	[1.39]	[1.46]	[0.46]	[-1.10]	[-0.89]
β_{CMA}	-0.23	-0.17	-0.12	-0.11	-0.15	0.07
	[-2.49]	[-3.07]	[-3.40]	[-2.75]	[-2.32]	[0.50]
β_{RMW}	-0.05	-0.03	0.03	0.04	0.04	0.08
	[-0.59]	[-0.65]	[0.93]	[0.81]	[0.56]	[0.62]
β_{UMD}	0.00	0.01	0.00	0.00	0.00	0.00
	[0.03]	[0.40]	[0.01]	[-0.29]	[-0.01]	[-0.02]
	Panel B: Net returns					
α	-0.23	-0.15	-0.11	-0.04	0.04	0.28**
	[-2.93]	[-2.75]	[-2.62]	[-0.81]	[0.61]	[2.11]
β_{MKTRF}	1.01	0.99	0.98	0.98	0.98	-0.03
	[43.34]	[56.34]	[69.40]	[56.61]	[40.03]	[-0.70]
β_{SMB}	0.34	0.18	0.16	0.19	0.33	-0.01
	[8.32]	[7.54]	[9.01]	[8.24]	[9.12]	[-0.19]
β_{HML}	0.05	0.06	0.04	0.02	-0.06	-0.11
	[0.59]	[1.39]	[1.47]	[0.47]	[-1.10]	[-0.89]
β_{CMA}	-0.23	-0.17	-0.12	-0.11	-0.15	0.07
	[-2.50]	[-3.09]	[-3.42]	[-2.75]	[-2.31]	[0.51]
β_{RMW}	-0.05	-0.03	0.03	0.04	0.04	0.08
	[-0.59]	[-0.66]	[0.92]	[0.79]	[0.55]	[0.62]
β_{UMD}	0.00	0.01	0.00	0.00	0.00	0.00
	[0.04]	[0.41]	[0.03]	[-0.26]	[0.01]	[-0.02]

Table 5. Active flow beta and mutual fund performance: Double portfolio sorts

This table reports the performance of fund portfolios sorted on their active flow beta (AFB) and skill-related fund characteristics from 2006Q1 to 2021Q4. At the beginning of each calendar quarter, I independently sort funds into four groups based on AFB and into four groups based on the following fund characteristics: Kacperczyk et al.'s (2008) *Return gap* (Panel A), Huang et al.'s (2011) *Risk shifting* (Panel B), Cremers and Petajisto's (2009) *Active share* (Panel C), Kacperczyk and Seru's (2007) *Reliance on public information* (Panel D), and Avramov et al.'s (2020) *Active fund overpricing* (Panel E). Construction details of these fund predictors can be found in Section B.2 in the Appendices. The portfolio performance is tracked for the subsequent three months. The rebalancing frequency is quarterly. I compute monthly equally-weighted average net returns on the portfolios, and report the risk-adjusted net returns based on the Fama and French (2015) five-factor model that is augmented with Carhart's (1997) momentum factor. The alphas are reported in monthly percentage. Newey-West adjusted $t-$statistics are shown in square brackets. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

Active flow beta	All	Low	2	3	High	High-Low
			Panel A: Return gap			
All		-0.23***	0.16	-0.06	0.04	0.27**
		[-3.04]	[0.59]	[-1.48]	[0.61]	[2.19]
Low	-0.14***	-0.26	-0.16	-0.12	-0.04	0.23*
	[-2.85]	[-3.24]	[-2.76]	[-2.22]	[-0.53]	[1.97]
2	-0.08*	-0.22	-0.01	-0.09	0.04	0.26**
	[-1.76]	[-2.62]	[-0.11]	[-2.00]	[0.58]	[2.00]
3	-0.08**	-0.20	-0.13	-0.03	0.06	0.26**
	[-2.36]	[-2.60]	[-2.83]	[-0.74]	[0.88]	[2.04]
High	-0.08*	-0.22	-0.12	-0.02	0.12	0.34***
	[-1.88]	[-3.15]	[-2.14]	[-0.43]	[1.46]	[2.68]
High-Low	0.06	0.04	0.04	0.10**	0.16***	
	[1.59]	[0.96]	[0.85]	[2.23]	[3.07]	

