Informational Advantages and Flow Hedging in Mutual Funds

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Abstract

This paper studies heterogeneity in flow-hedging behavior among active mutual funds. While recent evidence shows that the aggregate mutual fund industry hedges against common flow risk by tilting toward low-flow-beta stocks, I find that nearly half of U.S. active equity funds tilt their portfolios toward high-flow-beta stocks. To rationalize this finding, I propose an information-based model in which managers with more precise private signals about future flow shocks perceive lower uncertainty and hedge less aggressively. Empirically, funds with higher flow risk exposure are associated with proxies for informational advantages, and their flows predict aggregate industry and common flows. Moreover, funds that hedge against flow risk the least outperform those that hedge the most over 3% per year, suggesting that hedging against flow beta is costly.

Keywords: mutual funds, flow hedging, private information

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 et al., 2025). Notably, Dou et al. (2025) 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. (2025) provide extensive empirical evidence to support the first prediction, this paper examines the empirical evidence of the second.

The latter remains puzzling because it is unclear why funds would be willing to bear the cost of hedging against common flow risk. Over the 15-year sample period from 2006 to 2021, stocks with high flow risk earned approximately three percentage points higher annual returns than low-flow-risk stocks, suggesting that the cost of hedging is economically large. 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

[1] See Brown et al., 1996, Chevalier and Ellison, 1997, Sirri and Tufano, 1998, Huang et al., 2007, Chen and Pennacchi, 2009, Huang et al., 2011, Lee et al., 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.

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 first principal component of flows across all active funds (Dou et al., 2025). The red line illustrates the estimated coefficient obtained using the aggregate mutual fund portfolio. Consistent with Dou et al. (2025), 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 signals they receive about future flows. The key intuition is that a more precise signal reduces the informed investor's perceived uncertainty about future flow shocks, weakening the incentive to hedge flow risk. Consequently, the informed investor tilts more toward high-flow-beta stocks to capture their higher returns.

In the model, private signals about flows can be thought of as advance information on broad investor demand or shifts in aggregate investment opportunities that drive flows in and out of the equity market.[3] The model thus predicts that funds with higher exposure to flow risk should possess greater informational advantages about future flows. The empirical analyses seek to verify whether funds hedge flow risk less aggressively are indeed associated with proxies for informational advantages.

To capture active funds' exposure to flow risk, I use fund holdings data to construct an empirical measure called Active Flow Beta (AFB), defined as the covariance between deviations of a fund's portfolio weights from the market portfolio and

[3] Dou et al. (2025) model endogenous common flows driven by exogenous macroeconomic shocks such as economic uncertainty. Since this paper focuses on cross-sectional flow-hedging behavior, I assume common flows are exogenous.

its holdings' flow betas. Essentially, AFB measures the extent to which a fund tilts its portfolio away from the market benchmark toward stocks with higher (or lower) flow beta. Using holdings data for a sample of U.S. domestic active equity funds, I estimate AFB for each fund and quarter, and examine whether a fund's AFB is associated with its possession of informational advantages about future flows.

Before testing this central mechanism, I examine whether differences in compensation structure can explain variation in flow hedging. This analysis is motivated by Dou et al. (2025)'s argument that portfolio managers' compensation depends on fund size, which in turn is driven by fund flows. Funds' compensation structure is obtained from the disclosed information on portfolio managers' pay from funds' Statement of Additional Information (SAI) as in Ma and Tang (2019). I find that funds that tilt heavily toward stocks with high flow risk (i.e., high-AFB funds) are approximately 20% less likely to disclose compensation based on assets under management (i.e., AUM-based pay) relative to the sample mean. However, performance-based pay and peer-benchmark compensation are not significantly associated with high-AFB status, suggesting that the tilt toward high-flow-beta stocks does not simply reflect excessive risk-taking due to performance pay or peer competition incentives. For low-AFB funds, I find that compensation structure has little explanatory power.

A caveat in this analysis is that SAI-based compensation measures rely on coarse qualitative disclosures that may not fully capture the true compensation structure (Ibert et al., 2018; Cen et al., 2023). Despite this limitation, the results suggest that variation in disclosed compensation structure is associated with cross-sectional differences in flow hedging, but compensation incentives alone do not fully explain the heterogeneity in hedging behavior.

I next investigate the information channels through which funds observe advance signals about future flows. The theoretical framework predicts that fund managers with more precise signals about future flows hedge flow risk less aggressively. There are four fund-level channels that may contain such informational advantages: (1) retail clientele, whose flows often move early with market sentiment and macroeconomic news; (2) marketing intensity, which captures distribution relationships with brokers and advisers who may convey early signals about investor demand and reflects a fund's ability to monitor and forecast market conditions; and (3) fund-family scale and scope, which allow managers to observe cross-fund cash movements that may provide early indications of client flow activity. If these channels genuinely link informational advantages to flow-hedging behavior, funds with higher active flow beta should be associated with these proxies.

The empirical results support this prediction. I find that the proportion of retail shares, marketing expenses, fund-family scale, and fund-family scope are all positively associated with active flow beta. Moreover, each channel captures distinct variation in informational advantages, as the coefficient estimates remain statistically significant and similar in magnitude when all proxies are included simultaneously. These findings indicate that funds with heavier retail clientele, stronger distribution networks, and larger or more diversified fund families tilt more toward high-flow-beta stocks.

I provide further evidence of the informational advantage hypothesis by testing the predictive ability of fund-level flows. If a fund's flows tend to predict industry flows, the fund can observe early signals about market-wide demand shifts before they propagate to industry flows. Consistent with this argument, I find that only flows of higher-AFB funds predict subsequent aggregate industry and common flows. Collectively, these results support the economic channel that fund managers who hedge flow risk less receive advance signals about aggregate flows through their own fund flows.

Next, I quantify the cost of hedging flow risk by evaluating the performance of funds sorted on AFB. The theoretical framework predicts that funds hedging aggressively against flow risk forgo higher expected returns. Consistent with this prediction, I find that funds in the top quintile of AFB (i.e., funds that hedge the least) outperform funds in the bottom quintile (i.e., funds that hedge the most) by 0.28% per month, or 3.36% per year, after adjusting for standard risk exposures. This performance gap is both economically large and statistically significant. This result provides direct evidence that hedging against flow risk is costly, complementing and reinforcing the theoretical prediction of Dou et al. (2025).[4]

Finally, I examine how the precision of public information affects flow-hedging behavior and the associated hedging costs. The theoretical model predicts that when public information about stock value is less precise, the marginal benefit of possessing a more accurate private signal about future flows declines. Consequently, even funds with informational advantages have weaker incentives to tilt toward high-flow-beta stocks when fundamental uncertainty is high. To test this prediction, I construct two measures of public information imprecision based on the prior literature: the dispersion in analysts' earnings forecasts and stocks' idiosyncratic volatility. Consistent with the model's prediction, the coefficient on the interaction between flow beta and both disagreement measures is significantly smaller for high-AFB funds. This result is consistent with the notion that fundamental uncertainty diminishes the value of private flow signals, reducing high-AFB funds' incentives to tilt toward stocks with high flow risk.

This paper makes two contributions to the literature on mutual fund risk taking and performance. First, I document significant heterogeneity in flow-hedging behavior across U.S. active equity funds. While Dou et al. (2025) show that the aggregate mutual fund sector tilts toward stocks with low flow beta to hedge against common flow risk, I find that nearly half of active equity funds tilt their portfolios toward stocks with higher exposure to common flows. This finding points to meaningful

[4]The premium earned by high-AFB funds may arise from the informational advantage channel, the common flow risk channel, or both. This performance analysis focuses on quantifying the magnitude of the hedging cost rather than attributing it to a single source.

heterogeneity in flow hedging across active funds, and raises the question of why some funds hedge this risk substantially less than others.

Second, I rationalize this heterogeneity by proposing an information-based channel that incentivizes certain funds to hedge against flow beta less aggressively. I extend the theoretical model of Kacperczyk and Seru (2007) to show that fund managers with more precise private signals about future flows perceive lower uncertainty regarding flow shocks and therefore hedge flow risk less aggressively. The paper documents empirical evidence that supports this mechanism. It also documents that high-AFB funds significantly outperform low-AFB funds, consistent with the model's prediction that hedging against flow beta is costly.

There is an important limitation of the current framework. While the theoretical model provides an explanation for why some funds tilt toward stocks with high flow beta, it does not separate the two channels that drive the outperformance of these funds. Both the common flow risk channel and the informational advantage channel predict that high-AFB funds earn higher returns, either as compensation for bearing flow risk or as profits from exploiting informational advantages about future flows. Because econometricians do not directly observe fund managers' information sets, isolating the two channels is not feasible. Future research may exploit settings with exogenous variation in either information precision or flow risk compensation to separate these mechanisms.

The remainder of the paper is organized as follows. Section 2 presents the theoretical model. Section 3 develops testable hypotheses that connect the model's predictions with empirical proxies. Section 4 describes the data and the construction of active flow beta. Section 5 documents the empirical results, and Section 6 concludes.

2 Theoretical model

In this section, I extend the model of Kacperczyk and Seru (2007) to show that the precision of the private signal about asset flows that an informed investor receives can explain her larger holdings of high-flow-beta assets relative to an uninformed investor.

2.1 Model setup

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. (2025), 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.

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,

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

1999, Edelen and Warner, 2001, Ben-Rephael et al., 2012).[6] 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.[7]

2.2 Information structure and signals

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.

Because flows in this model come from common sources, private signals about flows can be thought of as advance information on broad investor demand or shifts in aggregate investment opportunities that drive flows in and out of the equity market. Such information may arise from observing a fund's own investor flows before they propagate to industry flows. It is worth noting that these private signals are not about firm-specific private information that can motivate informed trading.

The public and private signals have the following bivariate normal conditional

[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.

[7]The model is stylized to focus on the connection between information structure and portfolio decisions. Therefore, it rests on several simplifying assumptions that limit the scope of its testable predictions. I discuss these assumptions and the related caveats in detail in Internet Appendix Section A2.

