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COMMON FUND FLOWS: FLOW HEDGING AND FACTOR PRICING

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ABSTRACT

Active equity funds care about fund size, affected by fund flows that obey a strong factor structure with the common component responding to macroeconomic shocks. Funds hedge against common flows by tilting their portfolios toward low-flow-beta stocks, while household/retail and index investors overweight high-flow-beta stocks in equilibrium. Consequently, common flows earn a risk premium, leading to a multi-factor asset-pricing model resembling the ICAPM, even with myopic agents and unsophisticated fund clients. Exploiting quasi-experiments induced by the local-natural-disaster occurrences and the unexpected trade-war announcements, we find that an increased outflow risk faced by funds leads to more aggressive flow-hedging portfolio tilts.

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A data appendix is available at http://www.nber.org/data-appendix/w30234

1 Introduction

In this paper we propose a novel intermediary asset pricing mechanism. We show theoretically that, because of an agency friction between active equity funds and their investors, common fund flows in and out of active equity funds give rise to a compensated risk factor in equilibrium. Our main contribution is to establish empirical evidence for this mechanism by showing how stocks' exposures to common fund flows are reflected in the asset allocation decisions of active equity funds and cross-sectional differences in stock returns. Our analysis thus reinforces the insight that, as marginal investors, non-bank intermediaries play a unique role in linking stock prices and economic fundamentals, and it complements the existing theories on the role of intermediaries in asset pricing (e.g., Shleifer and Vishny, 1997; He and Krishnamurthy, 2013).

Over the past few decades, delegated asset management services, such as mutual funds and pension funds, have become a major force in the United States (US) financial markets (e.g., French, 2008). In 2016, mutual funds and pension funds combined held more than 44% of the US equity market. As a result, the portfolio choices and trading behavior of active equity funds — mainly active mutual and active pension funds — play a first-order role in determining stock prices. It is critical for our analysis that active equity funds may pursue objectives that deviate from those of their clients.[1] Specifically, this paper focuses on a particular form of agency friction caused by active equity mutual funds' incentives being closely related to fund size, as a consequence of the fact that active equity mutual funds charge asset management fees based on assets under management (AUMs).[2] Importantly, fees charged by active equity funds are rather rigid, so the market for services of active mutual funds clears largely through adjustments in their AUMs. The changes in AUMs are in turn driven to a significant degree by fund flows. Thus, fund flows reflect changes in fund clients' demand in response to fluctuations in investment opportunities and macroeconomic fundamentals (e.g., Berk and van Binsbergen, 2016*b*; Barber, Huang and Odean, 2016). From the perspective of the funds, fund flow shocks are effectively exogenous demand shocks, rather than an outcome of the funds' own fee-setting behavior. Under such conditions, funds have an incentive to tilt their portfolios to hedge

[1]Different forms of agency conflicts between funds and clients, ranging from effort shirking and risk shifting to fraudulent behavior, have been studied previously (e.g., Mahoney, 2004; Tkac et al., 2004). Purposeful portfolio distortions made by fund managers, as a major form of agency conflicts, are restrained by funds' investment mandates and portfolio flexibility (i.e., funds' capacity to deviate from client objectives), as examined theoretically and empirically in the literature (e.g., Heinkel and Stoughton, 1994; Chen, Goldstein and Jiang, 2008; Dybvig, Farnsworth and Carpenter, 2009; He and Xiong, 2013).

[2]Apart from fund revenue being (almost) proportional to the fund size, recent studies have shown that the compensation of fund managers in active equity mutual funds is also significantly and monotonically associated with fund size (e.g., Ibert et al., 2018).

against fund flow shocks. Both in our model and in the data, this happens at the cost of lower risk-adjusted excess fund returns — such agency conflict is central to our analysis, and differentiates our paper from other existing intermediary asset pricing theories.[3]

We show empirically that fund flows share a significant degree of common time-series variation at a frequency higher than that of business cycles, consistent with the findings of Goetzmann, Massa and Rouwenhorst (2000) and Ferson and Kim (2012). Moreover, the common flow component is closely related to fluctuations in macroeconomic fundamentals (e.g., economic uncertainty faced by investors). The yearly systematic volatility of fund-level flows is approximately 4%, which is economically significant relative to that of fund-level returns, 16%, especially after accounting for the low price elasticity of flows (approximately 20%) estimated by Gabaix and Koijen (2021) (see Online Appendix 4.2 for details). To hedge against the common fund flow shock, funds must tilt their portfolios away from the market portfolio toward stocks with low flow betas.

In equilibrium, market clearing dictates that other investors, not subject to the same flow-related incentives, must be induced to absorb the total hedging demand of active mutual funds, thus overweighting high-flow-beta stocks relative to the market portfolio. Consequently, such stocks must earn sufficiently high excess returns relative to the low-flow-beta stocks.[4] We find empirically that high-flow-beta stocks earn significantly higher excess returns and higher capital asset pricing model (CAPM) alphas in the cross-section; specifically, the spread between CAPM alphas at the extreme quintiles of flow betas is above 6% over our sample period. Importantly, we also show directly that active funds collectively tilt their portfolios away from high-flow-beta stocks. This finding is robust to defining the portfolio tilt using the market portfolio or a self-disclosed benchmark. In contrast, non-institutional investors, especially household/retail investors, and index funds deviate from the market in the opposite direction on average. These findings show that traditional hedging demand from non-institutional investors, in the spirit of the classic intertemporal capital asset pricing model (ICAPM) framework (Merton, 1973), cannot be the sole cause of the elevated risk premium of high-flow-beta stocks, as non-institutional investors, especially household/retail investors, overweight such stocks in their portfolios, benefiting from their relatively high risk premia.

[3]Prominent examples of such theories include Shleifer and Vishny (1997), Gromb and Vayanos (2002), Brunnermeier and Pedersen (2008), Basak and Pavlova (2013), He and Krishnamurthy (2013), Brunnermeier and Sannikov (2014), Frazzini and Pedersen (2014), and Drechsler, Savov and Schnabl (2018).

[4]Our findings support the general insight that compared with other investors, institutions have different demands for stock characteristics, which has important implications for stock prices (e.g., Gompers and Metrick, 2001; Frazzini and Pedersen, 2014; Koijen and Yogo, 2019).

We frame our discussion around a parsimonious equilibrium model of delegated asset management. Although the main contribution of our paper is empirical, the model facilitates the interpretation of the empirical findings above and motivates further empirical tests. Our model describes an exchange economy populated with three types of investors: direct investors, fund clients, and active fund managers. In the model, investors allocate their capital between a single risk-free asset and multiple risky assets. Direct investors form the entire portfolio on their own, while fund clients make only saving decisions and delegate management of their entire risky-asset portfolio to the active funds. Active funds collect a fee in proportion to the amount of delegated assets. Active fund managers operate the funds, consume their fund revenues, and can save to smooth their consumption across periods.

To highlight the role of fund flow risk, we assume that all investors are myopic — they do not need to anticipate and intertemporally hedge against possible changes in their investment environment as they would in the classic institution-free ICAPM framework. Instead, as fund clients adjust their asset allocations between the risky stocks and the risk-free asset in response to current market conditions, they expose active fund managers to aggregate fluctuations in fund flows. Active fund managers hedge the exposure of their net income to fund flow risk by tilting their funds' portfolios away from the tangency portfolio and toward low-flow-beta stocks (Theorem 1). Because of this hedging demand, market clearing conditions imply that the aggregate stock market portfolio deviates from the mean-variance efficient frontier in equilibrium. The risk premia of high-flow-beta stocks are relatively high in equilibrium (Theorem 2). Direct investors, who are mean-variance optimizers, deviate from the market portfolio in the direction of high-flow-beta stocks, thus absorbing the hedging demand of active fund managers.

For simplicity, we have a single state variable in the model, which describes market-wide uncertainty. When economic uncertainty increases, risk-averse fund clients pull their capital out of the active funds of the risky assets and invest in the risk-free asset (Proposition 3.3). Consequently, uncertainty shocks in our model drive common fund flows, and, in our myopic environment, this link between uncertainty shocks and common fund flows is responsible for the equilibrium risk premium on uncertainty shocks. This stands in contrast to the classic institution-free ICAPM setting, where the risk premium on uncertainty shocks arises because of households' intertemporal hedging demand.

Our model is flexible enough to incorporate multiple sources of heterogeneity in firms' flow betas, driven by both exposures to "fundamental" shocks, e.g., shocks to firms' cash flows, and exposures to "non-fundamental" liquidity shocks. For instance, heterogeneity may arise because firm cash flows have different exposures to the systematic shocks driving common flows, e.g., economic uncertainty shocks. Meanwhile, fund flow shocks may also affect stock prices directly due to imperfect liquidity, with an unequal price impact, which would again give rise to heterogeneous stock return betas on fund flows. We explore both possibilities in our empirical analysis.

We conduct additional empirical analyses to flesh out our hypothesis that active equity fund managers hedge against common flow shocks, and that this behavior, in turn, generates a positive cross-sectional relation between flow betas and risk premia. First, we explore which types of investors absorb the hedging demand of active equity funds. Motivated by Theorem 1, we show that index funds and household/retail investors significantly overweight stocks with high flow betas relative to their market weights.[5] These empirical results highlight a crucial distinction between our setting and traditional institution-free asset pricing models: shocks to common fund flows are priced on the basis of active equity funds' flow hedging motives, and the asset pricing behavior of common fund flows cannot be explained by appealing to households' intertemporal hedging of macroeconomic shocks that drive fund flows. More specifically, these empirical results show that households tilt their portfolios toward high-flow-beta stocks, thus benefiting from their elevated risk premia, and this accounts for the fact that the observed risk premia associated with the high-flow-beta stocks is unlikely owing to households' intertemporal hedging of macroeconomic shocks that drive fund flows.

Second, we show that flow betas reflect both the heterogeneous exposures of firms' cash flows to common fund flow shocks and the differences in the market liquidity of stocks. Motivated by Proposition 3.3, we show that the common fund flows of active equity funds are significantly negatively correlated with fluctuations in macro uncertainty, measured as economic policy uncertainty, realized and implied market volatility, or cross-sectional consumption growth dispersion. These findings are consistent with common fund flows endogenously responding to fluctuations in economic uncertainty.[6] We also show that flow betas are positively correlated with the price impact measures of non-fundamental trading shocks in the cross-section of firms. Both determinants of flow betas are important, and controlling for

[5]We measure the holdings of household/retail investors using two different approaches: we use the data on household/retail investor holdings following Barber and Odean (2000), and as an additional robustness check, we also use the data on non-institutional holdings following Koijen and Yogo (2019).

[6]We also show that the common fund flows of those bond mutual funds that hold low-risk assets are negatively correlated with the common flows of active equity funds, suggesting that low-risk bond mutual funds act as fund flow counterparties of active equity funds in the capital market.

various liquidity measures does not eliminate the relation between flow betas and expected returns.

Third, we provide direct evidence on the core mechanism of the agency conflict between active funds and their clients. Associated distortions in funds' portfolios should be more pronounced for funds with higher investment flexibility. We show that active equity funds with higher fund activeness tilt more aggressively toward low-flow-beta stocks to hedge against common fund flow shocks, and that the common fund flows of such funds have stronger asset pricing implications.[7]

Fourth, as additional evidence of funds' hedging behavior, we show that active equity funds hedge against other components of fund-level flows that are orthogonal to the common flow component. We consider the between-style fund flows that capture fund flows from growth to value funds within the sector of active equity mutual funds, and we extract the common component of such flows orthogonal to the common fund flows of all active funds. Consistent with our theory, we find that value funds indeed tilt their holdings away from stocks with high between-style flow betas, while growth funds do the opposite. In contrast to the common flow betas, we find that the between-style flow betas are not priced in the cross-section of stocks. This is because growth and value funds tilt in the opposite directions, thereby generating little net hedging demand for the between-style fund flows.

Finally, to strengthen the interpretation of the observed portfolio tilts as driven by the flow hedging motive, we use two quasi-natural experiments to show how funds respond to changes in the magnitude of their idiosyncratic outflow risk. In the first experiment, we examine changes of active equity mutual fund holdings following natural disaster shocks in the US. We find that active equity mutual funds experience an increase in outflow risk in the subsequent quarters when some of the stocks in their portfolios are negatively affected by natural disaster shocks. This heightened outflow risk increases funds' incentives to hedge against common fund flow shocks. Consistent with our theoretical predictions, active equity mutual funds tilt their holdings of the unaffected stocks more aggressively toward those with lower flow betas. Importantly, this portfolio tilt is economically costly, judging by its negative impact on the funds' investment performance. In the second experiment, we show that following the unexpected announcement of a possible US-China trade war made by the Trump administration, active equity mutual funds rebalance their portfolio holdings of China-unrelated stocks toward those with low flow betas.

[7]These findings are robust to using alternative measures of fund activeness: measures developed by Pástor, Stambaugh and Taylor (2020), Cremers and Petajisto (2009), and fund expense ratios.

Related Literature. Our paper contributes to the literature on the relation between mutual fund flows and asset prices in the capital market (see Christoffersen, Musto and Wermers, 2014, Chapter 5, for a survey). One strand of this literature focuses on the relation between aggregate mutual fund flows and market returns (e.g., Warther, 1995; Edelen and Warner, 2001; Goetzmann and Massa, 2003; Ben-Rephael, Kandel and Wohl, 2012; Pástor and Vorsatz, 2020). Another strand examines predictable price pressure induced by mutual fund flows (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008; Ben-Rephael, Kandel and Wohl, 2011; Lou, 2012; Shive and Yun, 2013; Akbas et al., 2015). Moreover, Greenwood and Nagel (2009) show that large inflows into mutual funds managed by inexperienced managers may contribute to the formation of asset price bubbles. Ben-Rephael, Choi and Goldstein (2021) show that intra-family flow shifts toward high-yield bond mutual funds can predict credit spreads. Similar to our paper, Kim (2020) also studies the asset pricing implications of fund flow betas. However, our paper is different from Kim (2020) in at least the following aspects: (i) we endogenize the pro-cyclical fund flow and countercyclical net alpha in the model, and show how market participants optimally choose their portfolios under endogenous fund flows; (ii) we show that mutual fund flow shocks obey a strong factor structure and that shocks to the common fund flow factor are priced in the cross-section of stock returns; and (iii) we use detailed holdings data and exploit quasi-natural experiments to provide evidence on the flow hedging behavior of active equity funds, and we document the association between flow betas and portfolio composition of index funds and household/retail investors, suggesting that the asset allocation decisions of active funds and fund flows are not a mere sideshow in generating the observed asset pricing patterns.

Our paper also contributes to the literature on the asset allocation of institutional investors (e.g., Grinblatt and Titman, 1989; Daniel et al., 1997; Wermers, 2000; Gompers and Metrick, 2001; Bennett, Sias and Starks, 2003; Brunnermeier and Nagel, 2004; Kacperczyk, Sialm and Zheng, 2005; Basak, Pavlova and Shapiro, 2007; Cremers and Petajisto, 2009; Hugonnier and Kaniel, 2010; Cuoco and Kaniel, 2011; Lewellen, 2011; Agarwal et al., 2013; Kacperczyk, Nieuwerburgh and Veldkamp, 2014; Sialm, Starks and Zhang, 2015; Blume and Keim, 2017; Lettau, Ludvigson and Manoel, 2018; Koijen and Yogo, 2019; Pástor, Stambaugh and Taylor, 2020, 2021). We add to this literature by showing that the portfolios of active mutual funds overweight stocks with low flow betas. We show that stock characteristics such as the book-to-market ratio are correlated with flow betas such that exploiting the predictive content of these characteristics renders funds more exposed to common fund flow shocks.

Our paper is related to the emerging literature on the role of intermediaries, particularly delegated portfolio management, in asset pricing (e.g., Brennan, 1993; Goldman and Slezak, 2003; Asquith, Pathak and Ritter, 2005; Cornell and Roll, 2005; Nagel, 2005; Cuoco and Kaniel, 2011; He and Krishnamurthy, 2011, 2013; Basak and Pavlova, 2013; Kaniel and Kondor, 2013; Vayanos and Woolley, 2013; Adrian, Etula and Muir, 2014; Koijen, 2014; He, Kelly and Manela, 2017; Drechsler, Savov and Schnabl, 2018; Koijen and Yogo, 2019; Haddad, Huebner and Loualiche, 2021; Dou, Wang and Wang, 2022). In a recent paper, Gabaix and Koijen (2021) estimate that flows in and out of the stock market exert a significant impact on stock prices because of the low price-elasticity of demand by many institutional investors, especially mutual funds. These findings suggest that inelastic demand by a subset of investors may further motivate the demand for hedging against common fund flow shocks and magnify the effect of flow-hedging behavior, which is the subject of this paper. Cuoco and Kaniel (2011), Kaniel and Kondor (2013), Basak and Pavlova (2013), Vayanos and Woolley (2013), Breugem and Buss (2018), Buffa and Hodor (2018), and Buffa, Vayanos and Woolley (2019), investigate the asset pricing implications of contractual distortions or restrictions among fund managers, fund companies, and fund clients, such as relative-performance-based compensation of fund managers, index-tracking restrictions, and adjustment frictions faced by fund clients. Similarly to the present study, Vayanos and Woolley (2013) highlight endogenous fund flow risk and its asset pricing implications for return momentum and reversals. Gabaix, Krishnamurthy and Vigneron (2007) show empirically that the risk of mortgage prepayment, which is a wash in the aggregate, is priced in the MBS market through the limits of arbitrage. We add to this literature by showing that common fund flow shocks play an important role in the financial markets; specifically, our paper is the first to highlight the role of endogenous fund flows as an invisible hand in the capital market, connecting the asset allocation choices of institutions, as well as their asset pricing implications, to the aggregate economic shocks affecting households.