(Continued on next page)

Table 5 (*continued*)

Active flow beta	All	Low	2	3	High	High-Low
			Panel B: Risk shifting			
All		-0.23***	0.16	-0.06	0.04	0.27**
		[-3.04]	[0.59]	[-1.48]	[0.61]	[2.19]
Low	-0.11*	-0.27	-0.14	-0.06	0.05	0.32**
	[-1.70]	[-3.08]	[-2.08]	[-0.92]	[0.53]	[2.40]
2	-0.09**	-0.20	-0.12	-0.05	0.05	0.25**
	[-2.17]	[-2.67]	[-2.41]	[-0.97]	[0.76]	[2.02]
3	-0.10***	-0.25	-0.12	-0.05	0.03	0.28**
	[-3.16]	[-3.25]	[-2.75]	[-1.14]	[0.48]	[2.29]
High	-0.08*	-0.21	-0.01	-0.08	0.05	0.26**
	[-1.82]	[-2.74]	[-0.09]	[-2.53]	[0.84]	[2.24]
High-P2	0.01	-0.01	0.11	-0.03	0.00	
	[0.16]	[-0.33]	[0.79]	[-0.62]	[0.02]	
			Panel C: Active share			
All		-0.23***	0.16	-0.06	0.04	0.27**
		[-3.04]	[0.59]	[-1.48]	[0.61]	[2.19]
Low	-0.06**	-0.22	-0.08	-0.09	0.05	0.27**
	[-2.09]	[-2.78]	[-0.73]	[-3.02]	[0.82]	[2.16]
2	-0.11**	-0.22	-0.15	-0.09	-0.02	0.20
	[-2.57]	[-2.79]	[-2.73]	[-1.71]	[-0.31]	[1.55]
3	-0.09*	-0.25	-0.07	-0.03	0.02	0.26**
	[-1.91]	[-3.21]	[-1.35]	[-0.46]	[0.24]	[2.26]
High	-0.11*	-0.22	-0.13	-0.07	0.04	0.26**
	[-1.75]	[-2.97]	[-1.59]	[-1.13]	[0.48]	[2.52]
High-Low	-0.04	0.00	-0.05	0.02	-0.01	
	[-0.71]	[-0.02]	[-0.43]	[0.39]	[-0.19]	

(Continued on next page)

Table 5 (*continued*)

Active flow beta	All	Low	2	3	High	High-Low
		Panel D: Reliance on public information				
All		-0.23***	0.16	-0.06	0.04	0.27**
		[-3.04]	[0.59]	[-1.48]	[0.61]	[2.19]
Low	-0.09**	-0.21	-0.11	-0.07	0.03	0.24*
	[-2.02]	[-2.69]	[-1.98]	[-1.35]	[0.40]	[1.85]
2	-0.06	-0.21	-0.03	-0.06	0.07	0.27**
	[-1.40]	[-2.83]	[-0.21]	[-1.34]	[0.89]	[2.15]
3	-0.10***	-0.23	-0.14	-0.05	0.04	0.27**
	[-2.81]	[-2.82]	[-2.90]	[-1.16]	[0.65]	[2.17]
High	-0.12***	-0.27	-0.14	-0.08	0.03	0.30**
	[-2.94]	[-3.65]	[-3.02]	[-1.61]	[0.42]	[2.54]
High-Low	-0.03	-0.07**	-0.03	-0.01	0.00	
	[-1.48]	[-2.30]	[-0.99]	[-0.36]	[-0.07]	
		Panel E: Active fund overpricing				
All		-0.35***	-0.15***	0.00	0.13	0.48**
		[-3.04]	[-2.72]	[0.08]	[1.39]	[2.59]
Low	-0.08*	-0.32	-0.17	0.02	0.15	0.47**
	[-1.83]	[-2.94]	[-3.05]	[0.32]	[1.49]	[2.56]
2	-0.07	-0.37	-0.09	0.01	0.16	0.53***
	[-1.44]	[-3.05]	[-1.22]	[0.19]	[1.77]	[2.80]
3	-0.10**	-0.39	-0.14	0.01	0.14	0.53***
	[-2.39]	[-3.56]	[-2.48]	[0.12]	[1.45]	[2.88]
High	-0.14***	-0.33	-0.19	-0.02	0.06	0.40**
	[-2.72]	[-2.72]	[-3.72]	[-0.47]	[0.68]	[2.13]
High-Low	-0.05*	-0.01	-0.02	-0.04	-0.08***	
	[-1.72]	[-0.29]	[-0.69]	[-1.47]	[-3.10]	