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.[8] The CARA util-

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

ity implies that the investor's asset allocation decision is to choose x^j that maximizes

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

2.3 Equilibrium and main prediction

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

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

Additional details of the optimal demands and equilibrium price can be found in Internet Appendix Section A1. 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 yields the model's main prediction: informed investors tilt their portfolios toward high-flow-beta stocks relative to uninformed investors. The key intuition is that informed investors who receive more precise signals about future flows perceive lower uncertainty and therefore have weaker incentives to hedge against flow risk.

It is worth clarifying the distinction between directional trading on the flow signal (i.e., private signal coefficient) and the reduction in hedging intensity against high-flow-beta assets (i.e., flow risk coefficient) implied by Equation 9. Since informed and uninformed investors have identical preferences, the reason their optimal portfolios differ is that the informed investor's private signal reduces the conditional variance of the future flow shock relative to that perceived by the uninformed (i.e., $\rho_2 < \rho_\theta$). Because part of the flow shock is anticipated, the informed investor perceives the flow-risk factor as less uncertain and therefore hedges it less aggressively. This weaker hedging motive shows up as a strictly positive coefficient on flow beta in Equation 9, independent of the realization of the private signal s_2. In other words, the private signal shifts the level of informed demand, while improved flow signal precision reduces perceived uncertainty and increases the slope of informed-uninformed demand with respect to flow beta.

Based on the preceding analysis, I conjecture that investors with more precise private information about future flows hold portfolios with 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 motivate an empirical measure that captures cross-sectional variation in flow risk exposure among U.S. active mutual fund managers. It is important to clarify what β_{flow} captures. Specifically, β_{flow} measures the co-movement between an asset's payoff and future flows. Extending this to a portfolio with N stocks in the context of an equity fund, it captures the co-movement between a stock's payoff and future flows into the fund's portfolio. Since Dou et al. (2025) show that flows in and out of mutual funds share a common structure, I use common flows to proxy for aggregate fund flows. That is, the empirical measure β_{flow} for a stock captures the co-movement between its return and common fund flows.

3 Hypothesis development

This section develops testable predictions from the theoretical framework in Section 2. First, I propose economic channels through which funds may observe early information about future common flows. Second, I develop testable hypotheses linking these informational advantages to predictive ability for aggregate flows and to fund performance.

3.1 Informational advantages and flow risk exposure

The theoretical framework predicts that fund managers with more precise signals about future flows hedge flow risk less aggressively because such signals reduce uncertainty about future flow shocks. Testing this prediction empirically requires identifying proxies that capture cross-sectional variation in informational advantages about future flows. Since econometricians cannot directly observe fund managers' information set about future flows, I develop indirect fund-level measures that can be economically linked to early information about aggregate investor demand. These measures include investor-base composition, marketing intensity and fund-family scale and scope.

First, I hypothesize that funds with a higher proportion of retail investors have greater informational advantages about future flows. Retail investors often react early to market sentiment and macroeconomic news, and funds with heavier retail clientele may observe these demand shifts sooner. For example, Frazzini and Lamont (2008) show that retail fund flows predict negative future returns at the stock level and Ben-Rephael et al. (2012) show that retail investor reallocations between equity and bond funds are contemporaneously related to market returns. These findings suggest that retail flows move early and contain information about aggregate demand that impacts market prices. Funds with larger retail investor base may observe these signals sooner, reducing their perceived uncertainty about future flow shocks and leading them to hedge flow risk less aggressively. Therefore, I predict a positive relationship between a fund's proportion of retail shares and its flow risk exposure.

Second, I hypothesize that funds with higher marketing expenses have earlier access to information about investor demand conditions. Because funds use marketing expenses to compensate brokers, financial advisers, and distribution platforms for selling and servicing mutual fund shares, these expenditures help funds maintain distribution relationships that may serve as an information channel about market demand. For example, Christoffersen et al. (2013) document that brokers respond to this compensation by actively directing client investments toward funds. These findings suggest that funds spending more on marketing may receive advance signals about market demand through their intermediary network. This advantage in turn reduces their perceived uncertainty about future flow shocks and weakens the incentive to hedge against flow risk. Therefore, I predict a positive relationship between a fund's marketing expenses and its active flow beta.

Third, I hypothesize that funds belonging to larger and more diversified fund families have greater informational advantages about future flows. Funds within large fund families may observe cash movements across member funds, providing them with earlier signals on aggregate investor demand. Similarly, families managing funds across diverse investment objectives (e.g., growth or value) may observe flows across different market segments, allowing managers to learn about shifts in aggregate demand sooner. For example, Brown and Wu (2016) document that a larger number of funds in the same family reduces their funds' sensitivity of flows to fund performance. Their findings suggest that funds in larger and more diversified families may receive advance signals about aggregate demand through their family-level observations. This information edge can in turn reduce their perceived uncertainty about future flow shocks, allowing them to have higher flow risk exposure. Thus, I predict positive relationships between fund-family scale, fund-family scope, and active flow beta.

3.2 Informational advantages and predictive ability

The prior hypotheses propose economic channels through which funds may receive early information about common flows. If these channels genuinely link informational advantages and fund flow-hedging behavior, flows of funds with higher flow risk exposure should contain information that can predict future aggregate flows. For example, if a fund's investor base receives early signals about market-wide demand shifts, the fund's own flows will reflect these signals before they propagate to industry flows.

This logic motivates a predictability test between aggregate industry flows and fund-level flows. If a fund's flows tend to predict industry flows, this suggests that the fund is exposed to early signals about investor demand, potentially through one or several channels proposed in the previous section. Based on this argument, I hypothesize that funds that have higher active flow beta experience flows that predict aggregate industry flows.

3.3 The cost of hedging

An important implication of the theoretical framework in Section 2 is that fund managers who hedge against flow risk more heavily do not have an informational edge about future flow shocks compared to those who tilt their portfolios toward high-flow-beta stocks. A natural prediction that follows is that this hedging behavior should be costly because it leads funds to forgo higher expected returns. Therefore, I hypothesize that funds with low active flow beta underperform funds with high active flow beta.

3.4 Flow hedging and public information precision

Equation 9 implies that the hedging behavior with respect to flow risk should vary with the precision of public information about the stock value.[9] Lower public-signal precision (i.e., an increase in the variance term ρ_1) increases posterior uncertainty about both stock value and future flows (see Equation A3 in the Internet Appendix). Although the private signal concerns flows, taking larger positions in stocks with higher flow beta increases exposure to flow risk. When fundamental estimates are less precise, the marginal benefit of having more precise signal about future flows (i.e., $\rho_\theta - \rho_2$) declines. Consequently, informed managers have weaker incentive to take riskier tilts toward high-flow-beta stocks. Therefore, the testable prediction is that the more imprecise the public information on stocks, the less informed funds tilt

[9]Taking the derivative of the flow risk coefficient in Equation 9 with respect to the public noise parameter shows that $\partial\Delta/(\partial\beta_{\text{flow}}\partial\rho_1) = -\left[(\rho_u\rho_F - \psi^2)^2(\rho_\theta - \rho_2)\right] / \left(\rho_1^2\kappa_1\kappa_2\right) < 0$.

toward stocks with high flow beta.

4 Data and sample construction

4.1 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.[10]. 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 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

[10] 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. I thank Kenneth French and Robert Stambaugh for making these data available.

data.

I follow Dou et al. (2025) 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.[11] I also remove funds for which fund names are missing. To address concerns related to omission bias (Elton et al., 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. Following Dannhauser and Spilker III's (2023) procedure, I also identify the family associated with each fund and keep only funds that are in a fund family.[12]

I supplement this sample with information on portfolio managers' compensation structure hand collected from funds' Statement of Additional Information (SAI). Following Ma and Tang (2019), I construct two indicator variables to identify whether the variable component in managers' pay 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*) or peer (*Peer benchmark*) indices to assess managers' performance. The variable *Pure and peer benchmarks* indicates whether

[11] 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'.

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

funds use both types of indices for performance assessment.

The final mutual fund sample contains 2,179 unique funds from 2006 to 2021.[13] 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 and Tang (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&P 500), 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.

4.2 Common flows and stock flow beta

Common flow shocks. I follow Dou et al. (2025) 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.[14] 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

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

[14] This is different from Dou et al.'s (2025) main procedure in which they use the full sample for estimation.

December 2005

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

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.[15] 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. (2025), 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 2 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

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

where $r_{i,t-\tau}$ is stock i's monthly excess returns, $\text{MKTRF}_{t-\tau}$ is the market excess returns, and $flow_{t-\tau}$ is the common fund flow shocks.[16] I require at least 12 months

[15] 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 et al., 2017, Sialm and Zhang, 2020).

[16] Dou et al. (2025) do not control for the market exposure. I include the market factor because the asset pricing model in Dou et al. (2025) represents an ICAPM model in which the market risk is priced.

of observations for each regression to ensure reliable estimation for $\beta_{\text{flow},i,t}$.

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. (2025), 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 natural logarithm of book-to-market ratio 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 A2 in the Internet Appendix provides the summary statistics for quintile portfolios of stocks sorted on their flow beta. Consistent with main findings in Dou et al. (2025), 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.[17] 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.

4.3 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 approach has been

[17]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).

analyzed and adopted in the literature on fund manager performance measures (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 and 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 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. (2025). 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 Internet Appendix Section A3 that the performance gap between high- and low-AFB funds do not change significantly when fund-specific benchmarks are used.

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 estimate of the performance gap significantly.

Table 2 shows the mean of fund characteristics for portfolios sorted by AFB. 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. (2025), 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 (e.g., *Return gap*). These results suggest that prominent fund performance predictors are unlikely 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 (2025) main argument that funds that are active hedge against flow risk more.