2 New Facts on Intermediary Asset Pricing

In this section we introduce a set of new empirical facts. We show that fund flows in and out of active equity funds exhibit a factor structure. We then find that stock return betas with respect to the leading common component of fund flow shocks are priced in the cross-section of stock returns, and that active equity funds tilt their portfolios away from stocks with high fund flow betas. We propose a theoretical interpretation of these facts, and conduct further empirical tests in the following sections. The data sources are detailed in Section 4.1.

2.1 Factor Structure of Fund Flow Shocks

Construction of Fund Flow Shocks. We define flows at the fund level as follows:

$$F_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + Ret_{i,t})}{Q_{i,t-1}}, \tag{2.1}$$

where $Q_{i,t}$ and $Ret_{i,t}$ are, respectively, the total net assets (TNA) and the net return for fund i in month t. Following Elton, Gruber and Blake (2001), we require the lagged TNA (i.e., $Q_{i,t-1}$) to be higher than \$15 million; otherwise, the flow observation is dropped for fund i in month t. We also address the incubation bias following Evans (2010).

In order to construct the unpredictable component in fund flows, we control for lagged fund flows because fund flows are persistent. We also control for lagged fund performance to account for flow-performance sensitivity.[8] Furthermore, the empirical measure, $F_{i,t}$ defined by equation (2.1), is an imperfect proxy for fund-flow shocks owing to intermediate, contemporaneous flows and returns within month t (e.g., Berk and Tonks, 2007). To mitigate this concern, we also control for contemporaneous fund performance by running a pooled panel regression as follows:

$$F_{i,t} = b_0 + \sum_{k=1}^{2} b_k \times ExRet_{i,t-k+1} + b_3 \times F_{i,t-1} + \theta_t + \varepsilon_{i,t}, \tag{2.2}$$

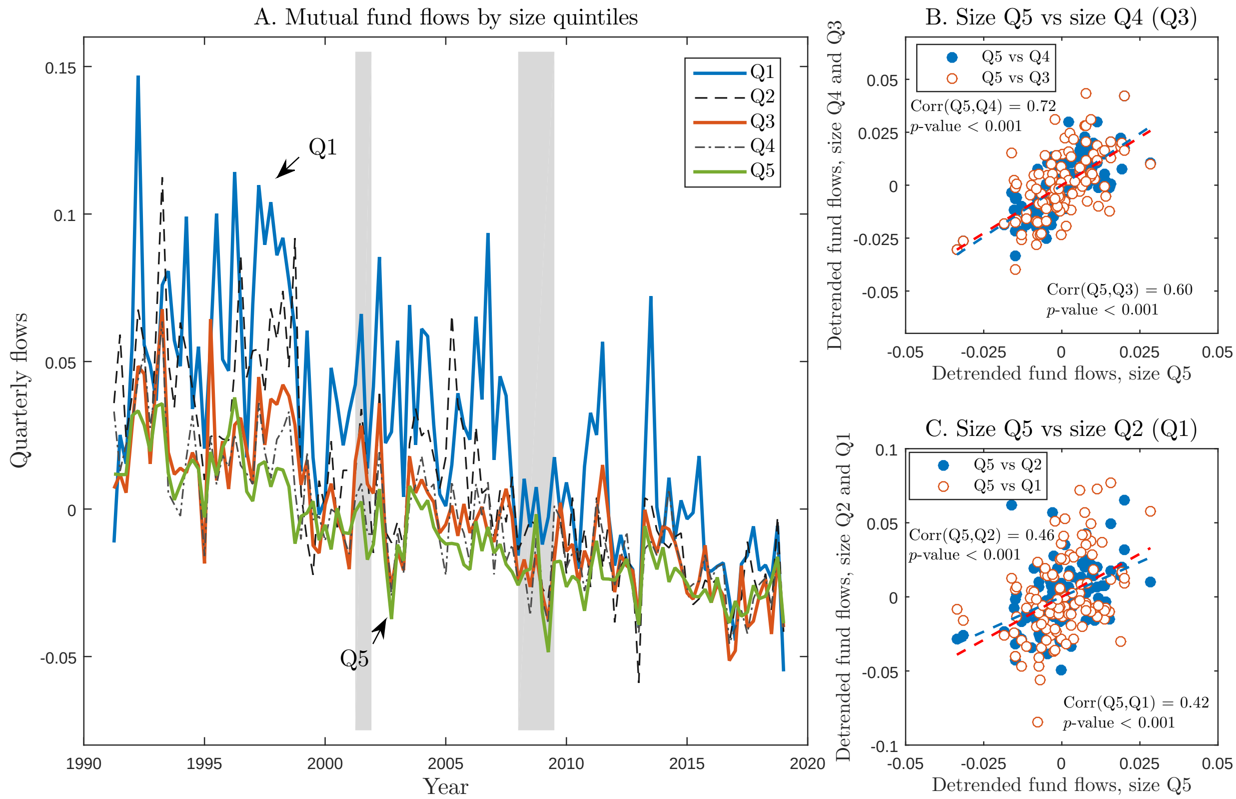
where $ExRet_{i,t}$ is the fund excess return relative to the market return, R_t^{mkt}, over month t, $F_{i,t-1}$ represents the lagged fund flows, and θ_t represents the month fixed effects. We then define the fund-flow shock after controlling for the flow-performance sensitivity at the fund level as follows:

$$flow_{i,t} = \theta_t + \varepsilon_{i,t}. \tag{2.3}$$

Construction of Common Fund Flow Shocks. Below, we show that there is one dominant common factor driving much of the common variation of fund flow shocks (i.e., one factor with a high eigenvalue).

To extract the common component of fund flow shocks empirically, we sort active funds

[8] See, e.g., Ippolito (1992), Brown, Harlow and Starks (1996), Chevalier and Ellison (1997), Sirri and Tufano (1998), Bergstresser and Poterba (2002), Del Guercio and Tkac (2002), Lynch and Musto (2003), Huang, Wei and Yan (2007), Frazzini and Lamont (2008), Chen, Goldstein and Jiang (2010), Pástor and Stambaugh (2012), Del Guercio and Reuter (2014), Pástor, Stambaugh and Taylor (2015), Berk and van Binsbergen (2016*b*), Barber, Huang and Odean (2016), Goldstein, Jiang and Ng (2017), Roussanov, Ruan and Wei (2020), and Song (2020).



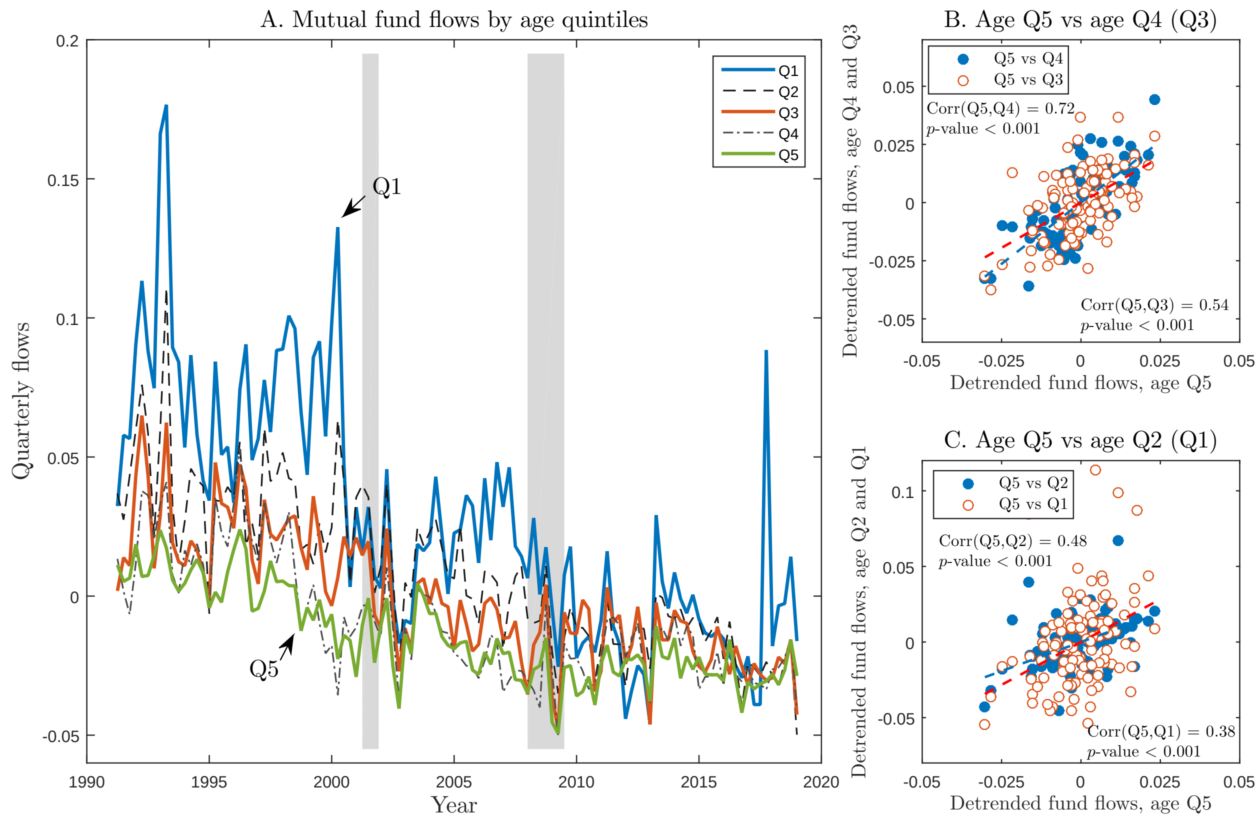
Note: Panel A plots active mutual fund flows by quintiles sorted on fund asset size after removing relative performance and lagged fund flows. We control for flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the National Bureau of Economic Research (NBER) recession periods. Panels B and C plot the detrended flows of the funds with the largest assets (Q5) against the detrended flows of the other asset size groups presented in panel A.

Figure 1: Mutual fund flows (by size) after removing relative performance and lagged flows.

into groups based on their characteristics. First, we use five groups of funds sorted on asset size. Among fund characteristics, asset size is one of the most informative about fund flows and performance (e.g., Sirri and Tufano, 1998; Chen et al., 2004; Pollet and Wilson, 2008; Pástor, Stambaugh and Taylor, 2015). Second, for comparison and robustness, we also consider the five groups of funds sorted on fund age, another important characteristic (e.g., Chevalier and Ellison, 1997; Berk and Green, 2004; Pástor, Stambaugh and Taylor, 2015). Consistent with the findings of Goetzmann, Massa and Rouwenhorst (2000) and Ferson and Kim (2012), we find that fund flow shocks obey a strong factor structure, and importantly, the fund flow shocks comove strongly with each other at a frequency higher than that of business cycles.[9]

Specifically, panel A of Figure 1 plots the value-weighted average fund flow shocks after

[9] Besides asset size and age, fund flow shocks sorted on other characteristics also exhibit a high degree of common time-series variation. Figures OA.4 and OA.5 in the online appendix plot the fund flow shocks sorted on industry concentration as defined by Kacperczyk, Sialm and Zheng (2005) and portfolio liquidity as defined by Pástor, Stambaugh and Taylor (2020). Similar to asset size and age, we find that fund flow shocks sorted on these characteristics also comove strongly at a frequency higher than that of business cycles.



Note: Panel A plots active mutual fund flows by quintiles of funds sorted on fund age after removing relative performance and lagged fund flows. We measure fund age by the number of years since inception date. We control for flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the NBER recession periods. Panels B and C plot the detrended flows of the oldest funds (Q5) against the detrended flows of the other age groups presented in panel A.

Figure 2: Mutual fund flows (by age) after removing relative performance and lagged flows.

removing both relative performance and lagged fund flows for each quintile of funds sorted on fund asset size. It is clear that fund flow shocks comove across different funds with different asset sizes. Panels B and C of Figure 1 plot the detrended fund flow shocks of the quintile 5 size group against the detrended fund flow shocks of the other size groups presented in panel A. We find that the fund flow shocks for funds of different sizes exhibit very similar time series patterns. The correlation coefficient between the fund flow shocks of size quintiles 5 and 4 is 0.72, with p-value < 0.001, and that between the fund flow shocks of size quintiles 5 and 1 is 0.42, with p-value < 0.001.

Similarly, panel A of Figure 2 plots the value-weighted average fund flow shocks after removing both relative performance and lagged fund flows for each quintile of funds sorted on fund age. The same high-frequency comovement across different groups of fund flow shocks with different ages robustly appears. Panels B and C of Figure 2 plot the detrended fund flow shocks of the quintile 5 age group against the detrended fund flow shocks of the other age groups presented in panel A. The correlation coefficient between the fund flow shocks of age quintiles 5 and 4 is 0.72, with p-value < 0.001, and that between the fund flow shocks of age quintiles 5 and 1 is 0.38, with p-value < 0.001.

To obtain the common fund flow shocks, we extract the first principal component (PC1) of the fund flow shocks across funds using principal component analysis (PCA).[10] The eigen-decomposition of the covariance matrix of the five groups of fund flow shocks exhibits a dominant highest eigenvalue and a fast decay for the rest of the eigenvalues. Figure 3 shows that there is one dominant factor driving much of the common variation in fund flow shocks, namely PC1.[11] With no loss of generality, we standardize the PC1 by removing the unconditional mean and normalizing the unconditional standard deviation to 1. We refer to the standardized PC1 as the *common fund flow shock*. Our construction of the common fund flow shocks using PC1 across groups of funds is analogous to the approach of Herskovic et al. (2016), who extract the common component in idiosyncratic volatility across groups of stocks.

Alternative Measures of Common Fund Flow Shocks. We consider two alternative measures of common fund flow shocks. In the construction of the first alternative measure, instead of performing PCA, we construct the common fund flow shocks using the AUM-weighted average of fund flow shocks defined in equation (2.3), which is simply the aggregate fund flow shock. Relative to the PCA approach, the AUM-weighted approach assigns more weight to the fund flow shocks of large funds. In the second alternative measure of common fund flow shocks, we adopt the fund flow measure of Berk and Tonks (2007) as follows:[12]

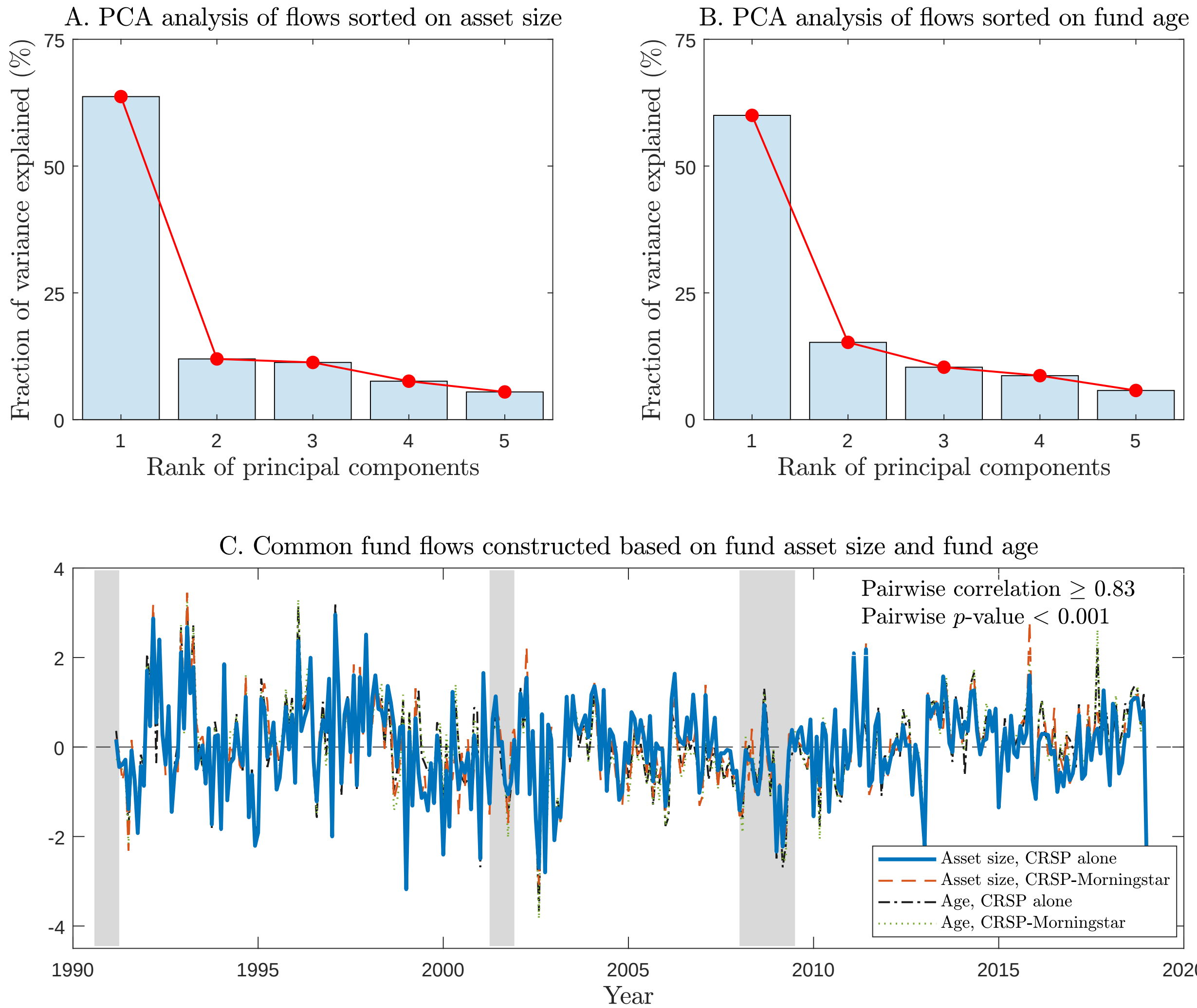
$$F_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + Ret_{i,t})}{Q_{i,t-1} \times (1 + Ret_{i,t})}, \tag{2.4}$$

where $Q_{i,t}$ and $Ret_{i,t}$ are, respectively, the TNA and the net return for fund i in month t. This fund flow definition differs from the definition in equation (2.1) in that the denominator is

[10]We detrend the fund flow of each quintile using a linear model before extracting the principal components, because fund flow is scaled by lagged TNA and thus exhibits a decreasing trend as the asset size of the mutual fund sector grows over time.