Table 6. Active flow beta and flow

This table reports results from regressions of fund flows on active flow beta from 2006Q1 to 2021Q4. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. *Flow* measures the quarterly percentage growth in asset under management. *Performance pay* (*AUM pay*) is an indicator equal to 1 if the variable component in portfolio managers' compensation is based on performance (AUM) and 0 otherwise. *Peer benchmark* is an indicator equal to 1 if the performance benchmark for portfolio managers' compensation is based only on peer indices and 0 otherwise. *Institutional fund* is an indicator equal to 1 if the fund only has institutional share classes and 0 otherwise. Control variables include current quarter's fund excess return, and previous quarter's fund excess return, total net asset, age, expense ratio, turnover ratio, flow and fund alphas from the six-factor model. The panel regressions include time fixed effects. Standard errors shown in parentheses are clustered at the fund level. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Quarterly flow				
	(1)	(2)	(3)	(4)	(5)
Active flow beta (AFB)	0.017***	0.009**	0.011**	0.014*	0.012**
	(0.005)	(0.004)	(0.005)	(0.007)	(0.005)
Institutional fund			0.006		
			(0.006)		
Institutional fund × AFB			-0.005		
			(0.008)		
Performance pay				-0.008	
				(0.006)	
Performance pay × AFB				-0.006	
				(0.008)	
AUM pay				-0.006*	
				(0.003)	
AUM pay × AFB				-0.009	
				(0.008)	
Peer benchmark					0.005
					(0.004)
Peer benchmark × AFB					-0.006
					(0.007)
Control variables		Yes	Yes	Yes	Yes
Adj. R^2	0.0035	0.0331	0.0331	0.0331	0.0331
# of obs.	68,637	68,637	68,637	68,637	68,637

Table 7. Flow hedging and precision of public information

This table reports results from Fama-MacBeth regressions of fund portfolios' deviations from benchmark allocations on active flow beta (AFB) and its interaction with measures of precision of public information from 2006Q1 to 2021Q4. Specifically, I estimate the following regression

$$\omega_{p,i,q+1} - \omega_{m,i,q+1} = \gamma_{0,p,q} + \gamma_{1,p,q}\beta_{\text{flow},i,q} + \gamma_{2,p,q}\beta_{\text{market},i,q} + \gamma_{3,p,q}\sigma_{i,q} + \gamma_{4,p,q}\beta_{\text{flow},i,q} \times \sigma_{i,q} + \varepsilon_{p,q+1},$$