5 Empirical results

5.1 Compensation structure and flow hedging

Before testing the model's main mechanism that links informational advantages to flow-hedging behavior, I investigate whether differences in compensation structure can explain variation in flow hedging. This analysis is motivated by Dou et al. (2025)'s central argument that portfolio managers' compensation depends on fund size, which in turn is driven by fund flows. Since prior studies (e.g., Ma and Tang, 2019) document significant heterogeneity in compensation packages among U.S. portfolio managers, cross-sectional variation in compensation packages may be associated with variation in flow-hedging behavior.[18]

Table 3 reports results from linear probability regressions of funds' hedging status on variables that capture funds' compensation structure. At the beginning of each calendar quarter from 2006 to 2021, I sort all funds into quintile portfolios according to AFB. In Panel A (B), the dependent variable is an indicator equal to one if a fund belongs to the top (bottom) quintile of AFB (*High AFB Fund*) (*Low AFB Fund*). The regressions control for fund size, age, active share, expense ratio, turnover ratio, flows, returns, and institutional ownership. All independent variables are lagged by one quarter. All specifications include fund family by time fixed effects to account for unobservable time-varying factors at the fund family level. Standard errors are clustered at the fund family and time level.

The results in Panel A show that *AUM pay* is negatively associated with high-AFB status. Across specifications, high-AFB funds are approximately 3.5 percentage points less likely to disclose AUM-based compensation compared to other funds, and

[18] It is worth noting that the compensation incentive channel proposed by Dou et al. (2025) differs from the information channel proposed in this paper. In particular, the compensation channel suggests that managers hedge flow risk to protect AUM-based pay, whereas the information channel suggests that managers without advance signals hedge more due to higher uncertainty about future flow shocks.

the coefficient estimate is statistically significant at the 1% level. Since the sample unconditional mean of *AUM pay* is 19%, this estimate implies that high-AFB funds are roughly 20% less likely to report AUM-based compensation.

Since performance-based contracts can lead to excessive risk-taking behavior (Lee et al., 2019), the tilt toward stocks with higher flow beta could reflect performance-based compensation incentives. 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 contracts. Moreover, compensation based on peer benchmarks also does not appear to be associated with hedging behavior, suggesting that the performance of high-AFB funds is unlikely to reflect extra effort stemming from peer competition (Evans et al., 2020).

Turning to low-AFB funds, I find little evidence that compensation structure determines their behavior. While low-AFB funds appear less likely to have performance-based compensation in univariate specifications, the statistical significance disappears after controlling for other fund characteristics. Both *AUM pay* and *Peer benchmark* are also unrelated to managers' tilt toward low-flow-beta stocks. These results suggest that compensation structure is less informative for explaining the hedging behavior of low-AFB funds.

A caveat to the interpretation of these results is that the SAI-based compensation measures rely on coarse qualitative disclosures regarding fund managers' compensation. Recent studies suggest that these disclosures may not fully capture the true compensation structure of fund managers. Cen et al. (2023) show that compensation for U.S. active equity fund managers is primarily driven by fund AUM, even though funds infrequently mention AUM-based bonus payments in their SAIs. Similarly, Ibert et al. (2018) examine Swedish equity funds and document a weak relationship between fund managers' pay and fund performance, but a strong relationship between pay and fund size. These findings suggest that the estimated effects in Table 3 may not fully reflect the true relationship between compensation types and flow-hedging behavior. Despite this limitation, the empirical findings in this section suggest that differences in compensation packages are associated with cross-sectional variation in flow hedging.

5.2 Informational advantages and flow hedging

In this section, I test whether funds with larger tilts toward high-flow-beta stocks have greater informational advantages about future flows. Based on the hypotheses developed in Section 3.1, I construct four ex ante measures of informational advantages. The first measure calculates the fraction of a fund's share classes that are retail to capture its investor-base composition (Chen et al., 2010). The second measure calculates marketing expenses as the sum of a fund's 12b-1 fees and front-end sales loads to capture a fund's marketing intensity and its distribution channels (Roussanov et al., 2021). The third and fourth measures capture fund-family scale and scope using the natural logarithm of total net assets across all actively managed funds in a family and the natural logarithm of the number of distinct CRSP investment objective codes within a family, respectively (Dannhauser and Spilker III, 2023).

Table 4 reports results from quarterly panel regressions testing whether funds with greater informational advantages about future flows exhibit higher active flow beta. The regressions include time fixed effects to account for unobservable time-varying factors that may affect all funds simultaneously. I also control for fund size, fund age, active share, expense ratio, turnover ratio, and lagged fund flows and returns. Standard errors are clustered at the fund and time level.

Column (1) of Table 4 shows that the proportion of a fund's retail shares is positively associated with its tilt toward high-flow-beta stocks. This result supports the first hypothesis that funds with heavier retail clientele observe early demand shifts, reducing their perceived uncertainty about future flow shocks and leading them to hedge flow risk less aggressively. Column (2) shows that a fund's marketing expenses are positively associated with its active flow beta. This finding implies that funds spending more to compensate brokers and financial advisers exhibit larger tilts toward high-flow-beta stocks, consistent with the second hypothesis that these distribution relationships serve as information channels about investor demand. Column (3) shows that both fund-family scale and fund-family scope are positively associated with active flow beta. These results indicate that funds belonging to larger and more diversified families tilt more toward high-flow-beta stocks, consistent with the third hypothesis that funds learn from within-family flow movements about aggregate demand and adjust their flow-hedging behavior accordingly. Column (4) includes all proxies simultaneously. The coefficients remain statistically significant and similar in magnitude, suggesting that each economic channel captures distinct variation in informational advantages. Collectively, these results support the theoretical prediction that funds with greater informational advantages about future flows hedge flow risk less aggressively.

5.3 Informational advantages and predictive ability

In this section, I test the hypothesis from Section 3.2 that funds with higher active flow beta experience flows that predict aggregate industry flows. I test this conjecture by running the following panel regression:

$$\begin{aligned}\text{IndustryFlow}_{-j,q} = \beta_1 \text{AFB}_{j,q-1} &+ \sum_{m=1}^{2} \beta_{2,m}\, \text{IndustryFlow}_{-j,q-m} \\ &+ \sum_{m=1}^{2} \beta_{3,m}\, \text{Flow}_{j,q-m} + \sum_{m=1}^{2} \beta_{4,m}\, \text{AFB}_{j,q-1}\, \text{Flow}_{j,q-m} \\ &+ \boldsymbol{\gamma}'\mathbf{Controls}_{j,q-1} + \boldsymbol{\varphi}'\mathbf{Z}_{q-1} + \theta_j + \varepsilon_{j,q},\end{aligned} \tag{15}$$

where $\text{IndustryFlow}_{-j,q}$ is the quarterly net flow of the mutual fund industry in quarter q, excluding fund j, and $\text{Flow}_{j,q-m}$ is fund j's quarterly net flow lagged m quarters. $\mathbf{Controls}_{j,q-1}$ is the vector of lagged fund-level control variables as in the prior section, and $\mathbf{Z}_{q-1}$ is a vector of lagged macroeconomic and financial predictors, including market excess return, market return volatility, dividend-to-price ratio, term spread and inflation rate.[19] The term θ_j denotes fund (or fund-family) fixed effects, and standard errors are clustered at the fund and time level.[20]

Table 5 reports results from the regression. The key variables of interest are interactions between a fund's active flow beta and its flows at various lags (i.e., $\beta_{4,m}$). I include up to two quarters of lags to assess the horizon over which flows exhibit predictive power. If high-AFB funds possess early information about common flows, their flows should anticipate industry movements, implying a positive coefficient $\beta_{4,m}$.

The results support the predictability hypothesis. Across different specifications, the coefficient on the interaction term between AFB and the fund's flow in the prior quarter is positive and statistically significant, indicating that flows of higher-AFB funds predict industry flows. The estimated effect is stable as I add fund-level controls in Column (2), add macroeconomic and financial controls in Column (3), and replace fund fixed effects with fund-family fixed effects in Column (4). This suggests that flows of funds with higher AFB may contain advance signals about future investor demand. Moreover, the coefficient estimates are substantially weaker at the longer horizon as $\beta_{4,2}$ is small and statistically insignificant throughout, suggesting that flows are more likely to contain short-term information about investor demand. Overall, these results are consistent with the hypothesis that funds that hedge flow risk less

[19]The macroeconomic and financial variables are obtained from Amit Goyal's website. I thank him for making the data available.

[20]Because the dependent variable is measured at the industry level, I do not include time fixed effects, which would absorb the aggregate flow variation that the test seeks to explain. I also exclude the contemporaneous fund flow, which is jointly determined with industry flow within the quarter through the shared common-flow component. Including it would create a near-collinearity problem and distort inference.

aggressively receive early signals about aggregate investor demand.[21]

Table 6 extends the analysis to the portfolio level. At the beginning of each quarter, I sort funds into quintile portfolios based on their active flow beta, and each portfolio is held for the subsequent three months. I construct monthly flows for each portfolio based on the aggregate assets under management of underlying funds, and test whether these flows predict the aggregate flow of the active equity fund industry and the common flow shock. In particular, I regress each dependent variable in month t on the portfolio's flows in months $t-1$, $t-2$, and $t-3$, and use the Wald statistic to test the joint null hypothesis that all lagged flow coefficients are equal to zero.

Panel A uses the monthly aggregate flow of active equity funds, excluding the focal portfolio, as the dependent variable. The results show that the ability of fund flows to predict future aggregate flows strengthens with AFB. On one hand, the flows of funds in the fourth and fifth AFB quintiles jointly predict future aggregate flows, with Wald p-values of 0.05 and 0.00, respectively. The prior-month flows of funds in the third quintile also appear to predict aggregate flows, although the joint evidence is weaker (Wald p-value = 0.26). On the other hand, the flows of funds in the lowest and second quintiles exhibit no such predictive power (Wald p-values of 0.64 and 0.60, respectively).

Panel B uses the common flow shock, constructed as in Section 4.2, as the dependent variable. The results reveal a similar pattern. On one hand, the flows of funds in the fourth and fifth AFB quintiles jointly predict the common flow shock, with Wald p-values of 0.00 and 0.05, respectively. On the other hand, the flows of funds in the three lowest quintiles exhibit no such predictive power (Wald p-values of 0.88, 0.59, and 0.88, respectively).

[21] In Internet Appendix Table A3, I provide an additional test that uses the common flow shock, rather than industry flows, as the dependent variable. Because the common flow shock is identical across funds within each period, standard panel inference may overstate precision. Therefore, I compute standard errors using a block bootstrap, and still find that the flows of higher-AFB funds predict future common flows.