[11]According to Figure 3, the *eigenvalue criterion*, *scree plot criterion*, and *Bartlett criterion* all suggest that one is the optimal number of PCs to capture the factor structure of the fund flow shocks. Jolliffe (2002) provides an excellent summary of approaches to selecting the number of PCs.

[12]Binsbergen, Kim and Kim (2021) also adopt equation (2.4) as an alternative measure in their study. This specification uses a different denominator from the widely used measure in equation (2.1). The latter is an imperfect proxy for fund flows because of intermediate contemporaneous flows and returns within month t. Large negative returns, in particular, can give rise to significant distortions. For example, liquidation of a fund ($Q_t = 0$) implies a flow of $-(1 + Ret_{i,t})$, according to equation (2.1), while the alternative fund flow in equation (2.4) recovers the correct value of -1.

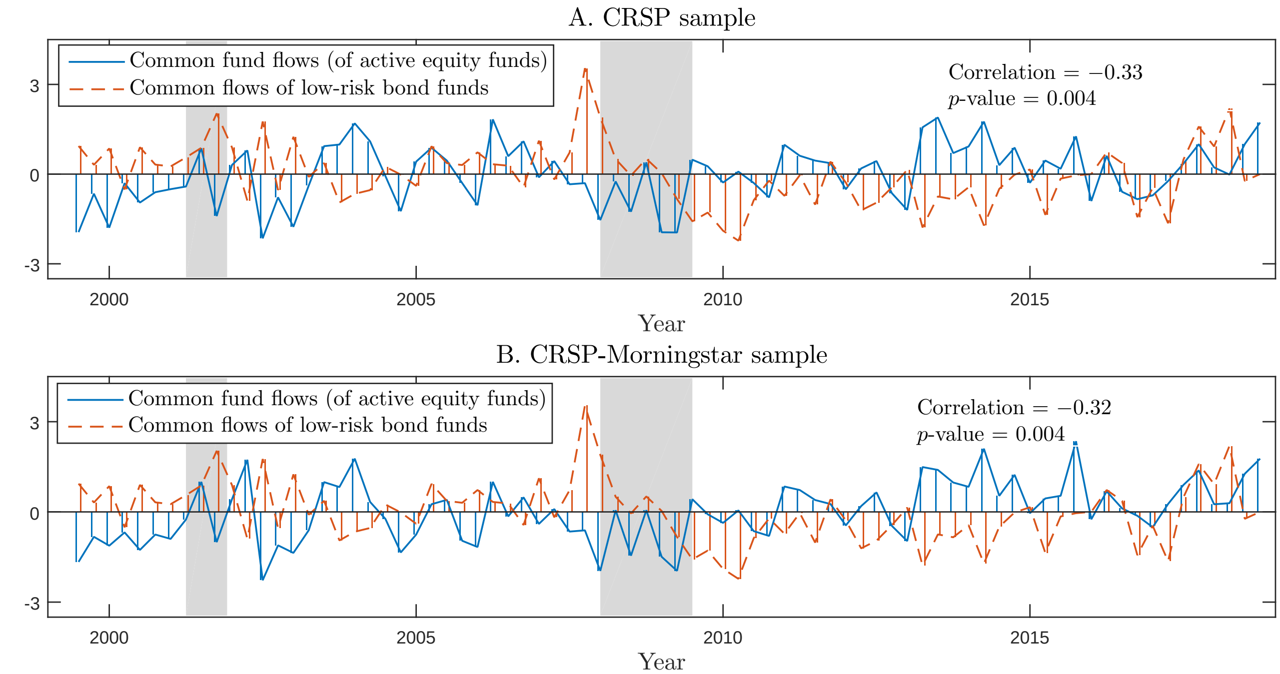


Note: Panel A plots the fraction of variance explained by different PCs according to the PCA of flows sorted on asset size. Panel B plots the fraction of variance explained by different PCs according to the PCA of flows sorted on fund age. Panel C plots the monthly common fund flows constructed based on fund asset size and fund age using the Center for Research in Security Practices (CRSP) mutual fund data and CRSP-Morningstar intersection mutual fund data. The four common flows are standardized to have means of 0 and standard deviations of 1. The pairwise correlation coefficients among these four common flows range from 0.83 to 0.95, with the pairwise p-values all being lower than 0.001. Gray areas represent the NBER recession periods.

Figure 3: Principal component analysis and common fund flow shocks.

$Q_{i,t-1} \times (1 + Ret_{i,t})$ instead of $Q_{i,t-1}$. We show in Table A.1 of the appendix that these two alternative measures of common fund flow shocks exhibit similar asset pricing and asset allocation results to our main measure of common fund flow shocks in equation (2.1). This mitigates the concern about the potential look-ahead bias in the asset pricing results or the potential distortion in the flow measure caused by contemporaneous intermediate returns and flows in the period of a month.[13]

[13]We use the PCA approach to construct our main common fund flow measure. The advantage of this approach is that it extracts the common component of the flows of all funds instead of merely the flows of the largest funds. There are several caveats of focusing only on the largest funds: (i) the central economic mechanism is about the



Note: This figure shows the common fund flow of low-risk bond funds and that of active equity funds. All time series are standardized to have zero mean and unit standard deviation. The time series are quarterly averages of monthly common fund flow shocks. The common fund flow (of active equity funds) in panel A uses the CRSP sample alone, and the series in panel B uses the CRSP-Morningstar intersection sample. Gray areas represent the NBER recession periods.

Figure 4: Common fund flow of low-risk bond funds vs. that of active equity funds.

Fund Flow Counterparties of Active Equity Funds. When fund clients move their capital in or out of the sector of active equity funds, they are likely to adjust their positions with other types of institutions that provide delegated asset management services, such as money market mutual funds, U.S. Treasury bond funds, and investment-grade corporate bond funds. That is, other types of institutions tend to absorb some of the fund flows experienced by active equity funds, effectively acting as their fund flow counterparties. A major group of such fund flow counterparties is bond mutual funds focused on low-risk assets, such as investment-grade corporate bond funds, short-duration corporate bond funds, short-duration government bond funds, and money-market funds. We show that the common fund flows of bond mutual funds holding low-risk assets are negatively correlated with the common flows of active equity funds. Similar to active equity funds, we compute the common fund flow shocks of low-risk bond funds by extracting the PC1 of the five fund groups sorted on asset size. The quarterly common

most active equity funds rather than the largest funds, but fund size is significantly negatively associated with fund activeness in the cross-section of active equity funds; (ii) the flows of the largest funds may exert the greatest impact on asset prices, but they attract a specific clientele and thus their fund flows fail to reflect the behavior of the typical fund client in response to fluctuations in investment opportunities and macroeconomic fundamentals; and (iii) the AUM-weighted average of flow shocks may be driven to a great degree by the composition effect in the population of funds, thus failing to properly capture relevant fund-level dynamics of flows, which is the purpose of our measures and the aim of this paper.

Table 1: Excess returns and CAPM alphas of portfolios sorted on flow beta.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. CRSP mutual funds alone			Panel B. CRSP-Morningstar intersection		
β_i^{flow} quintiles	Excess returns	CAPM α	Fund sector "α"	Excess returns	CAPM α	Fund sector "α"
Q1	5.22	-5.51^{**}	-4.07^{**}	4.84	-4.90^{**}	-4.05^{**}
	[1.22]	[−2.56]	[−2.12]	[1.26]	[−2.58]	[−2.31]
Q2	7.17^{**}	−0.97	0.33	7.75^{***}	0.51	1.38
	[2.34]	[−0.79]	[0.27]	[2.87]	[0.49]	[1.24]
Q3	8.18^{***}	0.57	1.90	7.93^{***}	0.03	1.00
	[2.88]	[0.52]	[1.59]	[2.77]	[0.03]	[0.96]
Q4	9.27^{***}	1.05	2.47^{**}	10.72^{***}	1.79	2.78^{**}
	[3.13]	[1.20]	[2.49]	[3.24]	[1.44]	[2.20]
Q5	12.02^{***}	2.10	3.65^{*}	13.34^{***}	1.80	2.84
	[3.02]	[1.02]	[1.80]	[2.83]	[0.70]	[1.16]
Q5 − Q1	6.81^{**}	7.62^{**}	7.72^{**}	8.50^{**}	6.70^{**}	6.89^{**}
	[2.19]	[2.42]	[2.47]	[2.56]	[2.02]	[2.09]

Note: This table shows the value-weighted average excess returns (columns (1) and (4)) and CAPM alphas (columns (2) and (5)) for stock portfolios sorted on flow beta. In June of year t, we sort firms into quintiles based on their average flow betas from January to June of year t. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Our sample includes firms listed on the NYSE, NASDAQ, and American Stock Exchange (Amex) with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We annualize the average excess returns and CAPM alphas by multiplying them by 12. In columns (3) and (6), we replace market returns with aggregate mutual fund returns in the CAPM, and tabulate the intercept from the time series regression of excess portfolio returns on the aggregate active equity fund excess returns. We also annualize this intercept by multiplying it by 12. The sample period spans from July 1992 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

fund flows are the averages of the monthly common fund flow shocks. Figure 4 shows that the quarterly common fund flows of low-risk bond funds and active equity funds are negatively correlated.

2.2 Flow Betas, Returns, and Portfolio Holdings

For each stock, we estimate its flow beta in each month by regressing its monthly excess returns on the common fund flows using a 3-year rolling window (if at least 12 monthly observations are available in the rolling window):

$$ret_{i,t-\tau} = a_{i,t} + \beta_{i,t}^{flow} \times flow_{t-\tau} + \varepsilon_{i,t-\tau}, \quad \text{with } \tau = 0, 1, \cdots, 35, \tag{2.5}$$

where $flow_{t-\tau}$ denotes the common fund flow in month $t-\tau$ and $\beta_{i,t}^{flow}$ denotes stock i's flow beta in month t.

We then perform portfolio sorting analyses. In June of each year, we sort firms into quintiles based on their flow betas. Table 1 shows the average excess returns and CAPM alphas of the long-short portfolios sorted on flow beta. We find that stocks with higher flow betas are associated with higher excess returns and higher CAPM alphas. The magnitudes of the return spreads are economically large. For common fund flows constructed using the CRSP mutual fund data (see panel A of Table 1), the spread in average excess returns between the stocks

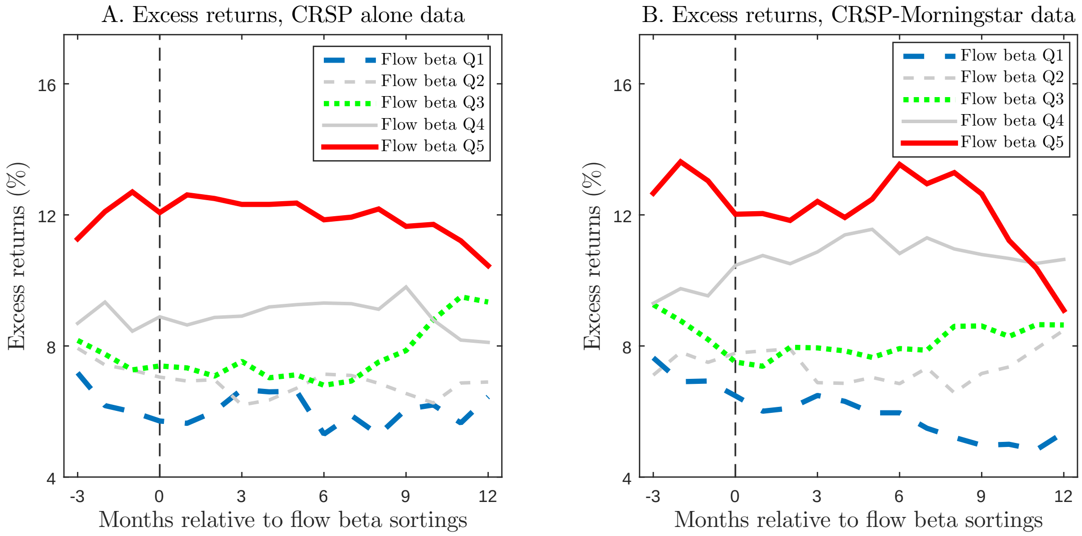


Figure 5: Excess returns after portfolio sorting based on quintiles of flow betas.

with the highest flow betas (Q5) and the stocks with the lowest flow betas (Q1) is 6.81%, while the spread in their CAPM alphas is 7.62%. These spreads are comparable in magnitude to the equity premium and the value premium.[14] We find a similar pattern when constructing common fund flows based on the CRSP-Morningstar intersection sample (see panel B of Table 1).

Figure 5 shows the annualized value-weighted excess returns of the quintile portfolios sorted on flow beta over a year-long post-formation window. We find that higher flow betas predict higher excess returns persistently over the 12-month window following portfolio formation, without strong reversal patterns. This suggests, in particular, that return predictability based on the flow beta is unlikely to be driven by the heterogeneous price impact of liquidity shocks across stocks (e.g., Lou, 2012). Our findings in Tables 7 and 8 below further strengthen this conclusion.

In addition to the portfolio-based analysis above, we perform Fama-MacBeth tests by regressing monthly stock returns on flow betas. As Table 2 shows, the slope coefficient for the flow beta is positive and statistically significant. The slope coefficient is also economically significant. According to column (1) of Table 2, a one-standard-deviation increase in the flow beta is associated with a 0.219- (2.628-) percentage-point increase in the monthly (annualized) stock returns. This result is robust to the choice of data for constructing common fund flows

[14]We further examine the risk premium associated with the fund flow betas from the perspective of the active equity funds, whose portfolios may deviate from the market portfolio on average. In column (3) of Table 1, we show that stocks with higher flow betas have higher average excess returns after adjusting for their exposure to the return on the aggregate active equity fund portfolio.