where $\omega_{p,i,q+1} - \omega_{m,i,q+1}$ is the deviation of stock i in portfolio's p from the market allocations and $\sigma_{i,q}$ is a measure of precision of public information for stock i. At the beginning of each calendar quarter, funds are sorted into quintiles according to their active flow beta, where *High* (*Low*) is the top (bottom) quintile portfolio. Panel A (B) uses the analysts' forecast dispersion (stocks' idiosyncratic volatility) to proxy for the imprecision of public information. All variables are standardized to have mean of 0 and standard deviation of 1. Standard errors are Newey-West adjusted and shown in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Analysts' disagreement				Panel B: Idiosyncratic volatility			
Portfolio	β_{flow}	β_{market}	σ	$\beta_{\text{flow}} \times \sigma$	β_{flow}	β_{market}	σ	$\beta_{\text{flow}} \times \sigma$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Low (P1)	-0.064***	-0.060***	-0.274***	-0.001	-0.072***	0.017	-0.487***	0.039***
	(0.008)	(0.013)	(0.024)	(0.010)	(0.009)	(0.014)	(0.026)	(0.012)
High (P5)	0.087***	-0.087***	-0.244***	-0.052***	0.092***	-0.029**	-0.396***	-0.073***
	(0.010)	(0.013)	(0.020)	(0.011)	(0.008)	(0.013)	(0.026)	(0.007)
High-Low	0.152***	-0.027	0.030	-0.052***	0.164***	-0.046**	0.090**	-0.112***
	(0.010)	(0.017)	(0.031)	(0.015)	(0.011)	(0.023)	(0.043)	(0.013)

Table 8. Precision of market information and mutual fund performance

This table reports the performance of quintile fund portfolios sorted on their active flow beta conditional on the periods of high variance in public information from 2006:01 to 2021:12. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. At the beginning of each calendar quarter, funds are sorted into quintiles according to their active flow beta, where *High* (*Low*) is the top (bottom) quintile portfolio. Panel A (B) use the analysts' forecast dispersion (stocks' idiosyncratic volatility) to proxy for the imprecision of public information. *Volatility indicator* is an indicator equal to 1 if the month belongs to the top quintile of the imprecision of public information. I compute monthly equally-weighted average net returns on the portfolios, and report the risk-adjusted net returns based on the Fama and French (2015) five-factor model that is augmented with Carhart's (1997) momentum factor. The alphas are reported in monthly percentage. Newey-West adjusted $t-$statistics are shown in square brackets. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Panel A: Analysts' disagreement		Panel B: Idiosyncratic volatility	
Portfolio	Carhart α	Volatility indicator	Carhart α	Volatility indicator
	(1)	(2)	(3)	(4)
Low (P1)	-0.18**	-0.45*	-0.22**	-0.20
	[-2.09]	[-1.82]	[-2.29]	[-0.83]
High (P10)	-0.05	0.53***	-0.01	0.41**
	[-0.61]	[2.74]	[-0.18]	[2.05]
High-Low	0.13	0.98**	0.21	0.62**
	[0.98]	[2.50]	[1.35]	[2.08]

Appendices

A Additional Tables and Figures

Table A1. Summary statistics: Stock characteristics across portfolio sort
This table reports the summary statistics for quintile stock portfolios sorted on stock flow beta from 2006:01 to 2021:12. The sample includes U.S. common stocks listed on the NYSE, NASDAQ, and Amex and has at least two years of data on Compustat. Following Dou et al. (2023), in June of each year t I sort all stocks into five portfolios based on the average flow betas from January to June and track the portfolios from July of year t to June of year $t+1$. β_{flow} is estimated monthly from a 36-month rolling regression of stocks' excess returns on the common flow shocks, controlling for the market excess return. $\beta_{\text{liquidity}}$ is estimated monthly from a 36-month rolling regression of stocks' excess returns on the market liquidity factor, controlling for the market return, the size and value factors, the momentum factor. $\beta_{\text{uncertainty}}$ is estimated monthly from a 36-month rolling regression of stocks' excess returns on macro economic uncertainty shocks, controlling for the market return, the size and value factors, the momentum factor, the market liquidity factor, and the investment and profitability factors. *AIM* is the Amihud's illiquidity measure.