Collectively, these results imply that funds with higher active flow beta may receive early signals about aggregate flows through their own fund flows, consistent with the theoretical prediction that informed fund managers hedge flow risk less aggressively.

5.4 The cost of hedging

Prior sections provide empirical evidence that funds with private information about future common flows hedge flow risk less aggressively. A natural question is whether this reduced hedging provides any compensation. In this section, I test whether aggressive hedging against flow risk is costly, following the hypotheses developed in Section 3.3.

To test this prediction, 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 three 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)

$$
\begin{aligned}
r_{p,t} - r_{f,t} = \alpha_p + &\beta_{p,\mathrm{MKTRF}}\mathrm{MKTRF}_t + \beta_{p,\mathrm{SMB}}\mathrm{SMB}_t + \beta_{\mathrm{p,HML}}\mathrm{HML}_t + \\
&\beta_{p,\mathrm{CMA}}\mathrm{CMA}_t + \beta_{p,\mathrm{RMW}}\mathrm{RMW}_t + \beta_{p,\mathrm{UMD}}\mathrm{UMD}_t + \varepsilon_{p,t},
\end{aligned}
\tag{16}
$$

where $r_{p,t} - r_{f,t}$ 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.[22]

Table 7 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

[22] When I add Pástor and Stambaugh's (2003) liquidity factor to the six-factor model to account for the portfolios' exposure to aggregate liquidity risk, the coefficient estimates and their statistical significance do not change materially.

that the six-factor alpha increases monotonically across AFB quintiles, from −0.14% per month for the lowest quintile to 0.14% per month for the highest quintile. The difference in gross alpha between high- and low-AFB funds is 0.28% per month, or 3.36% per year, and is statistically significant at the 5% level (t-statistic = 2.11).[23] Panel B shows that the alpha spread remains economically and statistically significant after adjusting for expense ratios ($\alpha = 0.28\%$, t-statistic = 2.11), indicating that the performance differential is not driven by differences in fund fees.

The performance gap between high- and low-AFB funds provides direct evidence of the cost of hedging flow risk. In their theoretical work, Dou et al. (2025) show that active funds tilt away from stocks with higher flow betas to hedge flow risk. Their model implies that hedging flow betas is costly because it leads funds to forgo the potential compensation for bearing common flow risk. The empirical findings here complement and reinforce their theoretical analysis by explicitly quantifying this cost: funds that hedge flow risk more aggressively underperform funds that hedge less aggressively by approximately 3.36% per year.

It is worth noting that the premium earned by high-AFB funds may arise from the informational advantage channel, the common flow risk channel, or both. While the results from Section 5.3 on the predictive ability of high-AFB funds' flows for macroeconomic variables suggest that informational advantages play a role, I do not rule out the possibility that compensation for bearing common flow risk also contributes to the performance differential.[24] Consequently, the performance analysis in this section focuses on quantifying the magnitude of the performance gap between high- and low-AFB funds rather than attributing it to a single source.[25]

[23]Since mutual funds cannot be shorted, this strategy is not implementable in practice. Therefore, the High−Low spread should be interpreted as the additional gross return that an investor would earn on average by investing in high-AFB funds rather than low-AFB funds.

[24]The absence of significant factor exposures reported in Table 7 for the high-minus-low portfolios also indicates that the outperformance of high-AFB funds does not reflect compensation for bearing common systematic risks. This finding provides further evidence supporting Dou et al. (2025), who show that common flow shocks represent a distinct and priced risk source.

[25]The Appendix provides further robustness tests to assess whether the cost of hedging can be

5.5 Flow hedging and public information precision

The previous analysis shows that funds with higher active flow beta incur lower hedging costs and have better performance. In this section, I test the last hypothesis developed in Section 3.4 about the relationship between flow-risk hedging and the precision of public information. Equation 9 implies that when public information about stock value is less precise, the marginal benefit of possessing a more accurate private signal about future flows declines. Consequently, even funds with informational advantages have weaker incentives to tilt toward high-flow-beta stocks when fundamental uncertainty is high. The testable prediction is that the more imprecise the public information on stocks, the less high-AFB funds deviate from the benchmark with respect to flow beta.

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 public information uncertainty. 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 portfolio-level holdings for each stock. I then perform the following quarterly Fama-MacBeth regressions for each portfolio:

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

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-AFB funds.

explained by other standard measures of fund performance.

Table 8 reports the coefficient estimates and their statistical significance from Equation 17 for the high- and low-AFB portfolios. Panels A and B use analysts' disagreement and stocks' idiosyncratic volatility as proxies for public information imprecision, respectively. The last row reports the difference in coefficients between the two portfolios. First, the difference in the coefficient on β_{flow} between high- and low-AFB funds is positive and statistically significant. This finding is consistent with the main prediction that funds with informational advantages about future flows deviate more from the benchmark with respect to flow beta. Second, the coefficient on $\beta_{\text{flow}} \times \sigma$ is smaller in the high-AFB portfolio by a large magnitude compared to the low-AFB portfolio. The difference is -0.052 and statistically significant at the 1% level. Consistent with the model's prediction, high-AFB funds reduce their deviation from the market benchmark when public information on stocks is less precise. This result suggests that when fundamental uncertainty reduces the marginal benefit of possessing a more accurate private signal about future flows, informed funds reduce their exposure to flow risk.

Finally, I examine whether the cost of hedging flow risk varies with aggregate market conditions. If low-AFB funds incur costs by hedging aggressively against flow risk, these costs may increase during periods of heightened disagreement for at least two reasons. First, the forgone flow risk premium is likely larger when fundamental uncertainty is high. Taking large positions in high-flow-beta stocks during such periods is riskier, and investors demand greater compensation for bearing this risk. Second, market disagreement is associated with lower liquidity and higher transaction costs (Sadka and Scherbina, 2007), making it more expensive for funds to rebalance their portfolios away from high-flow-beta stocks.

To test this hypothesis, I examine whether the performance difference between high- and low-AFB funds varies with aggregate public information imprecision. Following Huang et al. (2021), I construct aggregate versions of the two disagreement measures using stocks' market capitalization as weights. I then create an indicator variable ($VolatilityIndicator$) equal to one if a month falls in the top quintile of the aggregate disagreement measure, and zero otherwise. For each quintile portfolio sorted on AFB, I estimate a time-series regression that adjusts for risk exposures using the six-factor model:

$$\begin{aligned} r_{p,t} - r_{f,t} =& \alpha_p + \beta_{p,\text{vol}}\text{VolatilityIndicator}_t + \beta_{p,\text{MKTRF}}\text{MKTRF}_t + \beta_{p,\text{SMB}}\text{SMB}_t + \\ & \beta_{p,\text{HML}}\text{HML}_t + \beta_{p,\text{CMA}}\text{CMA}_t + \beta_{p,\text{RMW}}\text{RMW}_t + \beta_{p,\text{UMD}}\text{UMD}_t + \varepsilon_{p,t}. \end{aligned} \tag{18}$$

If the cost of hedging flow risk increases during periods of high disagreement, the performance gap should widen during these periods (i.e., positive β_{vol} for the high-minus-low portfolio).

Table 9 reports the results from Equation 18 for the high- and low-AFB 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 prediction that hedging costs are amplified during periods of elevated disagreement, the performance gap widens significantly during high-disagreement months. On average, high-AFB funds outperform low-AFB funds by 0.98% per month during periods when analysts have the most diverse opinions (Panel A), and by 0.62% per month when aggregate idiosyncratic volatility is high (Panel B). Both differences are economically large and statistically significant. [26]

6 Conclusion

There is a significant heterogeneity in flow-hedging behavior among U.S. domestic active equity mutual funds: nearly half of active equity funds tilt their portfolios to-

[26]This result is also consistent with a conditional asset-pricing interpretation in which the flow risk premium is time-varying and may increase during periods of heightened disagreement and risk aversion.

ward high-flow-beta stocks. I rationalize this finding in an extended model featuring informed and uninformed investors who differ in the precision of private signals about future flows. The key intuition is that more precise signals reduce perceived uncertainty about future flow shocks, leading informed investors to hedge less aggressively.

Empirical analyses show that funds with high exposure to flow risk are indeed associated with proxies for informational advantages, including investor-base composition, marketing intensity and fund-family scale and scope. I further validate this information-based mechanism by showing that flows of funds that hedge flow risk less predict aggregate industry flows and the common flow shock. In contrast, flows of funds with low flow risk exposure exhibit no such predictive ability. Moreover, hedging against flow beta is costly as funds that hedge the most underperform funds that hedge the least by over 3% annually.

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Figure 1. Distribution of fund tilts away from high flow-beta stocks

This figure shows the distribution of fund-level tilts 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 estimated tilting coefficients $\gamma_{1,j,q}$ across quarters 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's weight in fund j from its market weight in quarter $q+1$. β_{flow} is estimated following Dou et al. (2025) and described in details in Section 4.2, and β_{market} is estimated using a 60-month rolling regression of stock i's monthly excess returns on the market excess returns. All variables are standardized to have mean zero and unit standard deviation. The vertical red line illustrates the estimated coefficient obtained from the aggregate mutual fund portfolio as in Dou et al. (2025). The sample period is from 2006Q1 to 2021Q4.