Table 2: Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Panel A: Full sample						Panel B: Exclude microcap stocks					
	CRSP alone $Ret_{i,t}$ (%)			CRSP-Morningstar $Ret_{i,t}$ (%)			CRSP alone $Ret_{i,t}$ (%)			CRSP-Morningstar $Ret_{i,t}$ (%)		
$\beta^{flow}_{i,t-1}$	0.219***	0.131**	0.153***	0.181**	0.126**	0.142***	0.221***	0.147**	0.160***	0.162**	0.115**	0.141***
	[2.780]	[2.355]	[2.848]	[2.490]	[2.234]	[2.783]	[2.845]	[2.316]	[2.719]	[2.409]	[2.008]	[2.614]
$\beta^{MacroUnc}_{i,t-1}$		−0.141**	−0.082		−0.142**	−0.075		−0.196***	−0.154*		−0.205***	−0.162**
		[−2.521]	[−1.240]		[−2.492]	[−1.132]		[−2.750]	[−1.928]		[−2.918]	[−2.055]
$\beta^{mkt}_{i,t-1}$		0.089	0.174		0.076	0.148		0.034	0.067		0.016	0.043
		[0.720]	[1.560]		[0.626]	[1.353]		[0.259]	[0.628]		[0.124]	[0.414]
$Lnsize_{i,t-1}$		−0.368***	−0.103		−0.363***	−0.097		−0.057	−0.089		−0.044	−0.075
		[−2.870]	[−0.950]		[−2.833]	[−0.889]		[−0.696]	[−1.134]		[−0.533]	[−0.963]
$LnBEME_{i,t-1}$		0.238***	0.179***		0.247***	0.182***		0.097	0.040		0.110*	0.044
		[3.096]	[2.598]		[3.153]	[2.613]		[1.557]	[0.750]		[1.724]	[0.838]
$ST\_Reversal_{i,t-1}$			−0.838***			−0.838***			−0.157***			−0.170***
			[−8.234]			[−8.223]			[−2.796]			[−2.961]
$Momentum_{i,t-1}$			−0.142			−0.144			0.121			0.111
			[−1.111]			[−1.127]			[0.924]			[0.841]
$LT\_Reversal_{i,t-1}$			−0.220***			−0.227***			−0.293***			−0.294***
			[−3.599]			[−3.643]			[−3.686]			[−3.679]
$Liqbeta_{i,t-1}$			−0.063			−0.062			−0.062			−0.047
			[−1.154]			[−1.156]			[−1.029]			[−0.798]
$AIM_{i,t-1}$			0.910***			0.911***			0.045			0.027
			[3.200]			[3.201]			[0.082]			[0.048]
Constant	1.351***	1.302***	1.249***	1.314***	1.282***	1.230***	1.151***	1.104***	1.027***	1.108***	1.084***	0.997***
	[3.858]	[3.615]	[3.802]	[3.742]	[3.554]	[3.745]	[3.615]	[3.302]	[3.451]	[3.483]	[3.257]	[3.370]
Average obs./month	3023	2800	2433	3023	2800	2433	1682	1601	1438	1682	1601	1438
Average R-squared	0.01	0.03	0.05	0.01	0.03	0.05	0.01	0.05	0.07	0.01	0.05	0.07

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly stock returns ($Ret_{i,t}$) on lagged flow betas ($\beta^{flow}_{i,t-1}$) and a set of control variables, which includes betas to the macro uncertainty shock ($\beta^{MacroUnc}_{i,t-1}$), market betas ($\beta^{mkt}_{i,t-1}$), the natural log of market cap ($Lnsize_{i,t-1}$), the natural log of book-to-market ratio ($LnBEME_{i,t-1}$), stock returns of the month prior to the current month ($ST\_Reversal_{i,t-1}$), stock returns from 12 months to 2 months prior to the current month ($Momentum_{i,t-1}$), stock returns from 60 months to 13 months prior to the current month ($LT\_Reversal_{i,t-1}$), market liquidity betas ($Liqbeta_{i,t-1}$), and Amihud illiquidity ($AIM_{i,t-1}$). $\beta^{flow}_{i,t-1}$ and the control variables are standardized to have means of 0 and standard deviations of 1. Following Bali, Brown and Tang (2017), we estimate $\beta^{MacroUnc}_{i,t-1}$ using a rolling window approach by regressing stock returns on macro economic uncertainty shocks controlling for the market return, the size and value factors (Fama and French, 1993), the momentum factor (Carhart, 1997), the market liquidity factor (Pástor and Stambaugh, 2003), and the investment and profitability factors (Fama and French, 2015; Hou, Xue and Zhang, 2015). The sample in panel A includes firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. In panel B, we further exclude stocks whose market cap is in the bottom NYSE size decile. We compute standard errors using the Newey-West estimator with a 1-month lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1992 to 2018.

and flow betas (i.e., CRSP alone vs. CRSP-Morningstar intersection sample). The result is also robust to excluding microcap stocks. In columns (7) – (12) of Table 2, we remove stocks with market cap in the bottom NYSE size decile, similar to Jegadeesh and Titman (2001) and Lou (2012). We find that the main results remain unchanged.

We find that the main results also hold after controlling for stock betas with respect to the macro uncertainty shock (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021), which has been shown to be priced in the cross-section of equity returns (e.g., Bali, Brown and Tang, 2017).[15] This is important because economic uncertainty is an important driver of common fund flows (see Sections 3 and 4), and our analysis shows that the pricing of flow betas is not based solely on their relation to uncertainty betas. We also include several common stock characteristics in the cross-sectional regression, i.e., market beta, market cap, book-to-market ratio, momentum, short-term and long-term reversal, market liquidity beta, and Amihud illiquidity (Amihud, 2002). We find that flow betas contain nontrivial incremental information about expected excess returns: Although the coefficient of the flow beta decreases substantially after we include uncertainty betas and other stock characteristics, it remains statistically and economically significant. Moreover, the long-short portfolio sorted on flow betas continues to earn "abnormal" risk-adjusted returns when controlling for its exposure to common empirical risk factors, such as the small-minus-big (SMB) factor, the high-minus-low (HML) factor, and the liquidity factor, in addition to the market factor (see Table OA.8 of the online appendix).

We now show that active equity funds tilt their portfolio holdings (relative to their benchmarks) away from stocks with higher flow betas. We run the following regression:

$$w_{i,t}^{MF} - w_{i,t}^{mkt} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{mkt} + \varepsilon_{i,t}, \tag{2.6}$$

where $\beta_{i,t}^{flow}$, $\beta_{i,t}^{mkt}$, $w_{i,t}^{MF}$, and $w_{i,t}^{mkt}$ are the flow beta, the market beta, the weight of the aggregate active equity fund portfolio, and the weight of the market portfolio for stock i in quarter t, respectively. Specifically, the weight of the market portfolio, $w_{i,t}^{mkt}$, is defined as the market cap of stock i in month t divided by the aggregate market cap across all stocks in the CRSP stock universe in month t. The term, $w_{i,t}^{MF} - w_{i,t}^{mkt}$, is the deviation of the weight of the aggregate active equity fund portfolio, $w_{i,t}^{MF}$, from that of the market portfolio, $w_{i,t}^{mkt}$, for stock i in quarter t.

Columns (1) and (2) of Table 3 show the regression results. We perform panel regressions with quarter fixed effects in panel A, and Fama-MacBeth regressions in panel B. Both settings describe the cross-sectional relation between the portfolio tilts of active equity funds and the lagged flow betas of stocks. We find that the estimated coefficient $\hat{b}_1$ is significantly negative, suggesting that active equity funds tilt their portfolio holdings away from high-flow-beta stocks

[15]In Table OA.2 of the online appendix, we report the results of the Fama-MacBeth tests in which we regress stock returns on their uncertainty betas estimated based on various economic uncertainty measures, including a macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021), an economic policy uncertainty measure (Baker, Bloom and Davis, 2016), the VXO index, and the realized market volatility. Consistent with previous studies (e.g., Brogaard and Detzel, 2015; Bali, Brown and Tang, 2017), we find that the betas to the economic uncertainty measures are negatively priced at the cross-section of stocks.

Table 3: Active equity funds tilt their holdings away from stocks with high flow betas.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
Benchmark	Market portfolio		S&P 500 portfolio		Russell 1000 growth portfolio	
	Panel A: Panel regressions with time FE					
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$	
$\beta_{i,t-1}^{flow}$	-0.017^{***}	-0.033^{***}	-0.121^{***}	-0.078^{**}	-0.076^{***}	-0.074^{***}
	[−3.253]	[−5.884]	[−3.496]	[−2.416]	[−3.407]	[−3.327]
$\beta_{i,t-1}^{mkt}$	0.061^{***}	0.068^{***}	0.128^{***}	0.129^{***}	0.103^{***}	0.113^{***}
	[7.365]	[7.950]	[3.353]	[3.202]	[4.842]	[5.056]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	413321	413321	26208	26208	30780	30780
R-squared	0.01	0.01	0.02	0.01	0.01	0.01
	Panel B: Fama-MacBeth regressions					
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$	
$\beta_{i,t-1}^{flow}$	-0.026^{***}	-0.040^{***}	-0.116^{***}	-0.066^{***}	-0.118^{***}	-0.112^{***}
	[−5.157]	[−7.541]	[−7.650]	[−3.803]	[−7.685]	[−7.839]
$\beta_{i,t-1}^{mkt}$	0.084^{***}	0.091^{***}	0.131^{***}	0.129^{***}	0.118^{***}	0.124^{***}
	[10.706]	[11.305]	[12.938]	[11.197]	[15.101]	[15.189]
Avg. obs./quarter	3863	3863	437	437	513	513
Avg. R-squared	0.01	0.01	0.02	0.01	0.02	0.02

Note: This table reports the relation between the deviation of the weight of the aggregate active equity fund portfolio from the benchmark portfolio and lagged flow betas $\beta_{i,t-1}^{flow}$. We control for market betas $\beta_{i,t-1}^{mkt}$ in the regressions. We perform panel regressions with quarter fixed effects in panel A, and Fama-MacBeth regressions in panel B. In columns (1) and (2), we use the market portfolio as the benchmark portfolio. The variables $w_{i,t}^{MF}$ and $w_{i,t}^{mkt}$ are defined in equation (2.6). The difference $w_{i,t}^{MF} - w_{i,t}^{mkt}$ represents the deviation of the aggregate active equity fund portfolio from the market portfolio. For a given quarter t, we exclude the stocks with zero aggregate equity fund holdings in current quarter t and 8 preceding quarters (i.e., quarter $t-8$ to quarter $t-1$) from our analysis; namely, we only include stocks with zero aggregate equity fund weight if these stocks have a non-zero aggregate equity fund weight in any of the quarters in the previous 2 years. In columns (3) and (4), we focus on funds that use Standard and Poor's (S&P) 500 TR as the self-declared benchmark, while in columns (5) and (6), we focus on funds that use Russell 1000 Growth TR as the self-declared benchmark. We aggregate the active equity fund holdings with the corresponding self-declared benchmarks; specifically, the variable $w_{i,t}^{MF}$ is the weight of the aggregate portfolio of active equity funds with a given self-declared benchmark for stock i in quarter t, and the variable $w_{i,t}^{Benchmark}$ is the weight of stock i in the self-declared benchmark portfolio. The samples in columns (3) – (6) cover the stocks that are only included in the benchmark portfolios. Each of the variables $\beta_{i,t-1}^{flow}$, $\beta_{i,t-1}^{mkt}$, $w_{i,t}^{MF} - w_{i,t}^{mkt}$, and $w_{i,t}^{MF} - w_{i,t}^{Benchmark}$ is standardized to have a mean of 0 and standard deviation of 1. The analysis is performed at a quarterly frequency. The sample period of columns (1) and (2) spans from 1992 to 2018, and that of columns (3) – (6) spans from 2004 to 2018. Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE stands for fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. We perform a robustness check, as reported in Table OA.12 of the online appendix, by rescaling the stock weights in the aggregate equity fund portfolio and the market portfolio to ensure that the sum of the weights for the stocks included in the analysis is 1 in each quarter, and the results remain robust to the usage of the rescaled portfolio weights.

relative to the market portfolio. The finding is robust to the use of the CRSP alone sample versus the CRSP-Morningstar intersection sample.

One could argue that because active equity funds differ in their benchmarks, it is problematic to use the market portfolio as the universal benchmark portfolio. To address this concern, we use the self-declared benchmarks of active equity funds to compute the portfolio weight deviation. We focus on several of the most frequently used benchmarks, such as the S&P 500 TR and Russell 1000 Growth TR.[16] We aggregate the portfolio holdings of active equity

[16]Our data source is the Morningstar Direct platform, which only reports the latest self-declared benchmarks. According to Evans and Sun (2021), who have access to several snapshots of historical data, changes in the

funds with the same self-declared benchmark over the stocks in their benchmark, then run the following regression separately for each benchmark:

$$w_{i,t}^{MF} - w_{i,t}^{Benchmark} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{mkt} + \varepsilon_{i,t}, \tag{2.7}$$

where $w_{i,t}^{MF}$ is the weight of stock i held by the aggregate portfolio of active equity funds with the corresponding self-declared benchmark in quarter t, and $w_{i,t}^{Benchmark}$ is the weight in the self-declared benchmark portfolio in quarter t. The estimated coefficient $\hat{b}_1$ in columns (3) – (6) of Table 3 is significantly negative, strengthening the result that active equity funds tilt their portfolios, relative to their own benchmarks, away from stocks with higher flow betas. One potential alternative explanation for our empirical findings in Table 3 is that active equity funds may stay away from small-cap stocks for liquidity reasons, and small-cap stocks are likely to be those with high flow betas (as shown in Table 7). To address this concern, we emphasize that we only consider stocks that are included in the relevant benchmark portfolios, which are mostly large-cap stocks, for the analyses presented in columns (3) – (6) of Table 3.[17]

With the active equity funds tilting away from the high-flow-beta stocks, there must be some participants in the economy who absorb active equity funds' hedging demand. Our model (see Theorem 1 below) suggests that participants who absorb the demand for low-flow-beta stocks are the "direct" investors (i.e., the trading counterparties of the active equity funds). High-flow-beta stocks must earn higher expected returns in equilibrium to induce direct investors to overweight such stocks in their portfolios, as dictated by market clearing. To address this issue empirically, we examine the holdings of index funds and household/retail investors. Columns (1) and (2) of Table 4 show that the portfolio weights of index funds deviate from the market portfolio significantly toward stocks with high flow betas. For robustness, we measure the holdings of household/retail investors using two different approaches. In columns (3) and (4) of Table 4, we follow Koijen and Yogo (2019) to measure household/retail investors' holdings as non-institutional holdings, and in columns (5) and (6) of Table 4, we use the retail investor data of Barber and Odean (2000). We find that the portfolios of the household/retail investors

self-declared benchmarks are rare (approximately 2% per year). Thus, we backfill the benchmark data for 15 years to 2004 and perform our analysis in columns (3) – (6) of Table 3. Our results remain robust if we use a shorter sample. Our results also hold for other self-declared benchmarks, such as Russell 2000 TR, Russell Mid Cap Growth TR, Russell 2000 Value TR, Russell Mid Cap Value TR, Russell 3000 TR, Russell 3000 Growth TR, and Russell Mid Cap TR.

[17]The empirical result on $\beta_{i,t-1}^{mkt}$ in Table 3 is consistent with the findings in the literature that active mutual funds tilt toward high-market-beta stocks. This empirical pattern can be rationalized by various economic mechanisms (e.g., Karceski, 2002; Huang, Sialm and Zhang, 2011; Frazzini and Pedersen, 2014). Incorporating those mechanisms goes beyond the scope of this paper in which we seek to address how funds handle common fund flow risk and how their flow hedging behaviors affect asset prices.

Table 4: Index funds and households tilt holdings toward stocks with high flow betas.