	Low	2	3	4	High
β_{flow}	-2.075	-0.740	-0.084	0.553	1.671
Return (%)	0.899	0.970	0.815	0.966	1.148
β_{market}	1.048	0.911	0.833	0.840	0.977
Ln(Size)	9.230	10.008	10.300	10.237	9.410
Ln(Size)$_{\text{median}}$	0.117	0.120	0.088	0.095	0.140
Ln(BEME)	-1.037	-1.008	-1.025	-1.158	-1.200
$\beta_{\text{liquidity}}$	-0.028	-0.018	0.002	-0.004	0.003
$\beta_{\text{uncertainty}}$	-0.036	-0.011	0.009	0.018	-0.022
AIM	0.027	0.015	0.012	0.013	0.037

Table A2. Active flow beta and mutual fund performance: Seven-factor model
This table reports the performance of quintile fund portfolios sorted on their active flow beta (AFB) from 2006Q1 to 2021Q4. A fund's active flow beta is estimated as the sum of the product between the difference of the fund's portfolio weights from the market portfolio's weights and the underlying stock flow betas. Following Dou et al. (2023), each stock's flow beta is estimated at June of year t as its average flow betas from January to June of year t and remains from July of year t to June of year $t+1$. At the beginning of each calendar quarter, funds are sorted into quintiles according to their active flow beta and their performance is tracked for the subsequent three months. The rebalancing frequency is quarterly. *High* (*Low*) is the top (bottom) quintile portfolio. I report the risk-adjusted returns based on the Fama and French (2015) five-factor model that is augmented with Carhart's (1997) momentum factor and Pástor and Stambaugh's (2003) liquidity factor. Panel A (B) reports the results using gross (net) returns, respectively. The alphas are reported in monthly percentage. Newey-West adjusted $t-$statistics are shown in square brackets. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	2	3	4	High	High-Low
	Panel A: Gross returns					
α	-0.14	-0.06	-0.02	0.05	0.14	0.28**
	[-1.77]	[-1.10]	[-0.51]	[1.20]	[2.01]	[2.13]
β_{MKTRF}	1.00	0.98	0.97	0.97	0.97	-0.03
	[46.23]	[59.33]	[74.12]	[65.31]	[44.45]	[-0.77]
β_{SMB}	0.32	0.17	0.15	0.18	0.31	-0.01
	[8.81]	[7.60]	[8.54]	[7.61]	[8.65]	[-0.20]
β_{HML}	0.05	0.07	0.05	0.02	-0.06	-0.11
	[0.69]	[1.58]	[1.81]	[0.61]	[-0.93]	[-0.85]
β_{CMA}	-0.20	-0.15	-0.11	-0.10	-0.13	0.07
	[-2.61]	[-3.06]	[-3.04]	[-2.48]	[-2.06]	[0.56]
β_{RMW}	-0.05	-0.03	0.03	0.03	0.04	0.08
	[-0.64]	[-0.72]	[0.89]	[0.75]	[0.51]	[0.62]
β_{UMD}	-0.01	0.00	-0.01	-0.01	-0.01	0.00
	[-0.34]	[0.02]	[-0.48]	[-0.62]	[-0.34]	[-0.02]
β_{LIQ}	0.04	0.03	0.03	0.03	0.04	0.00
	[1.57]	[1.91]	[2.15]	[1.58]	[2.02]	[0.01]
	Panel B: Net returns					
α	-0.23	-0.14	-0.11	-0.03	0.05	0.28**
	[-2.94]	[-2.77]	[-2.67]	[-0.81]	[0.70]	[2.13]
β_{MKTRF}	1.00	0.98	0.97	0.97	0.97	-0.03
	[46.30]	[59.50]	[74.37]	[65.29]	[44.36]	[-0.76]
β_{SMB}	0.32	0.17	0.15	0.18	0.31	-0.01
	[8.81]	[7.60]	[8.53]	[7.59]	[8.63]	[-0.20]
β_{HML}	0.06	0.07	0.05	0.02	-0.06	-0.11
	[0.70]	[1.59]	[1.82]	[0.62]	[-0.93]	[-0.85]
β_{CMA}	-0.20	-0.15	-0.11	-0.10	-0.13	0.07
	[-2.63]	[-3.08]	[-3.06]	[-2.49]	[-2.06]	[0.57]
β_{RMW}	-0.05	-0.03	0.03	0.03	0.04	0.08
	[-0.65]	[-0.72]	[0.88]	[0.73]	[0.50]	[0.62]
β_{UMD}	-0.01	0.00	0.00	-0.01	-0.01	0.00
	[-0.33]	[0.03]	[-0.46]	[-0.60]	[-0.33]	[-0.02]
β_{LIQ}	0.04	0.03	0.03	0.03	0.04	0.00
	[1.56]	[1.90]	[2.14]	[1.58]	[2.00]	[0.01]