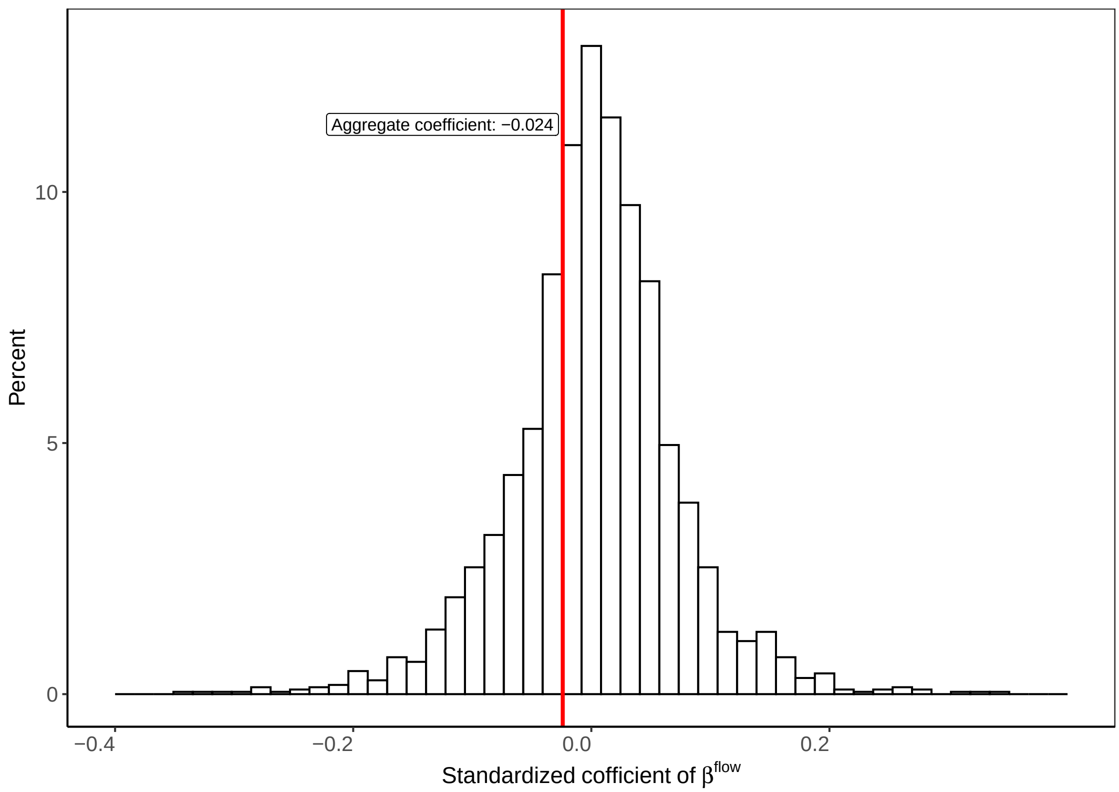


Figure 2. Common fund flows

This figure shows the monthly time-series of the common fund flows over the the sample period from 2006 to 2021. The common flows are constructed following Dou et al. (2025) and described in details in Section 4.2. Shaded areas denote NBER-dated recessions.

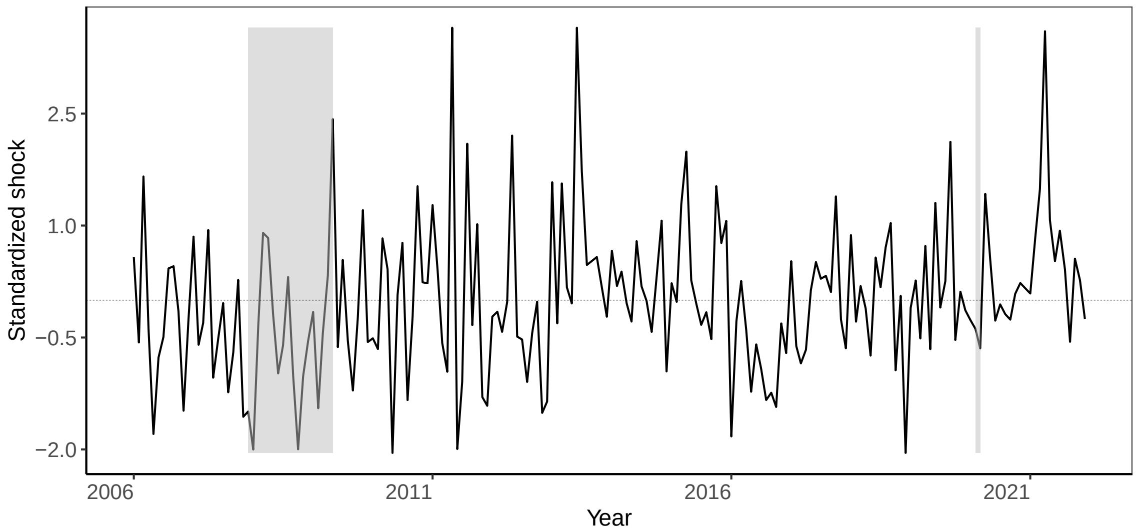


Table 1. Summary statistics

This table reports summary statistics for the stock and fund samples. Panel A reports statistics for the fund sample, which includes U.S. domestic actively managed equity funds. Data on compensation structures and benchmarks are obtained from funds Statement of Additional Information. Panel B reports statistics for the stock sample, which includes U.S. common stocks listed on the NYSE, NASDAQ, and AMEX with at least two years of Compustat data. β_{flow} is estimated monthly using a 36-month rolling regression of stock excess returns on common flow shocks, controlling for the market factor. Table A1 describes all variables in detail. The sample period is from Jan 2006 to Dec 2021.

	Mean	SD	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	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
Pure and peer 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
Size	6.316	2.070	3.611	4.778	6.287	7.748	9.068
$\text{Size}_{\text{median}}$	−0.005	0.613	−0.694	−0.268	0.003	0.307	0.671
Ln(Book-to-market)	−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 across active flow beta levels

This table presents summary statistics for fund characteristics across portfolios formed by sorting funds on active flow beta. Table A1 describes all variables in detail. Additional variables include Kacperczyk et al.'s (2008) *Return gap*, Huang et al.'s (2011) *Risk shifting*, Cremers and Petajisto's (2009) *Active share*, Amihud and Goyenko's (2013) R^2, Kacperczyk and Seru's (2007) *Response to public information (RPI)* and Avramov et al.'s (2020) *Active fund overpricing (AFO)*. The sample period is from 2006Q1 to 2021Q4. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	P2	P3	P4	High	High−Low
	(1)	(2)	(3)	(4)	(5)	(6)
TNA ($ million)	1462.445	2239.442	2519.223	2344.676	2394.392	931.947***
Age	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 (AFB)	−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. Flow hedging and fund compensation structure

This table reports results from quarterly panel regressions of fund active flow beta on fund characteristics and portfolios managers' compensation structure. Panel A (Panel B) presents results for funds in the top (bottom) quintile of the active flow beta distribution. The dependent variable is an indicator equal to one if a fund belongs to the top (bottom) quintile and zero otherwise. *Performance pay*, *AUM pay*, *Advisor-Profit pay*, *Deferred compensation* are indicator variables capturing different features of portfolio managers compensation structures. *Peer benchmark* is an indicator equal to one if the performance benchmark used in portfolio managers compensation is based solely on peer indices and zero otherwise. Control variables include fund size, fund age, active share, expense ratio, turnover ratio, fund flows, fund returns and institutional ownership, all measured in the prior period. Table A1 describes all variables in detail. Standard errors are clustered at the fund family and time level and are shown in parentheses. The sample period is from 2006Q1 to 2021Q4. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Panel A: High AFB fund (q)			
Performance pay (q-1)	−0.003		−0.003	−0.003
	(0.017)		(0.017)	(0.017)
AUM pay (q-1)	−0.036***		−0.036***	−0.036***
	(0.013)		(0.013)	(0.013)
Advisor-Profit pay (q-1)	0.008		0.008	0.009
	(0.012)		(0.012)	(0.012)
Deferred compensation (q-1)	−0.012		−0.012	−0.012
	(0.013)		(0.013)	(0.013)
Peer benchmark (q-1)		−0.001	−0.003	−0.006
		(0.020)	(0.020)	(0.019)
Adj. R^2	0.05	0.05	0.05	0.06
	Panel B: Low AFB fund (q)			
Performance pay (q-1)	−0.032*		−0.035**	−0.024
	(0.017)		(0.017)	(0.015)
AUM pay (q-1)	−0.000		0.001	−0.008
	(0.014)		(0.014)	(0.013)
Advisor-Profit pay (q-1)	−0.012		−0.014	−0.013
	(0.013)		(0.013)	(0.012)
Deferred compensation (q-1)	−0.004		−0.003	−0.001
	(0.013)		(0.013)	(0.012)
Peer benchmark (q-1)		0.026	0.031	0.018
		(0.019)	(0.019)	(0.017)
Adj. R^2	0.06	0.06	0.06	0.08
Fund family × Time FEs	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
# of obs.	63,355	63,355	63,355	63,355

Table 4. Flow hedging and informational advantages

This table reports results from quarterly panel regressions of fund active flow betas on fund characteristics that proxy for informational advantages on future flows. *Proportion of retail shares* is the fraction of a fund's share classes that are retail. *Marketing expenses* is a fund's combined 12b-1 fee and front load. *Fund-family scale* and *Fund-family scope* are the natural logarithms of the total net assets and the number of distinct CRSP investment objective codes, respectively, of all actively managed mutual funds in a fund family. Control variables include fund size, fund age, active share, expense ratio, turnover ratio, and fund flows and returns, all measured in the prior period. Table A1 describes all variables in detail. Continuous variables are standardized to have mean zero and unit standard deviation. Standard errors are clustered at the fund and time level and are shown in parentheses. The sample period is from 2006Q1 to 2021Q4. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Active flow beta (q)			
	(1)	(2)	(3)	(4)
Proportion of retail shares (q)	0.020***			0.019***
	(0.004)			(0.004)
Marketing expenses (q)		0.015***		0.010**
		(0.004)		(0.004)
Fund-family scale (q)			0.011*	0.011*
			(0.006)	(0.006)
Fund-family scope (q)			0.013**	0.014**
			(0.006)	(0.006)
Time FEs	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Adj. R^2	0.21	0.21	0.21	0.21
# of obs.	60,807	60,807	60,807	60,807