	(1) CRSP	(2) CRSP-MS	(3) CRSP	(4) CRSP-MS	(5) CRSP	(6) CRSP-MS	(7) CRSP	(8) CRSP-MS
	Panel A: Panel regressions with time FE							
	$w_{i,t}^{IF} - w_{i,t}^{mkt}$		$w_{i,t}^{NI} - w_{i,t}^{mkt}$		$w_{i,t}^{H} - w_{i,t}^{mkt}$		$w_{i,t}^{H,nonMF} - w_{i,t}^{mkt}$	
$\beta_{i,t-1}^{flow}$	0.027***	0.015*	0.010**	0.021***	0.031**	0.071***	0.032**	0.073***
	[5.253]	[1.947]	[2.145]	[4.378]	[2.119]	[6.014]	[2.180]	[6.233]
$\beta_{i,t-1}^{mkt}$	−0.025***	−0.020***	−0.079***	−0.084***	−0.043***	−0.051***	−0.038***	−0.047***
	[−3.839]	[−3.054]	[−12.301]	[−13.429]	[−4.233]	[−5.031]	[−3.673]	[−4.517]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395294	395294	582332	582332	60091	60091	58356	58356
R-squared	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02
	Panel B: Fama-MacBeth regressions							
	$w_{i,t}^{IF} - w_{i,t}^{mkt}$		$w_{i,t}^{NI} - w_{i,t}^{mkt}$		$w_{i,t}^{H} - w_{i,t}^{mkt}$		$w_{i,t}^{H,nonMF} - w_{i,t}^{mkt}$	
$\beta_{i,t-1}^{flow}$	0.035***	0.012*	0.013***	0.019***	0.042***	0.077***	0.044***	0.080***
	[9.622]	[1.836]	[3.837]	[5.313]	[3.235]	[7.485]	[3.339]	[7.783]
$\beta_{i,t-1}^{mkt}$	−0.017***	−0.008**	−0.091***	−0.094***	−0.054***	−0.061***	−0.049***	−0.056***
	[−5.404]	[−2.505]	[−22.896]	[−24.304]	[−8.106]	[−8.557]	[−7.262]	[−7.920]
Avg. obs./quarter	3694	3694	5442	5442	3163	3163	3071	3071
Avg. R-squared	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02

Note: This table reports the relation between the flow beta $\beta_{i,t-1}^{flow}$ and the portfolio tilt of index funds, non-institutional investors, and household/retail investors, relative to the market portfolio. We control for the market beta $\beta_{i,t-1}^{mkt}$ in the regressions. We perform panel regressions with quarter fixed effects in panel A and Fama-MacBeth regressions in panel B. $w_{i,t}^{IF}$, $w_{i,t}^{NI}$, $w_{i,t}^{H}$, and $w_{i,t}^{H,nonMF}$ are the portfolio weights of stock i in the aggregate portfolio holdings of index funds, non-institutional investors, household/retail investors, and household/retail investors who do not hold mutual funds in quarter t, respectively. $w_{i,t}^{mkt}$ is the weight of stock i in the market portfolio. We measure the non-institutional holdings of a given stock using the total shares outstanding minus the institutional holdings aggregated across all institutional investors covered by the 13F data (e.g., Koijen and Yogo, 2019). We obtain the holdings of household/retail investors from Barber and Odean's data (e.g., Barber and Odean, 2000), which contain 66,465 households with accounts at a large discount broker from 1991 to 1996. $w_{i,t}^{IF} - w_{i,t}^{mkt}$, $w_{i,t}^{NI} - w_{i,t}^{mkt}$, $w_{i,t}^{H} - w_{i,t}^{mkt}$, $w_{i,t}^{H,nonMF} - w_{i,t}^{mkt}$, $\beta_{i,t-1}^{flow}$, and $\beta_{i,t-1}^{mkt}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at a quarterly frequency. The sample period spans from 1992 to 2018 in columns (1) – (4), and spans from 1992 to 1996 in columns (5) – (8). Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE stands for fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

deviate significantly from the market portfolio toward stocks with high flow betas (see columns (5) and (6)). This is true even for those household/retail investors who do not invest in mutual funds (see columns (7) and (8)), suggesting that retail investors absorb active equity funds' hedging demand and thus earn the equity premium of the high-flow-beta stocks.[18]

[18] One subtle alternative interpretation of the pattern in columns (5) and (6) is an argument in the spirit of the Modigliani-Miller theorem that household/retail investors invest in active mutual funds and are sufficiently sophisticated to understand that the active mutual funds in their portfolios tend to tilt their positions against high-flow-beta stocks. To offset this tilt, household/retail investors may then overweight high-flow-beta stocks in their own direct investment portfolios. However, this alternative interpretation is unlikely to be true in reality for the following two reasons. First, columns (7) and (8) of Table 4 show that household/retail investors who do not invest in mutual funds still exhibit significant portfolio deviation toward high-flow-beta stocks from the market portfolio. Second, mutual fund clients are relatively unsophisticated in making investment decisions, as shown in previous studies (e.g., Frazzini and Lamont, 2008; Berk and van Binsbergen, 2016*b*; Barber, Huang and Odean, 2016; Ben-David et al., 2021).

2.3 Discussion

Our empirical findings on stock returns and portfolio holdings are difficult to address in a traditional institution-free theoretical framework. Tables 1 – 2 and Figure 5 show that the common fund flow is a systematic risk factor and is priced in the cross-section of stock returns. This result cannot be explained by the classic institution-free ICAPM hedging mechanism, according to which common fund flow shocks should be priced only on the basis of their correlation with shocks to aggregate investment opportunities faced by households, or, more broadly, with macroeconomic shocks affecting households' marginal utility. The difficulty with the traditional explanation is that the portfolio deviation of household/retail investors relative to the market portfolio is in the direction of high-flow-beta stocks (see columns (5) and (6) of Table 4 for empirical evidence) — hence, the relatively high risk premia earned by these stocks cannot be explained by household/retail investors' hedging against primitive macroeconomic shocks that endogenously drive common fund flows. Thus, there must exist another group of investors underweighting high-flow-beta stocks and driving up their risk premia. We find that active equity funds do just that, tilting their portfolios away from high-flow-beta stocks (see Table 3 for empirical evidence), which implies that the trading behavior of these funds is central to understanding the pricing of risk premia on common fund flow shocks.

As we show, active equity funds systematically overweight low-flow-beta stocks (see Table 3). Because these stocks have relatively low risk premia and negative alphas relative to the CAPM model, it appears that active equity funds fail to maximize the Sharpe ratio of their portfolios, thus pursuing an objective different from the simple mean-variance framework. This observation, combined with the fact that the average portfolio tilt of active equity funds along the flow-beta dimension of stocks is opposite to that of household/retail investors, suggests that the behavior of active equity funds reflects an agency friction. We argue that this friction is central to understanding why common fund flow shocks are priced and that, to explain our empirical findings in a theoretical model, we must incorporate a nontrivial intermediary sector that does not simply act on behalf of and in the best interest of households.

3 Model

In this section, we develop a stylized model to help interpret our empirical results and suggest further testable hypotheses based on the proposed economic mechanism. Proofs are in the online appendix.

We start with the observation that for active equity funds (including active equity mutual and pension funds), which control a large fraction of equity investments, revenue per period depends mainly on fund size. This is because their management fees are close to a fixed percentage of their AUM. Fund size is in turn affected by fund flows. Consequently, all active equity funds have an incentive to reduce their portfolio exposures to fund-flow shocks by tilting away from stocks with high betas on the common component of fund flows. As a result of this portfolio tilt, the equilibrium risk premium on high-flow-beta shocks rises in order to induce other investors to elevate their holdings of such stocks, as dictated by market clearing. Thus, common fund flow shocks are priced in equilibrium, leading to a multi-factor asset-pricing model similar to ICAPM and Arbitrage Pricing Theory (APT).[19] To contrast the main mechanism of our model with the classic institution-free ICAPM framework, we assume that all investors are myopic, and therefore equilibrium pricing patterns are not driven by their intertemporal hedging demand. This has a further advantage of reducing the informational burden on the households, particularly those who delegate their investments to active funds and thus do not perform any stock selection.

3.1 Assets and Returns

There are n risky assets, indexed by $i = 1, \cdots, n$. Their (gross) returns over period t are stacked in vector $R_{t+1} = [R_{1,t+1}, \cdots, R_{n,t+1}]^T$, and the log returns are $r_{t+1} \equiv \ln(R_{t+1})$ that follow

$$r_{t+1} - \mathbb{E}_t\left[r_{t+1}\right] = \sqrt{h_t}\left(Ku_{t+1} + \varepsilon_{t+1}\right), \tag{3.1}$$

where $u_t = [u_{1,t}, \cdots, u_{k,t}]^T$ are k primitive factors independently and identically distributed (IID). $N(0, I_k)$, and $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]^T$ are residuals IID $N(0, I_n)$. The $n \times k$ matrix K captures the loading coefficients of n log returns r_{t+1} on k factors u_{t+1}.[20] Univariate state variable h_t describes the time-varying uncertainty in the model, and is driven by k aggregate shocks u_t as

[19] Our model is similar in spirit to the intermediary asset-pricing theories emphasizing agency conflicts between funds and clients. For example, the seminal works by Shleifer and Vishny (1997) and He and Krishnamurthy (2013) showed that intermediaries are averse to assets that are relatively more exposed to funding liquidity shocks, and thus the risk premium of such assets rises with the funding liquidity risk in the economy. Another closely related example is that of Frazzini and Pedersen (2014), who argued that the observed flatness of the capital market line is caused by the systematic tilt of the funds towards the high-market-beta stocks. Our analysis differs from prior papers in its focus on the unique role of common fund flow shock.

[20] We assume that the number of assets, n, is high, and that various cross-sectional averages of residuals, e.g., $(1/n)\sum_{i=1}^{n} \varepsilon_i$, are approximately equal to 0, as in the setting of APT (Ross, 1976).

follows:[21]

$$h_{t+1} = \bar{h} + \rho(h_t - \bar{h}) + \sqrt{h_t}\sigma u_{t+1}, \quad \text{with } \rho \in (0,1) \text{ and } \sigma \in \mathbb{R}^{1\times k}, \tag{3.2}$$

where the $1 \times k$ vector $\sigma = [\sigma_1, \cdots, \sigma_k]$ has nonnegative elements, i.e., $\sigma_j \geq 0$ for $j = 1, \cdots, k$.

Similar to Kozak, Nagel and Santosh (2018), we assume that the supply of the risk-free bond is perfectly elastic, with a constant gross risk-free return of $R_f > 1$. Let $r_f \equiv \ln(R_f)$ denote the log risk-free interest rate. The conditional mean and covariance matrix of the log return are denoted by

$$\mu_t \equiv \mathbb{E}_t[r_{t+1}] \quad \text{and} \quad \Sigma_t \equiv \text{var}_t[r_{t+1}], \text{ respectively.} \tag{3.3}$$

Next, we derive equilibrium restrictions on $\Sigma_t = h_t\Sigma$, with $\Sigma \equiv I_n + KK^T$, and μ_t. In the spirit of APT, we are agnostic about the precise nature of common shocks u_t. For instance, some components of u_t may represent fundamental systematic shocks, such as cash flow news or uncertainty shocks, while others may represent broad sentiment shocks (e.g., Hirshleifer and Jiang, 2010; Stambaugh and Yuan, 2016; Kozak, Nagel and Santosh, 2018).[22]

Denote the log return of the portfolio $\phi \in \mathbb{R}^{n\times 1}$ by $r_{t+1}(\phi) = \ln[R_{t+1}(\phi)]$, where

$$R_{t+1}(\phi) \equiv R_f + \phi^T(R_{t+1} - R_f). \tag{3.4}$$

Following Campbell and Viceira (1999, 2001), we approximate the portfolio's log return as

$$r_{t+1}(\phi) \approx r_f + \phi^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi^T(v_t - \Sigma_t\phi), \tag{3.5}$$

where $v_t \equiv \text{diag}(\Sigma_t)$ is the vector that contains the diagonal elements of Σ_t.

3.2 Active Funds

To focus on common fund flows, we assume that active funds are homogenous. Active funds in the model are typically active equity funds (including active equity mutual and pension funds), while fund clients are typically retail individual investors and pension sponsors. Active funds can trade all assets and charge an advisory fee from fund clients, which is a constant f

[21] We impose a zero lower bound on h_t similar to Bansal and Yaron (2004) and Chen, Dou and Kogan (2021).

[22] As emphasized, for example, by Long et al. (1990), there need not be a clear-cut distinction between mispricing and risk compensation as alternative justifications for multi-factor models of expected return. Specifically, Long et al. (1990) showed that fluctuations in market-wide sentiment of noise traders give rise to a source of systematic risk for which rational traders require compensation. Thus, the mere existence of priced factors in stock returns does not guarantee that the premia on these factors reflect compensation for risk (e.g., MacKinlay, 1995; Kozak, Nagel and Santosh, 2018).

fraction of their AUM.[23]

Similar to the framework of Berk and Green (2004), we assume that active funds have skillful managers and information advantages to add value by generating expected excess returns relative to passive investment strategies. As argued by the literature,[24] some meaningful ways exist for active funds to add value to their investors as a group. The value extracted by active funds from capital markets is essentially a transfer of wealth from passive to active funds through various channels.[25]

Suppose an active fund controls Q_t in AUM. We model the value added by the active fund in reduced form as $\overline{\alpha} Q_t$. Expected excess return $\overline{\alpha}$ captures the gross alpha of the active fund before expenses and fees. Active funds incur a cost to investigate and implement active investment strategies, which we assume to be increasing and convex in fund's AUM, following Berk and Green (2004). Specifically, an active fund of size Q_t incurs a total cost of $\psi(q_t)W_t$, where W_t is the average wealth per agent, $q_t = Q_t/W_t$, and $\psi(q) \equiv \theta^{-1}q^2$. Our specification implies decreasing returns to scale for active funds. The expected excess total payout by active funds to their clients is $TP_t = \overline{\alpha}Q_t - \psi(q_t)W_t - fQ_t$, where $\overline{\alpha}Q_t$, $\psi(q_t)W_t$, and fQ_t are the value added, the fund costs, and the management fee charged by active funds, respectively. We define the net alpha as $\alpha_t \equiv TP_t/Q_t$, the expected return received by the fund clients in period t in excess of the benchmark return. Replacing TP_t with $\alpha_t Q_t$, we establish a relation between the net alpha, α_t, and the total amount of AUM of the funds, q_t:

$$\theta(\overline{\alpha} - \alpha_t) - \theta f = q_t. \tag{3.6}$$

The above relation is an important element of the model and characterizes the relation between the net alpha and fund size, determined by the technology and fee structure of the active funds.

[23]We assume exogenous constant expense ratio f for simplicity. The expense ratio can be endogenized similar to Kaniel and Kondor (2013).

[24]See, e.g., Vayanos and Woolley (2013), Berk and van Binsbergen (2015, 2016*a*), Pedersen (2018), and Leippold and Rueegg (2020), who examine whether an average active fund manager can add value in a fully rational equilibrium.

[25]For instance, one such channel is that active funds may act as informed arbitrageurs to make money at the cost of passive funds as uninformed participants when new price-sensitive information arrives (see Grossman and Stiglitz, 1980; García and Vanden, 2009, for the theoretical framework). Second, passive funds must track the benchmark indices closely, thereby forcing them to demand immediacy and incur additional costs. Active funds are not subject to the same index-tracking requirements, which in principle allows them to act as liquidity providers to the index funds. Third, the benchmark indices do not contain all available assets in markets such as frontier markets, emerging markets, and private markets. Active funds have scope to explore profitable investment opportunities outside benchmark indices (e.g., Vayanos and Woolley, 2013).

3.3 Myopic Agents

The economy is populated by three different types of agents: direct investors, fund clients, and active fund managers. All investors can invest in and trade the risk-free asset. Direct investors, labeled by d, have to trade risky assets directly on their own accounts or hold passive investments such as benchmark indices; they are mainly index funds, passive exchange-traded funds (ETFs), and individual retail investors. Fund clients, labeled by c, have to delegate their risky-asset investments to professional active fund managers.[26] Fund clients can be retail individual investors or institutional investors such as pension sponsors or university endowments (e.g., Gerakos, Linnainmaa and Morse, 2021). Active fund managers, labeled by m, operate the funds, consume their fund revenues, and can invest in the risk-free asset on their own accounts to smooth consumption over time.

All agents live for two periods, forming overlapping generations (OLGs). Cohort-t agents are born in period t and die in period $t+1$. All agents have the same Epstein-Zin-Weil preference with unitary elasticity of intertemporal substitution (EIS). Each agent in cohort t cares about her consumption in period t (when she is young) and the bequest to her descendants in period $t+1$ (when she is old). The utility function of agents of cohort t and type i is

$$U_{i,t} = (1-\beta)\ln\left(C_{i,t}\right) + \beta(1-\gamma)^{-1}\ln \mathbb{E}_t\left[\tilde{W}_{i,t+1}^{1-\gamma}\right], \quad \text{for } i \in \{d, c, m\}, \tag{3.7}$$

where $C_{i,t}$ and $\tilde{W}_{i,t+1}$ are cohort t's consumption and wealth in periods t and $t+1$, respectively.

A unit measure of newly born investors arrives at the beginning of each period. Investors are randomly assigned as fund clients with probability λ or as direct investors with probability $1-\lambda$. As a result, the newly-born direct investors are endowed with $(1-\lambda)W_t$ as their total initial wealth, while the newly-born fund clients are endowed with λW_t in total, where W_t is the total wealth of cohort t in period t. There is a unit measure of newly-born active fund managers with zero endowment.

We adopt an OLG framework to avoid tracking wealth shares as endogenous state variables when characterizing the equilibrium.[27] Moreover, we assume that agents in our model do not

[26] This is a simplification. In the online appendix, we present an extended model in which fund clients can choose to trade risky assets directly.

[27] Kaniel and Kondor (2013) showed how the constant wealth share of fund clients may arise endogenously as an equilibrium outcome. We can extend the model to endogenize the industry size of active equity funds, but we emphasize that it is not the focus of this paper to rationalize why a sizable industry of active equity funds would endogenously emerge as an equilibrium outcome. Rather, this paper explores how agency conflicts between active equity funds and their clients affect equity prices, given that active equity funds manage a large fraction of equity market investments.

internalize their descendants' utility beyond the wealth term in Equation (3.7) to ensure that agents in our model are myopic.[28]

Direct Investors. The total wealth of the cohort-t direct investors is $W_{d,t} = (1-\lambda)W_t$. Direct investors choose portfolio weights $\phi_{d,t}$ and consumption $C_{d,t}$ optimally to maximize the utility in Equation (3.7), subject to the dynamic budget constraint:

$$\tilde{W}_{d,t+1} = (W_{d,t} - C_{d,t} - \overline{\alpha}Q_t)R_{t+1}(\phi_{d,t}), \tag{3.8}$$

where $\overline{\alpha}Q_t$ is the transfer from direct investors to active funds as discussed in Section 3.2.