Table A3. Active flow beta and mutual fund performance: Active benchmark

This table examines the performance of quintile fund portfolios sorted on their active flow beta from 2006:01 to 2021:12 as in Table 4 but uses the active benchmark definition for the funds to estimate its portfolio weights' deviation. At the beginning of each calendar quarter, funds are sorted into quintiles according to the active flow beta and their performance is tracked for the subsequent three months. *High* (*Low*) is the top (bottom) quintile portfolio. I compute monthly equally-weighted average net returns on the portfolios, and report the average excess returns, the risk-adjusted returns based on the Carhart (1997) four-factor model, the Fama and French (2015) five-factor model that is augmented with Carhart's (1997) momentum factor, and the six-factor model that is augmented with Pástor and Stambaugh's (2003) liquidity factor. Active benchmarks are defined as in Cremers and Petajisto (2009). Particularly, a fund's specific benchmark is one of the 21 indices that minimizes its active share. The values are reported in monthly percentage. Newey-West adjusted $t-$statistics are shown in square brackets. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	2	3	4	High	High-Low
Average	0.72	0.73	0.77	0.86	0.96	0.24**
	[1.85]	[2.02]	[2.17]	[2.39]	[2.51]	[2.22]
Carhart	-0.25	-0.20	-0.15	-0.05	-0.01	0.24**
	[-3.42]	[-4.07]	[-3.60]	[-1.05]	[-0.07]	[2.09]
Six-factor model	-0.21	-0.16	-0.14	-0.05	0.01	0.22*
	[-2.83]	[-3.37]	[-3.49]	[-1.11]	[0.20]	[1.95]
Seven-factor model	-0.20	-0.16	-0.14	-0.05	0.02	0.22**
	[-2.82]	[-3.39]	[-3.61]	[-1.10]	[0.35]	[2.00]

B Supplemental Materials

B.1 Model Details

In this section, I provide additional details on the solution of the theoretical model in Section 2.1. Equation 8 shows that an investor's demand for the risky asset depends on her posterior about the asset's risk, return, flow and the covariance between its return and flow

$$x^{I*} = \frac{1}{\gamma}\frac{E_{\mathbf{s}}(u^I - p)}{\mathrm{Var}_{\mathbf{s}}(u^I)} - \beta^I_{\text{flow}}\frac{\mathrm{Var}_{\mathbf{s}}(F^I)}{\mathrm{Var}_{\mathbf{s}}(u^I)}. \tag{B1}$$