Table 5. Flow hedging and the predictive power of fund flows: Panel regressions

This table reports results from quarterly panel regressions of industry flows on active flow beta (AFB), fund flows, and their interaction. *Industry flow* is the quarterly growth rate of assets under management for the mutual fund industry, excluding the focal fund. *Flow* is the focal fund's quarterly growth rate of assets under management. Fund-level control variables include fund size, fund age, active share, expense ratio, turnover ratio, and fund flows and returns. Macroeconomic and financial control variables include market excess return, market return volatility, dividend-to-price ratio, term spread, and inflation rate. All control variables are measured in the prior period. Table A1 describes all variables in detail. Continuous variables are standardized to have mean zero and unit standard deviation. Standard errors are clustered at the fund and time level and are shown in parentheses. The sample period is from 2006Q1 to 2021Q4. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Industry flow (q)			
	(1)	(2)	(3)	(4)
AFB × Flow (q-1)	0.024*	0.028**	0.030***	0.026**
	(0.013)	(0.012)	(0.010)	(0.011)
AFB × Flow (q-2)	−0.001	0.006	0.007	0.001
	(0.009)	(0.010)	(0.009)	(0.009)
AFB (q-1)	0.071	0.131	0.103	0.038
	(0.126)	(0.129)	(0.123)	(0.091)
Flow (q-1)	0.015	−0.008	−0.008	−0.006
	(0.010)	(0.008)	(0.008)	(0.008)
Flow (q-2)	0.019*	−0.004	−0.001	0.004
	(0.010)	(0.009)	(0.008)	(0.007)
Industry flow (q-1)	0.449***	0.398***	0.297	0.301
	(0.137)	(0.138)	(0.181)	(0.183)
Industry flow (q-2)	−0.314***	−0.342***	−0.474***	−0.452***
	(0.107)	(0.114)	(0.135)	(0.137)
Fund FEs	Yes	Yes	Yes	
Fund family FEs				Yes
Fund-level controls		Yes	Yes	Yes
Macro & financial controls			Yes	Yes
Adj. R^2	0.21	0.27	0.35	0.34
# of obs.	61,191	61,191	61,191	61,219

Table 6. Flow hedging and the predictive power of fund flows: Portfolio sorts

This table reports results from monthly time-series regressions of industry flows (Panel A) and common flows (Panel B) on the flows of funds sorted by active flow beta. Funds are sorted into quintile portfolios based on their active flow beta at the beginning of each calendar quarter. Portfolio-level flows (*Flow*) are measured using changes in the aggregate assets under management across all funds within each portfolio. *Industry flow* is the monthly growth rate of assets under management for the mutual fund industry, excluding the funds in the sorted portfolio. *Common flow* is the first principal component of size-sorted fund-flow shocks. All regressions include a set of macroeconomic and financial control variables: market excess return, market return volatility, dividend-to-price ratio, term spread, and inflation rate. The p-value of the Wald statistic tests the joint null hypothesis that all lagged flow coefficients are equal to zero. The sample period is from Jan 2006 to Dec 2021. Newey-West adjusted standard errors are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Low	2	3	4	High
	(1)	(2)	(3)	(4)	(5)
	Panel A: Industry flow (t)				
Flow (t-1)	−0.048	−0.055	0.167*	−0.087	0.247***
	(0.098)	(0.086)	(0.095)	(0.078)	(0.078)
Flow (t-2)	−0.037	0.016	−0.050	−0.089	−0.064
	(0.084)	(0.062)	(0.072)	(0.075)	(0.081)
Flow (t-3)	0.078	0.094	0.044	0.181**	0.193***
	(0.079)	(0.077)	(0.083)	(0.072)	(0.064)
p-value Wald statistic	0.64	0.60	0.26	0.05	0.00
Adj. R^2	0.01	0.01	0.04	0.03	0.09
# of obs.	189	189	189	189	189
	Panel B: Common flow (t)				
Flow (t-1)	−0.008	0.092	0.061	0.120*	0.029
	(0.075)	(0.083)	(0.080)	(0.069)	(0.082)
Flow (t-2)	−0.044	−0.009	−0.018	0.100	0.028
	(0.067)	(0.081)	(0.080)	(0.065)	(0.086)
Flow (t-3)	−0.036	−0.037	−0.001	0.150***	0.158***
	(0.064)	(0.063)	(0.066)	(0.052)	(0.059)
p-value Wald statistic	0.88	0.59	0.88	0.00	0.05
Adj. R^2	0.04	0.04	0.04	0.08	0.06
# of obs.	189	189	189	189	189

Table 7. Flowing hedging and mutual fund performance

This table reports the performance of quintile fund portfolios sorted on active flow beta. At the beginning of each calendar quarter, funds are sorted into quintiles based on their active flow beta, and portfolio performance is evaluated over the subsequent three months. Portfolios are rebalanced quarterly. *High* (*Low*) denotes the top (bottom) quintile portfolio. Risk-adjusted returns are estimated using the Fama and French (2015) five-factor model augmented with the Carhart's (1997) momentum factor. Panel A (B) reports results based on gross (net) returns. Alphas are reported in monthly percentage. The sample period is from Jan 2006 to Dec 2021. Newey-West adjusted t-statistics are reported 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 8. Flow hedging and precision of public information

This table reports results from Fama-MacBeth regressions examining how deviations of fund portfolio allocations from benchmark allocations relate to active flow beta and its interaction with measures of the precision of public information:

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

where $\omega_{p,i,q+1} - \omega_{m,i,q+1}$ denotes the deviation of stock i's weight in portfolio p its market weight, and $\sigma_{i,q}$ denotes the precision of public information for stock i. At the beginning of each calendar quarter, funds are sorted into quintiles based on their active flow beta, with *High* (*Low*) denoting the top (bottom) quintile portfolio. Panel A (Panel B) uses analysts' forecast dispersion (idiosyncratic volatility) as a proxy for the imprecision of public information. All variables are standardized to have mean zero and unit standard deviation. The sample period is from 2006Q1 to 2021Q4. Newey-West adjusted standard errors are reported in parentheses. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

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

Table 9. Flow hedging, precision of public information and fund performance

This table reports the performance of quintile fund portfolios sorted on active flow beta conditional on periods of high public information imprecision. At the beginning of each calendar quarter, funds are sorted into quintiles based on their active flow beta, and portfolio performance is evaluated over the subsequent three months. Portfolios are rebalanced quarterly. *High* (*Low*) denotes the top (bottom) quintile portfolio. Panel A (B) analysts' forecast dispersion (idiosyncratic volatility) as a proxy for the imprecision of public information. *Volatility indicator* is an indicator equal to one if a given month falls in the top quintile of public information imprecision. I compute monthly equally-weighted average net returns on the portfolios, and report the risk-adjusted net returns using the Fama and French (2015) five-factor model augmented with the Carhart's (1997) momentum factor. Alphas are reported in monthly percentage. The sample period is from Jan 2006 to Dec 2021. Newey-West adjusted t-statistics are reported 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]

Internet Appendix

A1 Model details

In this section, I provide additional details on the solution of the theoretical model in Section 2. 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

$$x^{I*} = \frac{1}{\gamma} \frac{E_{\mathbf{s}}(u^I - p)}{\mathrm{Var}_{\mathbf{s}}(u^I)} - \beta^I_{\text{flow}} \frac{\mathrm{Var}_{\mathbf{s}}(F^I)}{\mathrm{Var}_{\mathbf{s}}(u^I)}. \tag{A1}$$

Using Bayes' rule, we can obtain the posterior distribution of the asset value and flow. For informed investor I, the distribution $(u^I, F^I | s^I)$ is bivariate normal with the conditional mean

$$\begin{bmatrix} \frac{\rho_1(\rho_2+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_1 s_1 + \rho_1\psi s_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} \\ \\ \frac{-\rho_2\psi\bar{u} + \rho_2(\rho_1+\rho_u)\bar{F} + \rho_2\psi s_1 + (\rho_F\rho_1 + \rho_u\rho_F - \psi^2)s_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} \end{bmatrix}. \tag{A2}$$

The conditional variance-covariance matrix is

$$\begin{bmatrix} \frac{\rho_1\kappa_1}{\rho_1(\rho_2+\rho_F)+\kappa_1} & \frac{\rho_1\rho_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} \\ \\ \frac{\rho_1\rho_2}{\rho_1(\rho_2+\rho_F)+\kappa_1} & \frac{\rho_2(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1(\rho_2+\rho_F)+\kappa_1} \end{bmatrix} \tag{A3}$$

The informed investors' optimal allocation then follows

$$\begin{aligned} x^{I*} = {} & \frac{\rho_1(\rho_2+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_1 s_1 + \rho_1\psi s_2 - p[\rho_1(\rho_2+\rho_F)+\kappa_1]}{\gamma\rho_1\kappa_1} \\ & - \beta^I_{\text{flow}} \frac{\rho_2(\rho_F\rho_1 + \rho_u\rho_F - \psi^2)}{\rho_1\kappa_1}. \end{aligned} \tag{A4}$$

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.

$$p = a_1\bar{u} - a_2\bar{F} + bs_1 + cs_2 - dt + e\bar{t} + g. \tag{A5}$$

This is also the equilibrium price. The uninformed investors obtain noisy signals θ

that is a random variable defined as

$$\theta = \frac{p - a_1\bar{u} - a_2\bar{F} - bs_1 + \bar{t}(d-e) - f}{c} = s_2 - (t - \bar{t})\frac{d}{c}. \tag{A6}$$

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

$$\theta \sim N\left(F, \left(\frac{d}{c}\right)^2 \eta + \rho_2\right). \tag{A7}$$

The posterior distribution of the asset value and flow for uninformed investor U $(u^U, F^U | s^U)$ then follows a bivariate normal distribution with the conditional mean

$$\begin{bmatrix} \frac{\rho_1(\rho_\theta+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_2 s_1 + \rho_1\psi s_2}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \\ \frac{-\rho_\theta\psi\bar{u} + \rho_\theta(\rho_1+\rho_u)\bar{F} + \rho_\theta\psi s_1 + (\rho_F\rho_1 + \rho_u\rho_F - \psi^2)\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \end{bmatrix}. \tag{A8}$$

The conditional variance-covariance matrix is

$$\begin{bmatrix} \frac{\rho_1\kappa_2}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} & \frac{\rho_1\rho_\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \\ \frac{\rho_1\rho_\theta}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} & \frac{\rho_\theta(\rho_F\rho_1+\rho_u\rho_F-\psi^2)}{\rho_1(\rho_\theta+\rho_F)+\kappa_2} \end{bmatrix}. \tag{A9}$$

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

$$\begin{aligned} x^{U*} = &\frac{\rho_1(\rho_\theta+\rho_F)\bar{u} - \rho_1\psi\bar{F} + \kappa_2 s_1 + \rho_1\psi s_2 - p[\rho_1(\rho_\theta+\rho_F)+\kappa_2]}{\gamma\rho_1\kappa_2} \\ &- \beta^U_{\text{flow}}\frac{\rho_\theta(\rho_F\rho_1 + \rho_u\rho_F - \psi^2)}{\rho_1\kappa_2}. \end{aligned} \tag{A10}$$

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

$$\alpha x^{I*} + (1-\alpha)x^{U*} = t. \tag{A11}$$

The solution for the equilibrium price is presented in Equation 7 in the main text. Plugging into Equations A4 and A10, 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.