Proposition 3.1. *The optimal consumption and portfolio policies of the direct investors are*

$$C_{d,t} = (1-\beta)(1-\lambda-\overline{\alpha}q_t)W_t \quad \text{and} \quad \phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right), \quad \text{respectively,} \tag{3.9}$$

where $\phi_{d,t}$ is the myopic mean-variance efficient portfolio with μ_t, Σ_t, and ν_t defined in Equations (3.3) to (3.5).

Fund Clients. Fund clients decide the amount of wealth to delegate to active funds, denoted by Q_t, and then active fund managers choose the allocation of the delegated funds across risky assets. Berk and van Binsbergen (2016*b*) and Barber, Huang and Odean (2016) found evidence that fund clients are not sophisticated in their assessment of fund performance and delegation decisions. To highlight this lack of sophistication, we assume that fund clients care about the net alpha of the active funds relative to a passive benchmark.[29]

The wealth of cohort-t fund clients is $W_{c,t} = \lambda W_t$, and they choose delegation Q_t and consumption $C_{c,t}$ optimally to maximize the utility in Equation (3.7) subject to

$$\tilde{W}_{c,t+1} = (W_{c,t} - C_{c,t} - Q_t)R_f + Q_t\left[R_{t+1}(\phi_{d,t}) + \alpha_t\right]. \tag{3.10}$$

Proposition 3.2. *If the perceived benefit from active management is sufficiently high relative to the cost of delegation, i.e., $\overline{\alpha} > \theta^{-1}\beta\lambda + f$, fund clients choose to delegate their portfolios to the active funds. In*

[28]Seminal works (e.g., Barro, 1974; Abel, 1987) showed that OLG models with operative bequests are formally equivalent to models with infinitely lived representative agents. Our assumption violates the conditions to ensure operative bequests. As a result, investors in our model are myopic.

[29]While we model the behavior of fund clients to be consistent with the main thrust of the recent literature on mutual fund flows, the precise behavioral assumptions we make are not essential for the key conclusions of our model on active fund hedging of common fund flow shocks, or the risk premium generated by the flow-hedging demand. The essential element of the fund client's behavior is that they vary the share of their wealth allocated to active funds, e.g., reduce it when facing heightened economic uncertainty.

this case, the optimal consumption and delegation of fund clients satisfy

$$C_{c,t} = (1-\beta)\lambda W_t \quad \text{and} \quad q_t = \beta\lambda\left(1+\frac{\alpha_t}{\overline{\gamma}h_t}\right), \tag{3.11}$$

where $\overline{\gamma}$ is a constant determined in equilibrium.

The above relation is another important element of the model and characterizes the demand curve for active funds' asset management services determined by the investment decision of the fund clients.

Active Fund Managers. The AUM of an active fund at the beginning of period t is Q_t and the revenue of the fund is advisory fee fQ_t. We assume that the fund manager of cohort t gets paid by fQ_{t+1} in period $t+1$, meaning that there is no agency conflict between the fund complex and the fund manager. A similar simplifying assumption has been commonly adopted in the literature.[30] What matters for our theoretical results is that active fund managers care about their fund's AUM, which is supported by the data (e.g., Ibert et al., 2018).[31]

Active fund managers in our model can save, and they don't have to consume fund revenues immediately period by period. But, importantly, we assume that active fund managers cannot invest in risky assets using their private wealth. This simplifying assumption has been widely adopted in the literature (e.g., Berk and Green, 2004; Cuoco and Kaniel, 2011; Kaniel and Kondor, 2013) for technical tractability, and enables us to avoid keeping track of active fund managers' private wealth, investment decisions, and associated constraints. Our theoretical results apply as long as the fund manager is unable to hedge against the flow risk fully by trading on a personal account for reasons such as liquidity constraints, leverage constraints, and frictions associated with short sales.

The active fund manager of cohort t chooses fund portfolio $\phi_{m,t}$ and consumption $C_{m,t}$

[30] E.g., Brennan (1993), Gómez and Zapatero (2003), Basak, Pavlova and Shapiro (2007), Chapman, Evans and Xu (2010), Cuoco and Kaniel (2011), Kaniel and Kondor (2013), Basak and Pavlova (2013), and Koijen (2014).

[31] Lee, Trzcinka and Venkatesan (2019) and Ma, Tang and Gómez (2019) suggested that active fund managers' pay may depend on relative performance even after controlling for fund size in the US, while Ibert et al. (2018) provided strong evidence, based on Swedish data, that managers' pay is not sensitive to relative performance after controlling for fund size. Ibert et al. (2018) found a concave dependence of mutual fund managers' compensation on their fund's AUM, sufficing to ensure the key conclusions of our model about fund managers' flow hedging motives. As long as the incentives of active funds and their managers are aligned, even partially, active fund managers should have incentives to hedge fund-flow shocks. Our specification assumes for simplicity that the pay of an active fund manager depends exclusively on fund size.

optimally to maximize the utility in Equation (3.7) subject to the budget constraint:

$$\tilde{W}_{m,t+1} = fQ_{t+1} - C_{m,t}R_f, \quad \text{with} \tag{3.12}$$

$$Q_{t+1} = \underbrace{Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t\right]}_{\text{fund returns}} + \underbrace{Q_t flow_{t+1}}_{\text{fund flows}}, \tag{3.13}$$

where Q_t is the delegation characterized in Equation (3.11) given net alpha α_t and aggregate state h_t, and $Q_t flow_{t+1}$ is the net fund flow into the active fund.[32]

Equation (3.13) essentially gives the definition of the fund flow, denoted by $flow_{t+1}$:

$$flow_{t+1} \equiv \frac{Q_{t+1} - Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t\right]}{Q_t}. \tag{3.14}$$

The dynamic budget constraint in Equation (3.13) is very intuitive. The total asset valuation at the beginning of period $t+1$ is $Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t\right]$ because active fund managers would consume management fees fQ_t and incur costs $\psi(q_t)Q_t$ to add value $\overline{\alpha}Q_t$ for active funds. The total AUM at the beginning of period $t+1$ is the sum of the fund return and fund flow: $Q_{t+1} = Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t + flow_{t+1}\right]$.

3.4 Equilibrium Relations and Hypothesis Development

We define competitive equilibrium formally in the appendix. Below we characterize equilibrium dynamics.

Endogenous Flows. Fund flow $flow_{t+1}$ is endogenously driven by aggregate shocks in equilibrium. In Proposition 3.3, we show that the equilibrium level of delegation depends negatively on uncertainty, and thus money flows out of active funds when aggregate uncertainty rises.

Proposition 3.3 (Fund flows and uncertainty)**.** *When the benefits from active management are high relative to the cost of delegation, i.e., $\overline{\alpha} > \theta^{-1}\beta\lambda + f$, the equilibrium amount of delegation q_t can be expressed as a monotonically decreasing function of uncertainty h_t:*

$$q_t = q(h_t), \quad \textit{with} \;\; q'(\cdot) < 0,$$

[32] We assume that active fund managers are myopic to highlight that our equilibrium results do not require any agents to engage in intertemporal hedging. This assumption is in fact consistent with active fund managers' short-term focus stemming from their career concerns (e.g., Prat, 2005; Hermalin and Weisbach, 2012).

where q_t is defined in Proposition 3.3. Equilibrium fund flows satisfy

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t} A u_{t+1}, \;\; \textit{with } A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma \in \mathbb{R}^{1\times k}, \tag{3.15}$$

where σ is defined in Equation (3.2). In particular, fund flows are conditionally negatively correlated with uncertainty shocks:

$$Cov_t[flow_{t+1}, h_{t+1} - h_t] < 0.$$

Proposition 3.3 offers an empirically testable hypothesis that common fund flows comove negatively with fluctuations in economic uncertainty. We verify this relation empirically in Tables 5 and 6 of Section 4.2 and with additional empirical evidence in Online Appendix 4.3.

Importantly, the common fund flows studied in Proposition 3.3 are capital flows across asset classes (or across different types of funds that focus on different asset classes), as in Gabaix and Koijen (2021). Our model therefore implies that, when uncertainty rises, fund clients' money flows from the active funds of risky equities to the bond funds of low-risk securities, such as investment-grade corporate bond funds, short-duration corporate bond funds, short-duration government bond funds, and money market funds. That is, bond funds holding low-risk securities are the recipients of fund flows out of the active equity funds. Aside from the evidence shown in Figure 4 and Table 5, there is extensive empirical evidence in the literature supporting this aspect of our model (e.g., Chen and Qin, 2017; Wang and Young, 2020; Chan and Marsh, 2021).

Flow Betas of Stock Returns. Proposition 3.4 shows that flow betas depend on the exposures of stock returns to the entire vector of systematic shocks u_t. Recall that u_t may contain both the "fundamental" shocks, e.g., cash-flow news, and "non-fundamental" liquidity shocks. In equilibrium, all of these shocks earn a risk premium proportional to their effect on common fund flows in the model.

Proposition 3.4 (Endogenous flows and flow betas)**.** *Under the same assumptions of Proposition 3.3, flow betas of stock returns, defined by $\mathcal{B}^{flow} \equiv Cov_t\left[r_{t+1}, flow_{t+1}\right] / \mathrm{var}_t\left[flow_{t+1}\right]$, are*

$$\mathcal{B}^{flow} \approx \left[\frac{q'(\bar{h})}{q(\bar{h})}\right]^{-1} K\sigma^T(\sigma\sigma^T)^{-1}. \tag{3.16}$$

where K is the loading matrix of returns on shocks u_{t+1}, defined in Equation (3.1).

In Section 4.3, we analyze sources of heterogeneity in flow betas across stocks empirically. We show flow betas to be related to both the cash flow betas of stocks (Table 9) and the various price-impact measures (Table 7), which may reflect the effect of fund flows on stock prices as liquidity shocks.

Portfolio Tilts of Active Funds. Theorem 1 shows that, relative to the market portfolio, active funds tilt their portfolios toward low-flow-beta stocks. In contrast, the portfolio holdings of mean-variance optimizing direct investors overweight high-flow-beta stocks relative to the market portfolio, induced by the differential general-equilibrium asset-pricing effects of active funds' flow-hedging tilt on stocks with different fund-flow betas. The tilt of active funds and the deviation of direct investors, relative to the market portfolio, offset each other at the aggregate level to ensure market clearing.

Theorem 1 (Portfolio tilts and flow betas)**.** *In equilibrium, the portfolio tilts of active funds relative to the market portfolio tend to be more positive for stocks with lower flow betas, while the portfolio deviations of the direct investors from the market portfolio tend to be more positive for stocks with higher flow betas:*

$$\widehat{Cov}\left[\mathcal{B}^{flow}, \phi_{m,t} - \phi_t^{mkt}\right] < 0 \quad \text{and} \quad \widehat{Cov}\left[\mathcal{B}^{flow}, \phi_{d,t} - \phi_t^{mkt}\right] > 0, \quad \text{for each } t, \tag{3.17}$$

where $\mathcal{B}^{flow}$ is defined in Proposition 3.4, ϕ_t^{mkt} is the market portfolio, and $\widehat{Cov}[\cdot,\cdot]$ denotes the covariance over the cross-section of risky assets.[33]

The first result of Theorem 1 on the portfolio tilt of active funds, $\phi_{m,t} - \phi_t^{mkt}$, rationalizes the central empirical finding of this paper — the tilt in portfolio holdings of active equity mutual funds away from high-flow-beta stocks, as shown in Table 3. Intuitively, active funds in our model have incentive to hedge against common-flow shocks and, hence, tilt their portfolios away from high-flow-beta stocks. The second result of Theorem 1 on the portfolio tilt of direct investors, who act as trading counterparties of the active funds in our model, $\phi_{d,t} - \phi_t^{mkt}$, motivates our empirical analysis of the equilibrium portfolio deviation of index funds and household/retail investors from the market portfolio. As we show in Table 4 in Section 4.5, these investors tend to overweight high-flow-beta stocks relative to the market portfolio in their holdings, thus absorbing the hedging demand of active equity funds. We emphasize that different from active funds' portfolio tilts, direct investors' deviations from the market portfolio result from the general-equilibrium asset-pricing effects rather than their "active" asset selections or portfolio tilts.

[33] The sign of the cross-sectional covariance between portfolio weights and flow betas is what one would estimate empirically in a cross-sectional regression, making the result of the theorem directly testable.

Excess Returns and Endogenous Flow Risk. In equilibrium, common fund flows respond to aggregate economic shocks, and thus, risk premia analogous to the hedging term in ICAPM emerge even in a myopic environment, as summarized in Theorem 2.

Theorem 2 (Equilibrium price of flow risk)**.** *The risk premium of each asset is explained by its covariances with the log market return, denoted by r^{mkt}_{t+1}, and its covariance with the common fund flow, denoted by $flow_{t+1}$:*

$$\mathbb{E}_t\left[r_{t+1}\right] - r_f\mathbf{1} + \frac{1}{2}\nu_t \;\approx\; \underbrace{\gamma Cov_t\left[r_{t+1},\, r^{mkt}_{t+1}\right]}_{\text{explained by market beta}} \;+\; \underbrace{\eta_t\gamma Cov_t\left[r_{t+1},\, flow_{t+1}\right],}_{\text{explained by flow beta}}$$

where $\nu_t/2$ is the Jensen's term, and $\eta_t \equiv q_t/\left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right]$ depends on the amount of delegation in equilibrium.

The result of Theorem 2 on the equilibrium relation between risky assets' expected returns and their flow betas rationalizes the empirical patterns in Tables 1 and 2 above.

Corollary 3.1 (CAPM holds when there is no delegation)**.** *When there is no delegation in the economy, i.e., $\lambda = 0$, Theorem 2 implies the conditional CAPM:*

$$\mathbb{E}_t\left[r_{t+1}\right] - r_f\mathbf{1} + \frac{1}{2}\nu_t \approx \gamma Cov_t\left[r_{t+1},\, r^{mkt}_{t+1}\right]. \tag{3.18}$$

It further implies that the CAPM holds:

$$\mathbb{E}\left[r_{t+1} - r_f\mathbf{1} + \frac{1}{2}\nu_t\right] \approx \beta^T\mathbb{E}\left[r_{t+1} - r_f\mathbf{1} + \frac{1}{2}\nu_t\right], \tag{3.19}$$

where $\beta \equiv Cov\left[r_{t+1},\, \check{r}^{mkt}_{t+1}\right]/Var\left[\check{r}^{mkt}_{t+1}\right]$ is the market beta with $\check{r}^{mkt}_{t+1} \equiv r^{mkt}_{t+1} - \mathbb{E}_t\left[r^{mkt}_{t+1}\right]$.

When there are no fund clients in the economy (i.e., $\lambda = 0$), equilibrium delegation level $q_t \equiv 0$ according to Proposition 3.3, leading to $\eta_t \equiv 0$. In this case, every investor consumes $C_t = (1-\beta)W_t$ and holds the mean-variance efficient portfolio $\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f + \frac{1}{2}\nu_t\right)$.

Our analysis shows that common fund flow shocks can earn a risk premium, leading to a multi-factor asset pricing model similar to ICAPM, even with all agents being relatively unsophisticated and behaving myopically. Although our theory is silent on why fund clients may not properly optimize and engage in intertemporal hedging, it shows that, even with them behaving myopically, common fund flows may act as an "invisible hand" to generate an ICAPM-like relation. Our findings suggest that focusing on common fund flows, in addition to cross-fund flows considered in the prior literature, reveals important incremental asset-pricing information. Specifically, while cross-fund flows are informative about fund clients' preferences and asset-pricing models they use (e.g., Berk and van Binsbergen, 2016*b*; Barber, Huang and Odean, 2016), we show that common fund flows affect portfolio decisions of active equity funds and lead to a cross-sectional relation between risk premia of stocks and their return betas with respect to common fund flow shocks.

4 Empirical Analysis

4.1 Data

Data on Mutual Fund Returns and Assets. We obtain fund names, monthly returns, monthly TNAs, investment objectives, and other fund characteristics from the CRSP Survivorship-Bias-Free Mutual Fund Database. Similar to prior studies (e.g., Kacperczyk, Sialm and Zheng, 2008; Huang, Sialm and Zhang, 2011), we identify actively managed US equity mutual funds based on their objective codes and disclosed asset compositions. To gain more precision on the classification, we further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data. We provide details in Appendix B. Because data coverage on monthly TNAs prior to 1991 is scarce and poor, the sample in our paper spans from January 1991 to December 2018.