Using Bayes' rule, we can obtain the posterior distribution of the asset value and flow. For informed investor I, the distribution is bivariate normal with the conditional mean and variance-covariance matrix given as

$$u^I, F^I|s^I \sim N\left(\begin{bmatrix} \frac{\rho_1(\rho_2+\rho_F)\bar{u}-\rho_1\psi\bar{F}+\kappa_1 s_1+\rho_1\psi s_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} \\ \frac{-\rho_2\psi\bar{u}+\rho_2(\rho_1+\rho_u)\bar{F}+\rho_2\psi s_1+(\rho_F\rho_1+\rho_u\rho_F-\psi^2)s_2}{\rho_1(\rho_2+\rho_F)+\kappa_1}\end{bmatrix}, \begin{bmatrix} \frac{\rho_1\kappa_1}{\rho_1(\rho_2+\rho_F)+\kappa_1} & \frac{\rho_1\rho_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} \\ \frac{\rho_1\rho_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} & \frac{\rho_2(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1(\rho_2+\rho_F)+\kappa_1}\end{bmatrix}\right) \tag{B2}$$

The informed investors' optimal allocation then follows

$$x^{I*} = \frac{\rho_1(\rho_2+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_1 s_1 + \rho_1\psi s_2 - p[\rho_1(\rho_2+\rho_F)+\kappa_1]}{\gamma\rho_1\kappa_1} - \beta^I_{\text{flow}}\frac{\rho_2(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1\kappa_1}. \tag{B3}$$

Uninformed investors do not directly observe private signals s_2. Instead they infer the signals from the price induced by the informed investors' demand. They conjecture the price in a form as a linear combination of the variables in the model.

$$p = a_1\bar{u} - a_2\bar{F} + bs_1 + cs_2 - dt + e\bar{t} + g. \tag{B4}$$

This is also the equilibrium price. The uninformed investors obtain noisy signals θ that is a random variable defined as

$$\theta = \frac{p - a_1\bar{u} - a_2\bar{F} - bs_1 + \bar{t}(d-e) - f}{c} = s_2 - (t-\bar{t})\frac{d}{c}. \tag{B5}$$

It is straightforward to verify that θ has the following normal distribution

$$\theta \sim N\left(F, \left(\frac{d}{c}\right)^2 \eta + \rho_2\right). \tag{B6}$$

The posterior distribution of the asset value and flow for uninformed investor U then follows

$$u^U, F^U | s^U \sim N\left(\begin{bmatrix} \frac{\rho_1(\rho_\theta+\rho_F)\bar{u}-\rho_1\psi\bar{F}+\kappa_2 s_1+\rho_1\psi s_2}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \\ \frac{-\rho_\theta\psi\bar{u}+\rho_\theta(\rho_1+\rho_u)\bar{F}+\rho_\theta\psi s_1+(\rho_F\rho_1+\rho_u\rho_F-\psi^2)\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \end{bmatrix}, \begin{bmatrix} \frac{\rho_1\kappa_2}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} & \frac{\rho_1\rho_\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \\ \frac{\rho_1\rho_\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} & \frac{\rho_\theta(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \end{bmatrix}\right) \tag{B7}$$

The uninformed investors' optimal holdings of the risky asset can be obtained as

$$x^{U*} = \frac{\rho_1(\rho_\theta+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_2 s_1 + \rho_1\psi s_2 - p[\rho_1(\rho_\theta+\rho_F)+\kappa_2]}{\gamma\rho_1\kappa_2} - \beta^U_{\text{flow}}\frac{\rho_\theta(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1\kappa_2}. \tag{B8}$$

To solve for the equilibrium price, we impose the market clearing condition that the total supply must equal the total demand for the risky asset

$$\alpha x^{I*} + (1-\alpha)x^{U*} = t. \tag{B9}$$

The solution for the equilibrium price is presented in Equation 7 in the main text. Plugging into Equations B3 and B8, we obtain the solution for the optimal demand of informed and uninformed investors in terms of the model's variables and parameters, respectively. Subtracting the equations leads to the difference in holdings between two types of investors as in Equation 9.

B.2 Variable Construction

In this section, I provide additional details on the construction of mutual fund predictors.