A2 Model assumptions and limitations

The theoretical model in the paper is stylized to deliver tractable and testable predictions, and this tractability rests on several simplifying assumptions. In this section, I discuss the three assumptions that limit the predictions the paper can make and verify with empirical data: (1) the model does not distinguish between investors and mutual fund managers; (2) the model features only a single risky asset; and (3) the model treats the common flow as exogenously specified rather than micro-founded.

First, the model does not distinguish between investors and mutual fund managers, and treats investors as delegated agents who observe flows and make portfolio decisions. This assumption ignores agency frictions between fund managers and their clients that may affect portfolio choices (e.g., career concerns or compensation incentives). As a result, the model cannot generate predictions about how agency conflicts interact with informational advantages in determining flow-hedging behavior.

Second, the model features only a single risky asset, which helps it to focus on the key mechanism that connects information precision with flow-hedging behavior. However, this simplification limits the model's ability to generate predictions about within-style heterogeneity in flow hedging that may arise from cross-asset correlations. In a multi-asset framework, flows in and out of different assets may reflect style or strategy chasing (e.g., moving between growth and value funds), and managers may hedge differently depending on the flow characteristics of their investment style. With a single-asset framework, the model cannot generate predictions about why, for example, growth funds hedge flow risk differently than value funds.

Third, the model treats the common flow component as exogenously specified rather than micro-founded. In Dou et al. (2025), flows are endogenously driven by aggregate shocks, which provides a structural explanation for potential sources of flow shocks. In contrast, this paper's model is agnostic about the economic drivers behind common flows. This in turn limits the identification of exact structural sources that provide information about future flow shocks. Thus, the empirical analyses rely on economically motivated proxies that are plausibly associated with early information about aggregate investor demand. Future research could extend the model to endogenize the information acquisition process, which would provide clearer guidance on the sources of informational advantages.

A3 Robustness tests

In this section, I report additional robustness tests. I first show that the predictive relation between flows of higher-AFB funds and aggregate flows is robust to using the common flow shock as the dependent variable. I then examine the robustness of the performance gap between high- and low-AFB funds to alternative explanations and the choice of fund benchmark.

A3.1 Predicting common flow shocks

The panel regressions in Section 5.3 use industry flows as the dependent variable. An alternative test of whether high-AFB funds are informed about broad common flows would be replacing industry-flow measure with the common-flow measure. However, using the common flows as the dependent variable in full-sample panel regressions raises an inference concern. Because the common flow shock is identical across funds within a given quarter, the effective variation in the dependent variable is closer to the time-series dimension than the fund-quarter panel suggests, so standard fund-level inference may overstate precision.

To address this concern, I re-estimate the panel regression with the common flows as the dependent variable, and obtain coefficient estimates and compute standard errors using a quarter block bootstrap. Specifically, in each of 10,000 replications, I draw blocks of L consecutive quarters with replacement until the resampled panel reaches the full-sample length, retain all fund observations within the sampled quarters, and re-estimate the regression with the OLS method. Resampling adjacent quarters rather than individual fund-quarter observations preserves both the within-quarter commonality and the serial dependence of the common flows. I report results for block lengths of four, six, and eight quarters.

Table A3 reports the estimates. Consistent with the main result, the interaction between active flow beta and prior quarter's flow is positive across all three block lengths and statistically significant at the 10% level, reinforcing the evidence that high-AFB funds' flows anticipate common flow movements.

A3.2 Persistence of flow hedging behavior

A natural question is whether the performance difference between high- and low-AFB funds reflects a persistent characteristic of funds or a transitory deviation. If high-AFB funds earn a premium for bearing flow risk, this premium should persist as long as funds maintain their exposure to high-flow-beta stocks. To examine this, I track 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. I then track the portfolio rank and AFB of each fund for the subsequent ten 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 across the full sample to obtain the trajectory of portfolio ranks and active flow betas.

Figure A1 plots the trajectory of the portfolio rank (Panel A) and the active flow beta (Panel B). Panel A shows that funds in the high-AFB portfolio continue to rank in the top quintile for more than ten quarters, or over two years. Conversely, funds in the low-AFB portfolio remain at the bottom for a similar period. Panel B shows that the persistence in ranking reflects persistence in the underlying AFB measure as top-quintile funds maintain positive AFB throughout the tracking period. These findings suggest that the performance difference between high- and low-AFB funds reflects a stable characteristic of funds' exposure to flow risk.

A3.3 Double portfolio sorts

The main analysis shows that funds with higher AFB earn higher risk-adjusted returns. However, the literature has documented several fund characteristics that also predict future performance. An important question is whether the AFB premium simply reflects other established predictors of fund performance. To address this, I test whether AFB provides incremental information for fund performance above and beyond what other characteristics have provided.

I consider five established fund characteristics: Kacperczyk et al. (2008)'s *Return gap*, Huang et al. (2011)'s *Risk shifting*, Cremers and Petajisto (2009)'s *Active share*, Kacperczyk and Seru (2007)'s *Reliance on public information* (RPI), and Avramov et al. (2020)'s *Active fund overpricing* (AFO). I adopt independent double portfolio sorts to examine whether the AFB premium remains robust after controlling for each characteristic. Specifically, at the beginning of each calendar quarter from 2006 to 2021, I independently sort all funds into quartile portfolios according to AFB and, simultaneously, into quartile portfolios according to one of the five characteristics. I compute equal-weighted returns for each of the resulting 16 portfolios in the first month of each quarter and track their excess returns over the next three months. Portfolios are rebalanced quarterly. I report risk-adjusted returns according to the six-factor model.

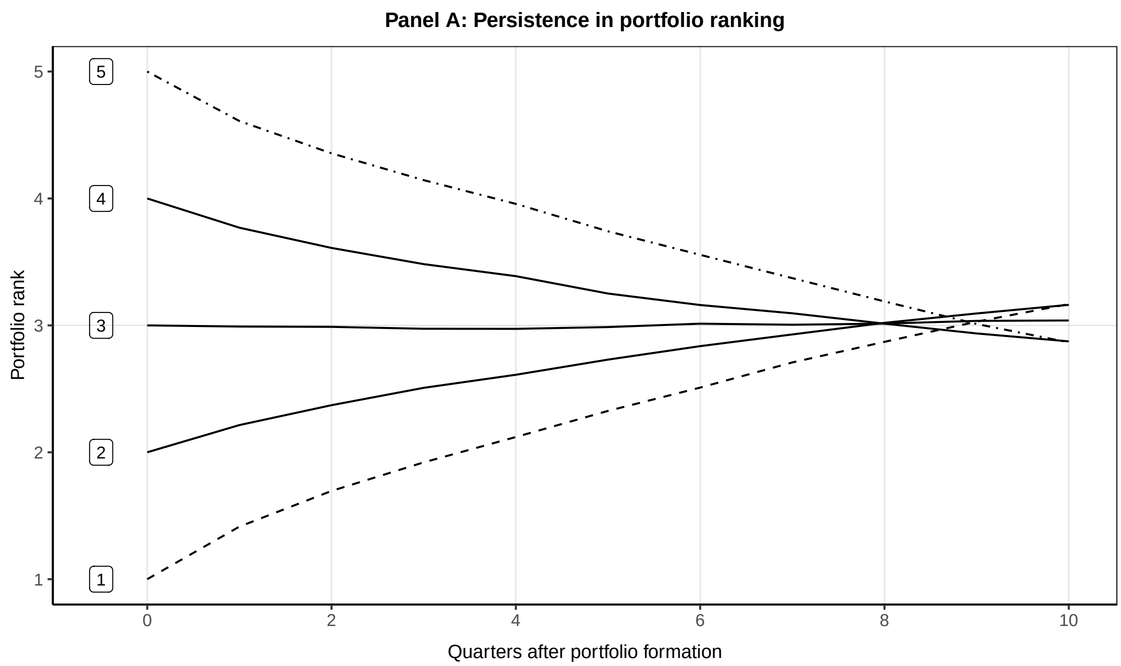
Table A4 summarizes the results. Across all five characteristics, AFB remains a strong predictor of future fund returns within each quartile. The high-minus-low AFB alpha is consistently large and statistically significant, suggesting that the AFB premium is distinct from unobserved managerial actions, risk-shifting behavior, compensation for deviating from the benchmark, reliance on public versus private information, and stock-selection ability. Collectively, these results indicate that the premium earned by high-AFB funds do not reflect the return from established sources of fund performance.

A3.4 Alternative fund benchmark

The main analysis constructs AFB under the assumption that all funds use the market portfolio as their benchmark. Since funds differ in their actual benchmarks, I examine the robustness of the performance gap between high- and low-AFB funds using fund-specific benchmarks. Following Cremers and Petajisto (2009), I identify each fund's benchmark, obtained from Martijn Cremers' website, as the index (among a set of 21 indices) against which the fund has the lowest active share. Following Jiang and Zheng (2018), I obtain benchmark holdings using the holdings of index funds that closely track the underlying indices. I then compute the deviation of each fund's holdings from its fund-specific benchmark and repeat the portfolio test from Equation 16. Table A5 reports the results. While the economic magnitude of the return difference between high- and low-AFB portfolios is smaller, the net alpha remains statistically significant. This finding confirms that the AFB premium is robust to the choice of benchmark.