We use the Morningstar database to cross-check the accuracy of the monthly fund returns and TNAs in the CRSP data, following recent studies (e.g., Berk and van Binsbergen, 2015; Pástor, Stambaugh and Taylor, 2015). Specifically, we define a share class as a well matched one if and only if (i) the 60th percentile (over the available sample period) of the absolute value of the difference between the CRSP and Morningstar monthly returns is fewer than five basis points, and (ii) the 60th percentile of the absolute value of the difference between the CRSP and Morningstar monthly TNAs is less than $100,000.[34] After applying the aforementioned procedure, around 63% of fund share-month observations in the CRSP panel data are matched with the Morningstar data. Among the unmatched 37%, around 2% of share-month observations in the CRSP panel data are not matched with the Morningstar data because of the discrepancies in the reported returns and TNAs across the two datasets, while the remaining 35% are not matched because of no coverage in the Morningstar data. The above summary statistics for the matching percentages are similar to those of Pástor, Stambaugh and Taylor

[34] The cutoffs of five basis points and $\$100,000$, as well as the 60th percentile, are the same as those used by Pástor, Stambaugh and Taylor (2015).

(2015). Throughout this paper, we present all empirical results of our analysis based on two versions of common fund flows. The first version is constructed based on the sample in the CRSP mutual fund data alone, and the second uses the sample that is well-matched between the CRSP and Morningstar databases. We show that our results are robust for both versions of common fund flow.

Data on Mutual Fund Portfolio Holdings and Benchmarks. We obtain the quarterly portfolio holdings of mutual funds from Thomson Reuters mutual fund holdings data (S12) and CRSP mutual fund holdings data. Recent studies have shown that Thomson's portfolio holdings data suffer from problems such as missing funds after 2008 (Zhu, 2020), while CRSP portfolio holdings data are "inaccurate prior to the fourth quarter of 2007" (Schwarz and Potter, 2016). To minimize data quality concerns, we use Thomson's portfolio holdings data up to the second quarter of 2008 and use CRSP portfolio holdings data after the third quarter of 2008 following the recommendation of previous studies (e.g., Shive and Yun, 2013; Zhu, 2020). We obtain the self-declared benchmarks of mutual funds from the Morningstar database.[35] The composition and weights of stocks in the benchmarks are from Financial Times Stock Exchange (FTSE) Russell index holdings data and Compustat index constituents data, both obtained from Wharton Research Data Services (WRDS).

Data on Natural Disasters. We obtain information on the property losses caused by natural disasters hitting US territory from the Spatial Hazard Events and Loss Database for the United States (SHELDUS). The types of natural disaster covered by SHELDUS include natural hazards (such as thunderstorms, hurricanes, floods, wildfires, and tornados) and perils (such as flash floods and heavy rainfall). SHELDUS has been widely used in recent finance literature.[36] We map public firms in Compustat-CRSP to the SHELDUS data using firm headquarters. We obtain headquarters information of public firms based on textual analysis of Electronic Data Gathering, Analysis, and Retrieval (EDGAR) filings. We also use establishment-level data provided by the Infogroup Historical Business database to refine the mapping between public firms and SHELDUS as an additional robustness test.

[35]The data are downloaded from the Morningstar Direct platform.

[36]e.g., Barrot and Sauvagnat (2016), Bernile, Bhagwat and Rau (2017), Cortés and Strahan (2017), Alok, Kumar and Wermers (2020), Dou, Ji and Wu (2020), and Dou et al. (2021).

Data on Firm Exposure to China. We measure firms' exposures to China using several datasets. We use Factset Revere data to measure firms' revenues from China. We use the bill of lading data from the US Customs and Border Protection to measure the import of firms from China. We also use the text-based offshoring network dataset (Hoberg and Moon, 2017, 2019) to identify whether a firm sells goods to or purchases inputs from China.

Other Data Sources. Stock returns are from the CRSP database, and financial variables the Compustat database. We download the measures for market liquidity shocks (Pástor and Stambaugh, 2003) from L'uboš Pástor's website. The total macro uncertainty measure is obtained from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). The economic policy uncertainty index is obtained from Baker, Bloom and Davis (2016). The S&P 100 volatility index (VXO) and crude oil ETF volatility index are obtained from Chicago Board Options Exchange (CBOE). We construct the consumption dispersion using the Consumer Expenditure Survey (CEX) data from the Bureau of Labor Statistics. We measure discount rates using the dividend-to-price ratio and the smoothed earnings-price ratio (Campbell and Shiller, 1988, 1998). The two measures are constructed based on data downloaded from Robert Shiller's website. We measure sentiments using the investor sentiment index of Baker and Wurgler (2006). We construct hedge fund flows based on the Thomson Reuters Lipper Hedge Fund Database (TASS). We obtain institutional (13F) holdings from Thomson Reuters. We obtain holdings of household/retail investors from the data constructed by Barber and Odean (e.g., Barber and Odean, 2000), containing 66,465 households with accounts at a large discount broker during 1991 to 1996.

4.2 Common Fund Flows and Economic Uncertainty

We now examine the relation between common fund flows and economic uncertainty. Consistent with the result in Proposition 3.3, we show that the common fund flow is negatively related to the measures of macro uncertainty, economic policy uncertainty, market volatility, and idiosyncratic consumption dispersion. Our findings are consistent with those of Ferson and Kim (2012), who show that common mutual fund flows correlate with various macroeconomic variables including market volatility. Furthermore, Hoopes et al. (2016) show volatility-driven sales to be prevalent across sectors from 2008 to 2009 and mutual fund sales by household/retail investors to respond more strongly to increased volatility than stock sales.

We first perform regression analysis to examine the relation between common fund flow

Table 5: Common fund flow shocks and uncertainty shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Active equity funds, CRSP alone				Active equity funds, CRSP-MS				Low-risk bond funds			
	$flow_t$				$flow_t$				$flow_t$			
$MacroUnc\_shock_t$	-0.100^{**}				-0.140^{***}				0.133^{**}			
	[−1.979]				[−2.795]				[2.443]			
EPU_shock_t		-0.148^{***}				-0.162^{***}				0.104^{*}		
		[−3.230]				[−3.164]				[1.675]		
VXO_shock_t			-0.236^{***}				-0.292^{***}				0.143^{***}	
			[−3.560]				[−4.963]				[2.634]	
$MktVol\_shock_t$				-0.160^{***}				-0.238^{***}				0.134^{**}
				[−2.955]				[−4.035]				[2.166]
$flows_{t-1}$	0.097^{*}	0.081	0.115^{**}	0.089	0.211^{***}	0.199^{***}	0.232^{***}	0.197^{***}	0.099	0.111^{*}	0.098	0.105^{*}
	[1.660]	[1.397]	[2.096]	[1.538]	[3.887]	[3.633]	[4.491]	[3.681]	[1.642]	[1.754]	[1.624]	[1.737]
Observations	334	334	334	334	334	334	334	334	237	237	237	237
R-squared	0.02	0.03	0.07	0.04	0.07	0.07	0.13	0.10	0.03	0.02	0.03	0.03

Note: Columns (1) to (8) examine the relation between the uncertainty shock and the common flows of active equity funds. Columns (9) to (12) examine the relation between the uncertainty shock and the common fund flow shock of low-risk bond funds. The common fund flow shocks in month t are denoted by $flow_t$. $MacroUnc\_shock_t$ is the shock to the macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021) in month t estimated by an AR(6) model. We control for six monthly lags to compute $MacroUnc\_shock_t$ following Ludvigson, Ma and Ng (2021). EPU_shock_t is the shock to the news based policy uncertainty index (Baker, Bloom and Davis, 2016) in month t estimated by an AR(1) model. VXO_shock_t is the shock to the CBOE S&P 100 volatility index in month t estimated by an AR(1) model. $MktVol\_shock_t$ is the shock to the market volatility in month t estimated by an AR(1) model. The monthly market volatility is the standard deviation of the daily returns of the S&P 500 index in month t. All variables are standardized to have means of 0 and standard deviations of 1. The constant term is omitted in the table for brevity. The analysis is performed at a monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1991 to 2018 in Columns (1) to (8) and from 1999 to 2018 in Columns (9) to (12).

shocks and economic uncertainty shocks. Specifically, we regress the common fund flow shocks on the contemporaneous shocks to various economic uncertainty measures. As we show in Table 5, active equity funds experience outflows when economic uncertainty rises. This negative relation is significant both statistically and economically. A one-standard-deviation increase in the shocks to the macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021), the economic policy uncertainty index (Baker, Bloom and Davis, 2016), the VXO index, and the market volatility are associated with a 0.100-, 0.148-, 0.236-, and 0.160-standard-deviation decline, respectively, in common fund flows constructed from the CRSP mutual fund data and asset size groups. In Panel B, we find similar results for common fund flows constructed from the CRSP-Morningstar intersection data and asset-size groups. One can also observe the negative relation between common fund flows and economic uncertainty in the time-series plots in Figure OA.3 in Online Appendix 4.3. In addition, consistent with previous studies (e.g., Chen and Qin, 2017; Wang and Young, 2020; Chan and Marsh, 2021), we find that the common fund flows of low-risk bond funds are positively correlated with uncertainty shocks (see Columns (9) to (12) of Table 5), which is the opposite pattern to that shown by active equity funds.

We next examine the relation between the common fund flow shocks and shocks to the

Table 6: Common fund flow shocks and consumption dispersion shocks.

	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$flow_t$		$flow_t$	
$Consumption\_disp\_shock_t$	-0.134^{**}	-0.124^{**}	-0.139^{**}	-0.127^{**}
	[−2.287]	[−2.333]	[−2.318]	[−2.358]
$flow_{t-1}$	0.115^{*}	0.142^{**}	0.222^{***}	0.254^{***}
	[1.951]	[2.528]	[3.982]	[4.490]
Ret_t^{mkt}		0.319^{***}		0.365^{***}
		[5.286]		[6.653]
Ret_{t-1}^{mkt}		−0.003		−0.004
		[−0.057]		[−0.082]
Observations	322	322	322	322
R-squared	0.03	0.13	0.07	0.20

Note: This table shows the relation between the consumption dispersion shock and the common fund flow shock of active mutual funds, denoted by $flows_t$. $Consumption\_disp\_shock_t$ is the consumption dispersion shock, which is the AR(1) shock to the cross-sectional dispersion of the growth rate of household consumption in the CEX data. Ret_t^{mkt} is the market return in month t. All variables are standardized to have means of 0 and standard deviations of 1. The constant term is omitted in the table for brevity. The analysis is performed at a monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1991 to 2017.

idiosyncratic consumption dispersion, measured by the dispersion of consumption growth rates (e.g., Brav, Constantinides and Geczy, 2002; Vissing-Jørgensen, 2002; Jacobs and Wang, 2004). Table 6 shows that active equity mutual funds experience outflows when there is an increase in idiosyncratic consumption dispersion.

Lastly, we emphasize that economic uncertainty is not the only primitive driver behind common fund flows. While in our model we limit our attention to uncertainty shocks for parsimony, more broadly, these represent just one of the important forces affecting fund investors' delegation decisions. Exploring what other economic shocks cause investors to move their capital in and out of active funds is an important question for future research. As a partial step toward this goal, we show in Table OA.4 of Online Appendix 4.5 that common fund flow shocks comove negatively with shocks to aggregate discount rates. In the same table, we also show that common fund flow shocks comove positively with shocks to sentiment, although this relation is statistically insignificant.

4.3 Primitive Forces Behind Flow Betas

Flow Betas and Price Impact. As explained by Proposition 3.4, stock fund-flow betas could reflect both their fundamental risk and the price impact of non-fundamental liquidity shocks. We first study the relation between the flow beta and the price impact of trading caused by different types of investor (e.g., mutual funds, household/retail investors, investor advisors, and pension funds). We obtain price impact measures from Koijen and Yogo (2019), who

Table 7: Relation between flow betas and price impact measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: CRSP mutual funds alone								
	$Lnsize_{i,t}$	$LnBEME_{i,t}$	$AIM_{i,t}$	$Liqbeta_{i,t}$	$FIT_{i,t}$	$PI\_MF_{i,t}$	$PI\_HH_{i,t}$	$PI\_IA_{i,t}$	$PI\_PF_{i,t}$
$\beta^{flow}_{i,t}$	-0.057^{***}	0.055^{***}	0.045^{***}	0.179^{***}	-0.002	0.001	0.066^{***}	0.013^{**}	0.010^{*}
	[−9.917]	[8.227]	[8.231]	[12.871]	[−0.373]	[0.183]	[6.498]	[2.267]	[1.701]
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1785679	1433429	1779558	1795592	1006605	1153941	1184689	1115219	885404
R-squared	0.13	0.14	0.13	0.15	0.16	0.15	0.14	0.15	0.17
	Panel B: CRSP-Morningstar intersection								
	$Lnsize_{i,t}$	$LnBEME_{i,t}$	$AIM_{i,t}$	$Liqbeta_{i,t}$	$FIT_{i,t}$	$PI\_MF_{i,t}$	$PI\_HH_{i,t}$	$PI\_IA_{i,t}$	$PI\_PF_{i,t}$
$\beta^{flow}_{i,t}$	-0.080^{***}	0.022^{***}	0.051^{***}	0.209^{***}	-0.004	0.009^{*}	0.081^{***}	0.022^{***}	0.032^{***}
	[−12.141]	[3.549]	[10.196]	[13.387]	[−0.897]	[1.916]	[8.975]	[4.237]	[4.958]
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1785679	1433429	1779558	1795592	1006605	1153941	1184689	1115219	885404
R-squared	0.14	0.15	0.14	0.17	0.17	0.16	0.15	0.16	0.19

Note: This table shows the relation between flow betas ($\beta^{flow}_{i,t}$) and various stock characteristics, which include natural log of market cap ($Lnsize_{i,t}$), natural log of book-to-market ratio ($LnBEME_{i,t}$), market liquidity betas ($Liqbeta_{i,t}$), Amihud illiquidity ($AIM_{i,t}$), flow-induced trading (FIT) pressure ($FIT_{i,t}$), price impact of mutual funds ($PI\_MF_{i,t}$), price impact of households ($PI\_HH_{i,t}$), price impact of investor advisors ($PI\_IA_{i,t}$), and price impact of pension funds ($PI\_PF_{i,t}$). We compute $FIT_{i,t}$ following Lou (2012). We obtain price impact measures from Koijen and Yogo (2019). The analysis is performed at a monthly frequency. All variables are standardized to have means of 0 and standard deviations of 1. We include t-statistics in brackets. Standard errors are double clustered at the stock and month levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. FE is fixed effects. The sample spans from 1992 to 2018.

estimate price impact based on an asset-pricing model with flexible heterogeneity in asset demand across different types of investor. Columns (6) to (9) of Table 7 show that flow betas are positively correlated with price impact measures in the cross-section of stocks.[37] We then examine the asset-pricing implications of flow betas by double-sorting on price impact. As we show in Panel A of Table 8, flow betas remain significantly priced in the cross-section of stock returns after controlling for price impact.

Next, we show that the cross-sectional return predictability of flow betas is not simply caused by the predictable reversal pattern due to shocks in trading pressure, even though price impact is an important force behind flow betas. Specifically, we study the relation between flow beta and FIT pressure. Existing literature has documented that fund flows can exert substantial price impact that affects short-term stock returns, which reverts over a longer horizon (e.g., Coval and Stafford, 2007; Frazzini and Lamont, 2008; Lou, 2012), and affects return volatility (e.g., Greenwood and Thesmar, 2011). Because flow betas are estimated based on 36-month rolling windows, we would like to rule out the possibility that different flow betas simply reflect that stocks have experienced different FIT pressure or are at different

[37] The results are especially strong for the price impact caused by household/retail investors and investment advisors. Household/retail investors are direct retail investors, and investment advisors are mainly hedge funds, which have no explicit role in affecting asset prices in the model, given their rather minimal market share as a whole in the data. The positive relation between flow betas and price impact caused by mutual funds and pension funds is slightly weaker, potentially because Koijen and Yogo (2019) include both active and passive funds in their sample of mutual funds and pension funds to estimate price impact.

Table 8: Double-sort on flow betas and price impact or FIT.