Return gap. I follow Kacperczyk et al. (2008) to measure a fund's return gap in each quarter as the difference in the fund's net return and the return of the fund's holdings using the most recently disclosed holding positions, net of expense ratios. Particularly, the return gap RG of fund j in quarter q is defined as

$$RG_{j,q} = R_{j,q} - (HR_{j,q} - EXP_{j,q}),$$

where $R_{j,q}$ is fund j's net return in quarter q, $HR_{j,q}$ is fund j's holdings return, and $EXP_{j,q}$ is the expense ratio. For portfolio sorts, I follow Kacperczyk et al. (2008) and use average return gaps during the 12 months prior to the portfolio formation.

Reliance on public information. I follow Kacperczyk and Seru (2007) to measure a fund's RPI in each quarter as the R^2 from the regression of the fund's changes in holdings from previous quarter on the changes in analysts' recommendation for the holdings in the last five quarters. Particularly, I estimate the following regression for each fund and quarter

$$\begin{aligned}\%\Delta Hold_{j,i,q} = \beta_{0,j,q} + \beta_{1,j,q}\Delta REC_{i,q-1} + \beta_{2,j,q}\Delta REC_{i,q-2} + \beta_{3,j,q}\Delta REC_{i,q-3} \\ + \beta_{4,j,q}\Delta REC_{i,q-4} + \varepsilon_{j,q}, \quad i = 1, \ldots, N,\end{aligned}$$

where $\%\Delta Hold_{j,i,q}$ is the percentage change in stock split-adjusted holdings of stock i in fund j from quarter $q-1$ to quarter q, and $\Delta REC_{i,q-p}$ is the change in the recommendation of the consensus forecast of stock i from quarter $q-p-1$ to $q-p$.

Active share. Cremers and Petajisto (2009) construct the measure for mutual fund j, holding N stocks in the portfolio, at the end of each quarter q as

$$\mathrm{AS}_{j,q} = \frac{1}{2}\sum_{i=1}^{N} |\omega_{j,i,q} - \omega_{b,i,q}|,$$

where $\omega_{j,i,q}$ is the portfolio weight of stock i in fund j in quarter q, and $\omega_{b,i,t}$ is the weight of stock i in a benchmark portfolio. The authors use 21 benchmark indices and define the active share with respect to the benchmark that minimizes its value (*Active share (Min)*). I obtain the quarterly active share data from Martijn Cremers' website (`https://activeshare.nd.edu/data/`).[20]

***R^2*.** Similar to Amihud and Goyenko (2013), I obtain the R^2 for each fund and month from 24-month rolling regressions

$$R_{j,t} - RF_t = \alpha_p + \beta_{MKTRF} \times MKTRF_t + \beta_{SMB} \times SMB_t + \beta_{HML} \times HML_t + \beta_{UMD} \times UMD_t + \varepsilon_{j,t},$$

where $R_{j,t} - RF_t$ is a fund j's excess return over the risk free rate, $MKTRF_t$, SMB_t, HML_t, and UMD_t are the market, size, value, and momentum factor in the Carhart's (1997) model.

[20] I thank Martijn Cremers for making these data available.

Active fund overpricing. Similar to Avramov et al. (2020), I measure a fund's AFO as the covariance between deviations of its portfolio weights from the market portfolio and the underlying stock mispricing score. Particularly, at the end of each quarter, AFO is measured as

$$\mathrm{AFO}_{j,q} = \sum_{i=1}^{N_j} (\omega_{j,i,q} - \omega_{m,i,q}) \mathrm{O}_{i,q}.$$

where $\omega_{j,i,q}$ is the portfolio weight of stock i in fund j in quarter q, and $\omega_{m,i,q}$ is the weight of stock i in the market portfolio. $\mathrm{O}_{i,q}$. is the stock i's mispricing score. The composite score is calculated based on the stocks' rank among 11 firm characteristics as in Stambaugh, Yu, and Yuan (2012). The higher a stock's score is, the more overpriced the stock is.