Figure A1. Persistence of active flow beta

This figure illustrates the average portfolio rank and active flow beta for mutual fund portfolios sorted on fund active flow beta over ten-quarter periods between 2006 and 2021. At the beginning of each quarter, funds are sorted into quintiles based on their active flow beta, and each portfolio is then tracked over the subsequent ten quarters. Panel A reports the equal-weighted average quintile rank, while Panel B reports the equal-weighted average active flow beta.



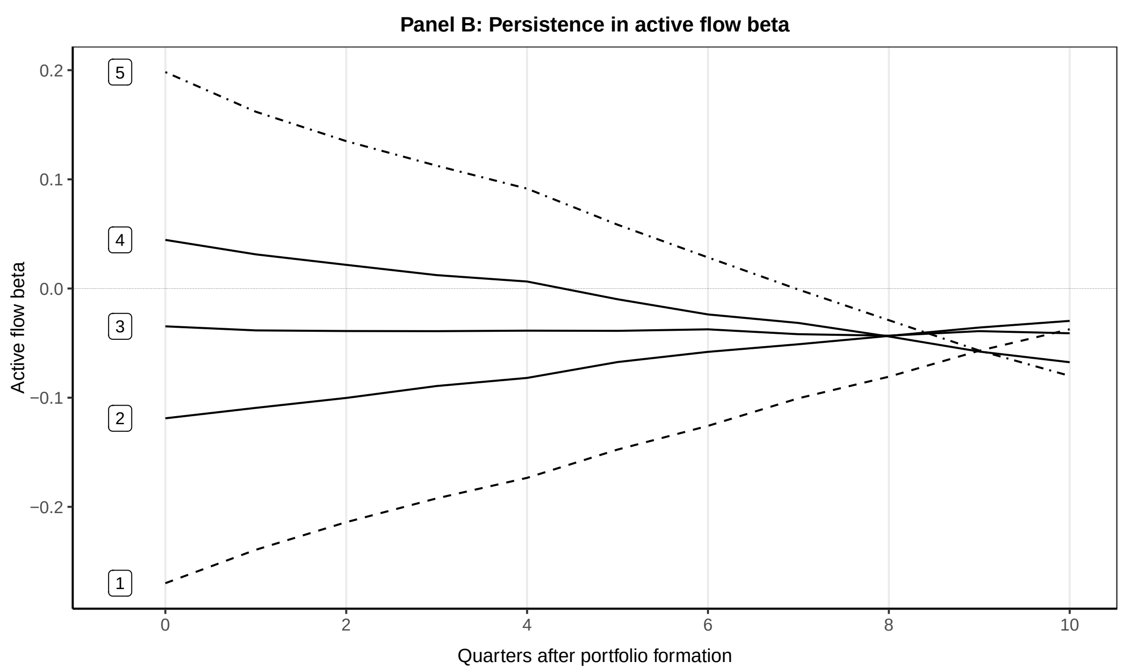


Table A1. Variable definitions

This table defines the main variables used in the empirical analyses.

Variable	Description
Stock-level variables	
β_{flow}	Estimated monthly from a 36-month rolling regression of excess stock returns on common flow shocks, controlling for the market factor.
Size	Natural logarithm of the firm market capitalization.
Ln(Book-to-market)	Natural logarithm of the book-to-market ratio.
$\beta_{\text{liquidity}}$	Estimated monthly from a 36-month rolling regression of excess stock returns on the market liquidity factor, controlling for the market return and the size, value, and momentum factors.
$\beta_{\text{uncertainty}}$	Estimated monthly from a 36-month rolling regression of excess stock returns on macroeconomic 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	Amihud's illiquidity measure.
Fund-level variables	
Active flow beta (AFB)	Sum of the products of the differences between the fund's portfolio weights and the market portfolio's weights and the corresponding stock-level flow betas.
High AFB	Indicator equal to one if a fund belongs to the top quintile of the active flow beta distribution in a given quarter, and zero otherwise.
Low AFB	Indicator equal to one if a fund belongs to the bottom quintile of the active flow beta distribution in a given quarter, and zero otherwise.
TNA	Fund total net assets measured monthly.
Fund size	Natural logarithm of the total net assets.
Fund-family scale	Natural logarithm of the total net assets of all actively managed mutual funds within a fund family.
Age	Natural logarithm of fund age measured in years.
Quarterly return	Quarterly net fund return.
Quarterly flow (Flow)	Quarterly growth rate of assets under management.
Expense ratio	Annual fund expense ratio.
Turnover ratio	Annual fund portfolio turnover ratio.
Performance pay	Indicator equal to one if the variable component of portfolio managers' compensation is based on performance, and zero otherwise.
AUM pay	Indicator equal to one if portfolio managers' variable compensation is based on assets under management, and zero otherwise.
Advisor-Profit pay	Indicator equal to one if portfolio managers' compensation depends on advisory firm profits, and zero otherwise.
Deferred compensation	Indicator equal to one if portfolio managers receive deferred compensation, and zero otherwise.
Pure benchmark	Indicator equal to one if the compensation benchmark is based solely on a pure market index, and zero otherwise.
Peer benchmark	Indicator equal to one if the compensation benchmark is based solely on peer fund indices, and zero otherwise.
Pure and peer benchmarks	Indicator equal to one if the compensation benchmark uses both pure and peer benchmarks, and zero otherwise.
Proportion of institutional shares	Fraction of a fund's share classes that are institutional.
Proportion of retail shares	Fraction of a fund's share classes that are retail.
Marketing expenses	Sum of a fund's 12b-1 fee and front-end load.
Fund-family scope	Natural logarithm of the number of distinct CRSP investment objective codes among actively managed funds within a fund family.
Industry flow	Growth rate of assets under management for the mutual fund industry, excluding the focal fund.
Macro & financial variables	
Market excess return	Returns on the S&P 500 in excess of the Treasury bill rate.
Market return volatility	Sum of squared daily returns on the S&P 500 within a specific period.
Dividend-to-price ratio	Log of aggregate dividends divided by the aggregate stock market value.
Term spread	Difference between the long-term government bond yield and the Treasury bill rate.
Inflation rate	Growth rate of the Consumer Price Index.

Table A2. Stock characteristics across portfolio sort

This table reports summary statistics for quintile stock portfolios sorted on stock flow beta. The sample includes U.S. common stocks listed on the NYSE, NASDAQ, and Amex with at least two years of available Compustat data. Following Dou et al. (2025), 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 using a 36-month rolling regression of stock excess returns on common flow shocks, controlling for the market excess return. Table A1 describes other variables in detail. The sample period is from Jan 2006 to Dec 2021.

	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
Size	9.230	10.008	10.300	10.237	9.410
$\text{Size}_{\text{median}}$	0.117	0.120	0.088	0.095	0.140
Ln(Book-to-market)	−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 A3. Flow hedging and the predictive power of fund flows: Common flow shocks
This table reports a robustness test of the predictive regression in Table 5, replacing industry flows with the common flow shock as the dependent variable. *Common flow* is the first principal component of size-sorted fund-flow shocks, constructed as described in Section 4.2. I adopt a block bootstrap design by drawing, in each of 10,000 replications, $[T/L]$ blocks of L consecutive quarters over T total number of quarters with replacement and retaining all fund observations within the sampled quarters. Columns (1)–(3) report results for block lengths $L = 4$, 6, and 8 quarters, respectively. Each draw then re-estimates the regression by OLS without fixed effects. The reported coefficients are bootstrap means, and the standard errors (in parentheses) are the standard deviations of the bootstrap distribution. Fund-level controls include fund size, fund age, active share, expense ratio, turnover ratio, and fund flows and returns. Macroeconomic and financial controls include market excess return, market return volatility, dividend-to-price ratio, term spread, and inflation rate. All control variables are measured in the prior period. Table A1 describes all variables in detail. Continuous variables are standardized to have mean zero and unit standard deviation. The sample period is from 2006Q1 to 2021Q4. $***$, $**$, and $*$ represent statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable: Common flow (q)		
	(1)	(2)	(3)
AFB × Flow (q-1)	0.034*	0.035*	0.037*
	(0.020)	(0.020)	(0.019)
AFB × Flow (q-2)	−0.006	−0.005	−0.005
	(0.009)	(0.009)	(0.009)
AFB (q-1)	0.226*	0.226*	0.230*
	(0.125)	(0.126)	(0.124)
Flow (q-1)	−0.003	−0.003	−0.003
	(0.008)	(0.009)	(0.009)
Flow (q-2)	0.001	0.001	0.002
	(0.007)	(0.007)	(0.006)
Industry flow (q-1)	0.523**	0.528**	0.530**
	(0.236)	(0.240)	(0.234)
Industry flow (q-2)	−0.003	−0.002	−0.002
	(0.098)	(0.091)	(0.085)
Fund-level controls	Yes	Yes	Yes
Macro & financial controls	Yes	Yes	Yes
Block length (quarters)	4	6	8
Bootstrap draws	10,000	10,000	10,000

Table A4. The cost of hedging: Double portfolio sorts

This table reports performance of fund portfolios sorted on active flow beta (AFB) and other performance measures. 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). Portfolio performance is evaluated over the subsequent three months, and portfolios are rebalanced 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 augmented with the Carhart's (1997) momentum factor. Alphas are reported in monthly percentage. The sample period is from Jan 2006 to Dec 2021. Newey-West adjusted t-statistics are reported 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]	
		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]	

(Continued on next page)

Table A4. The cost of hedging: Double portfolio sorts (Continued)

Active flow beta	All	Low	2	3	High	High−Low
			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]	
			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 A5. The cost of hedging: Active benchmark

This table examines the performance of quintile fund portfolios sorted on active flow beta using active benchmark definitions to measure deviations in portfolio weights. For each quintile and high-minus-low portfolio, I 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 augmented with the Carhart's (1997) momentum factor, and the six-factor model augmented with the Pástor and Stambaugh's (2003) liquidity factor. Following Cremers and Petajisto (2009), a fund's active benchmark is one of the 21 indices that minimizes its active share. Alphas are reported in monthly percentage. The sample period is from Jan 2006 to Dec 2021. Newey-West adjusted t-statistics are reported 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]