First-sort measures	Panel A: Price impact				Panel B: Flow-induced trading (FIT)			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
β_i^{flow} quintiles	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α
Q1	5.34	-5.41^{**}	5.29	-4.25^{***}	6.61^{*}	-4.04^{**}	5.64	-3.81^{**}
	[1.24]	[−2.59]	[1.47]	[−2.69]	[1.67]	[−2.34]	[1.64]	[−2.19]
Q2	6.56^{*}	−1.42	6.86^{**}	−0.23	6.76^{*}	−1.55	7.18^{*}	−0.27
	[1.88]	[−0.77]	[2.23]	[−0.23]	[1.83]	[−0.78]	[1.95]	[−0.20]
Q3	7.96^{**}	0.14	7.67^{**}	−0.14	7.43^{*}	−0.55	7.76^{***}	−0.08
	[2.12]	[0.09]	[2.35]	[−0.14]	[1.95]	[−0.32]	[2.64]	[−0.10]
Q4	9.93^{***}	1.37	10.93^{***}	2.13	9.61^{***}	1.80	11.12^{***}	2.33^{*}
	[3.39]	[1.17]	[3.54]	[1.63]	[3.31]	[1.48]	[3.68]	[1.69]
Q5	11.63^{***}	2.22	12.33^{***}	1.55	11.83^{***}	2.47	11.99^{***}	1.16
	[3.61]	[1.24]	[3.30]	[0.71]	[4.03]	[1.33]	[3.07]	[0.53]
Q5 − Q1	6.29^{***}	7.63^{**}	7.04^{***}	5.80^{**}	5.22^{**}	6.51^{**}	6.35^{***}	4.96^{*}
	[2.74]	[2.58]	[3.13]	[2.04]	[2.46]	[2.54]	[2.91]	[1.94]

Note: This table shows the results from the double-sort analysis. In each June, we first sort stocks into five groups based on price impact (Panel A) and FIT pressure (Panel B). Next, we sort stocks within each group into quintiles based on their average flow betas from January of year t to June of the same year. We then pool the firms in the same flow beta quintiles together across the groups of the first-sort measures. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Our sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. The price impact measure is the price impact from households obtained from Koijen and Yogo (2019). FIT pressure is computed following Lou (2012). We annualize the average excess returns and CAPM alphas by multiplying them by 12. The sample period spans from July 1992 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

stages in the FIT pressure cycle. To address this concern, we construct the FIT measure following Lou (2012) and examine its relation with flow betas. Column (5) of Table 7 shows insignificant cross-sectional association between the flow beta and the contemporaneous FIT measure. Moreover, as we show in Table OA.9 of the online appendix, the flow beta also has an insignificant cross-sectional correlation with the lagged FIT measure and the FIT measure accumulated across different time horizons (i.e., past two quarters, 1 year, 2 years, and 3 years). Given these weak associations, it is not surprising that flow betas remain significantly priced in the cross-section of stock returns after controlling for FIT measures (see Panel B of Table 8). Taken together, the asset pricing implications of flow betas are unlikely to be a side effect of flow-driven price pressure.

Flow Betas and Cash-Flow Loadings. Besides the non-fundamental liquidity channel through which dispersion in flow betas across stocks may emerge, our model (Proposition 3.4) also implies that flow betas should capture heterogeneous exposure of stocks to the systematic shocks affecting the common fund flow. To test this channel, we estimate the cross-sectional relation between flow betas and firms' cash flow loadings on the common fund flow. We follow Cohen, Polk and Vuolteenaho (2003, 2009) and Campbell, Polk and Vuolteenaho (2010) in

Table 9: Relation between returns' flow betas and cash flow loadings.

Panel A: Portfolio-level analysis												
	CRSP mutual funds alone						CRSP-Morningstar intersection					
$\beta_{i,t}^{flow}$ quintiles	Q1	Q2	Q3	Q4	Q5	Q5 − Q1	Q1	Q2	Q3	Q4	Q5	Q5 − Q1
	$\sum_{j=0}^{2}\rho^j ROE_{p,t+j}$						$\sum_{j=0}^{2}\rho^j ROE_{p,t+j}$					
$flow_t$	0.037	0.007	0.032	0.049*	0.136**	0.099**	0.022	0.012	0.007	0.081**	0.079*	0.057**
	[0.952]	[0.283]	[1.246]	[1.966]	[2.311]	[2.570]	[0.821]	[0.449]	[0.380]	[2.152]	[2.022]	[2.150]
Observations	23	23	23	23	23	23	23	23	23	23	23	23
R-squared	0.052	0.011	0.074	0.116	0.246	0.164	0.026	0.003	0.021	0.200	0.167	0.087

Panel B: Stock-level analysis				
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$\sum_{j=0}^{2}\rho^j ROE_{i,t+j}$		$\sum_{j=0}^{2}\rho^j ROE_{i,t+j}$	
$flow_t \times \beta_{i,t-1}^{flow}$	0.008***	0.011***	0.006**	0.010***
	[3.070]	[3.659]	[2.395]	[3.435]
$flow_t \times FIT_{i,t-1}$		0.004		0.006
		[1.112]		[1.492]
$flow_t$	0.027***	0.005	0.024***	−0.001
	[6.565]	[1.196]	[5.176]	[−0.221]
Observations	85459	54123	85459	54123

Note: This panel shows the relationship between common flow betas and cash flow loadings. Panel A shows portfolios' loadings of cash flows on the common flows. We follow Cohen, Polk and Vuolteenaho (2003), Cohen, Polk and Vuolteenaho (2009), and Campbell, Polk and Vuolteenaho (2010) to use the discounted sum of ROE as a measure of cash-flow fundamentals. Specifically, $\sum_{j=0}^{2}\rho^j ROE_{p,t+j}$ is the accumulated ROE of stock portfolio p from year t to year $t+2$. Following Campbell, Polk and Vuolteenaho (2010) and Santos and Veronesi (2010), we set ρ to 0.96 and calculate ROE in year t as the ratio of clean-surplus earnings in year t and book equity in year $t-1$, where clean-surplus earnings in year t are the changes in book equity from year $t-1$ to year t plus dividends in year t. Panel B performs stock-level analysis. $\sum_{j=0}^{2}\rho^j ROE_{i,t+j}$ is the accumulated ROE of stock i from year t to year $t+2$. $FIT_{i,t-1}$ is the FIT pressure at year $t-1$. Time series $flow_t$, $\beta_{i,t-1}^{flow}$, and $FIT_{i,t-1}$ are all standardized to have means of 0 and standard deviations of 1. The sample period spans from 1992 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

using the discounted sum of return on equity (ROE) as a measure of cash flow fundamentals. Specifically, the cash flow fundamental for stock i in year t is measured by $\sum_{j=0}^{2}\rho^j ROE_{i,t+j}$, which is the accumulated ROE of stock i from year t to year $t+2$. Following Campbell, Polk and Vuolteenaho (2010) and Santos and Veronesi (2010), we set ρ to 0.96 and calculate ROE in year t as the ratio of clean surplus earnings in year t and book equity in year $t-1$, where clean surplus earnings in year t are the changes in book equity from year $t-1$ to year t plus dividends in year t.

We could have estimated cash-flow loadings at the firm level year by year, running sliding-window regressions for each stock. One caveat of this approach is that the estimation of cash-flow loadings can be noisy because cash-flow fundamentals are measured at a yearly frequency over a relatively short sample period (1992 to 2018). We use two alternative approaches to alleviate this concern. First, we examine the cash-flow loadings of stock portfolios sorted on flow beta. Specifically, we sort stocks into quintiles based on flow beta, and then we compute the accumulated ROE of stock portfolio p from year t to year $t+2$ (i.e., $\sum_{j=0}^{2}\rho^j ROE_{p,t+j}$) and estimate each portfolio's loading of the accumulated ROE (i.e., cash flows) on the common fund flow shock. Panel A of Table 9 tabulates the cash-flow loadings of the portfolios sorted on flow beta, showing that stocks with higher flow betas tend to have evidently higher cash-flow loadings on the common fund flow. Second, we use the predictive beta approach to examine the relation between cash-flow loadings and stock returns' flow betas. Specifically, we run the following regression:

$$\sum_{j=0}^{2} \rho^j ROE_{i,t+j} = a_0 + Predicted\_\beta^{CF}_{i,t-1} \times flow_t + \varepsilon_{i,t}, \quad \text{where} \tag{4.1}$$

$$Predicted\_\beta^{CF}_{i,t-1} = a_1 + a_2 \times \beta^{flow}_{i,t-1} + a_3 \times FIT_{i,t-1}. \tag{4.2}$$

As shown in Panel B of Table 9, coefficient $\hat{a}_2$ is positive and statistically significant, suggesting that the cash flows of stocks with higher flow betas load significantly more positively on common fund flows. Moreover, not surprisingly, FIT pressure does not affect stock returns and their dynamics through a fundamental channel of firms' cash flows.

Firm Characteristics and Flow Betas. We examine the relation between flow betas and various stock characteristics by running panel regressions with time fixed effects. As Table 7 shows, stocks with high flow betas tend to be small, value, illiquid, and high-liquidity-risk stocks. In Table OA.7 of the online appendix, we show the mean values of the stock characteristics across the stock quintile portfolios sorted on flow beta. Consistent with Table 7, we find that stocks with higher flow betas tend to have higher book-to-market ratios, higher market liquidity betas, and higher Amihud illiquidity measures. Although previous studies have shown that the above characteristics are priced in the cross-section of stock returns,[38] Table 2 shows that flow betas remain significantly priced in the cross-section of stock returns after controlling for these characteristics. This suggests that the asset-pricing implications of flow betas cannot be entirely subsumed by the above characteristics. On the contrary, the pricing mechanism behind flow betas may eventually help explain why some of these characteristics forecast stock returns.

Our findings also shed light on some of the puzzling patterns found by Lettau, Ludvigson and Manoel (2018), who show that active equity mutual funds do not systematically tilt their portfolios toward profitable return factors, such as stocks with high book-to-market ratio (i.e., value stocks). As we show, book-to-market ratio and flow beta are positively correlated in the

[38]See, e.g., Pástor and Stambaugh (2003), Acharya and Pedersen (2005), and Amihud (2019).

cross-section of stocks (see Column (2) of Table 7). This means that a value tilt in its portfolio tends to raise a fund's exposure to common flow shocks — and is thus costly.

4.4 Fund Activeness and Common Flows

Conceptually, active equity funds (i.e., delegated equity funds in the model) are different from their trading counterparties (i.e., direct equity investors in the model) in three ways: (i) active equity funds are open-end funds featuring daily redemption obligations; (ii) revenue of active equity funds depends largely on their AUM, because of their explicit AUM-based fee structure; and (iii) active equity funds have significant discretion over their portfolio choices, that is, they are not tied to benchmarks as closely as index funds.

By contrast, index funds have much less discretion in their portfolio choices, and aim to mimic a given index. Hedge funds differ qualitatively because of their explicit performance-based fee structures and limited redemption rights granted to their investors.[39] By their nature, index funds should be classified as direct investors in the model. It is not reasonable, theoretically or empirically, to bundle hedge funds together with active equity funds in our analysis, because the economics of hedge fund flows are intrinsically different from those of active mutual funds.

As we show in Table OA.5 and OA.6 of Online Appendix 4, the long-short portfolios sorted on both the betas to common flow shocks of index funds and those to common flow shocks of hedge funds have insignificant average (risk-adjusted) returns. This is consistent with our theoretical model, where common fund flow shocks are priced because of the flow-hedging behavior of active equity mutual funds. The common flow shocks of index funds fail to share the same properties because index fund managers have little allocation discretion to actively hedge against their fund-flow risks. So do the common flows of hedge funds, possibly because they differ from active mutual funds in fee structures and redemption rules.

Heterogeneity in Activeness of Active Equity Funds. Active equity mutual funds differ significantly in how active they truly are, with some behaving as closet index funds. Here, we explore differences in fund activeness among active mutual funds. According to our model, common fund flows of active equity funds with higher activeness should have stronger asset pricing implications. This is because funds with lower fund activeness have lower capacity to

[39] Hedge funds often contain "lock-up" provisions, which impose limitations on the frequency of redemptions and require advance-notice periods for redemptions.

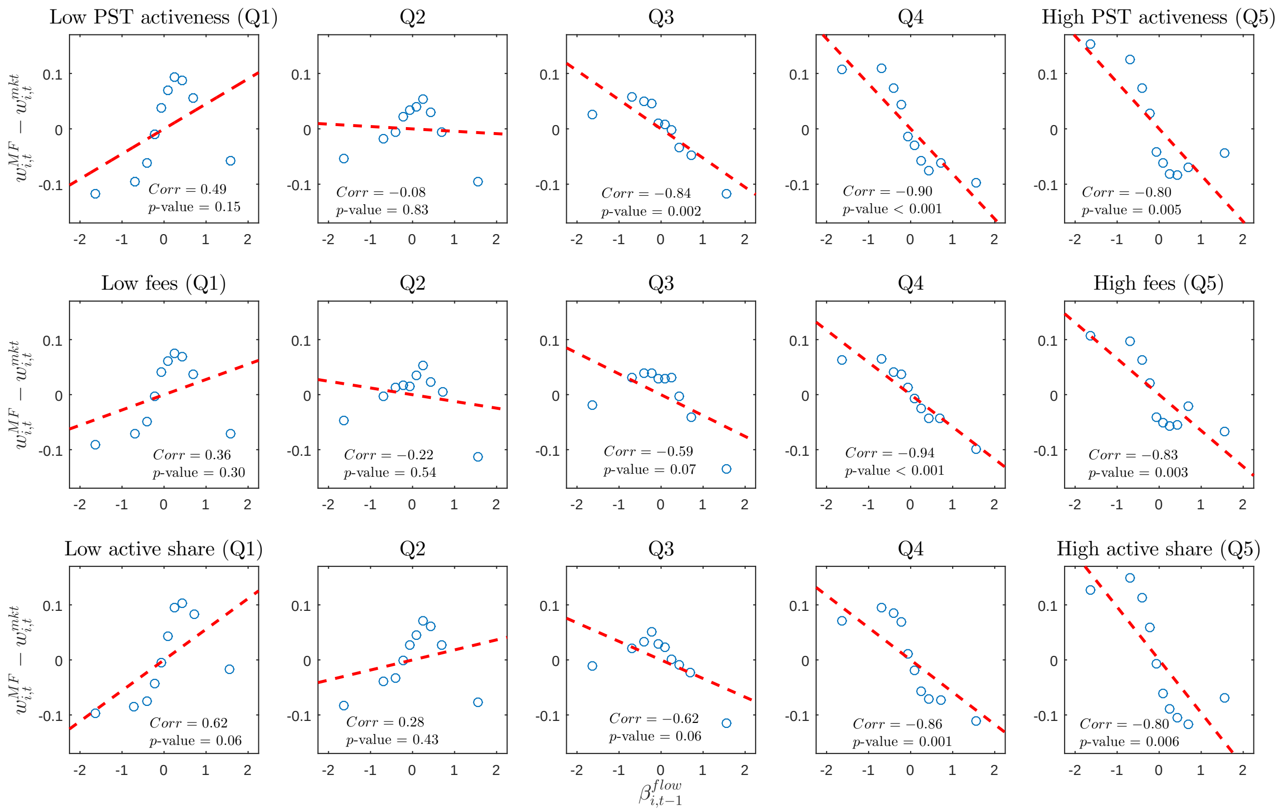
Table 10: Heterogeneity in activeness across active equity funds and pricing of common fund flow shocks.

	Panel A: PST activeness				Panel B: Fund expense ratios				Panel C: Active share			
Subsamples	Top 80%		Bottom 20%		Top 80%		Bottom 20%		Top 80%		Bottom 20%	
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
β_i^{flow} quintiles	CAPM α		CAPM α		CAPM α		CAPM α		CAPM α		CAPM α	
Q1	-5.59^{**}	-5.30^{***}	0.00	-1.12	-6.01^{***}	-4.33^{**}	-1.80	-3.47^{*}	-5.11^{**}	-3.93^{**}	-1.01	-3.37^{*}
	[−2.28]	[−2.82]	[0.00]	[−0.87]	[−2.72]	[−2.47]	[−0.94]	[−1.93]	[−2.24]	[−2.35]	[−0.72]	[−1.69]
Q2	-3.24^{**}	-1.54	1.77^{*}	1.82^{*}	-1.84	-0.17	-0.03	0.28	-1.81	-0.90	-0.05	1.75^{*}
	[−2.58]	[−1.39]	[1.90]	[1.87]	[−1.51]	[−0.16]	[−0.02]	[0.29]	[−1.49]	[−0.88]	[−0.06]	[1.76]
Q3	-0.68	1.08	-0.14	0.45	-0.27	0.56	2.10^{**}	2.90^{***}	1.08	1.20	2.41^{***}	0.51
	[−0.64]	[1.15]	[−0.13]	[0.48]	[−0.24]	[0.62]	[2.33]	[3.24]	[1.20]	[1.37]	[2.61]	[0.55]
Q4	1.97^{**}	1.07	-1.25	1.11	1.03	1.65	0.30	-0.30	0.83	0.86	0.80	1.40
	[2.13]	[1.01]	[−0.65]	[0.60]	[1.16]	[1.37]	[0.19]	[−0.20]	[0.98]	[0.71]	[0.49]	[0.98]
Q5	2.62^{*}	3.52	-3.43	0.10	2.93	2.72	-0.15	-0.63	1.68	2.82	-1.08	0.12
	[1.87]	[1.53]	[−1.12]	[0.04]	[1.63]	[1.07]	[−0.06]	[−0.22]	[1.05]	[1.12]	[−0.36]	[0.05]
Q5 − Q1	8.21^{***}	8.82^{***}	-3.43	1.22	8.94^{***}	7.05^{**}	1.64	2.84	6.79^{**}	6.76^{***}	-0.07	3.50
	[2.69]	[2.96]	[−0.88]	[0.36]	[2.95]	[2.20]	[0.47]	[0.80]	[2.42]	[2.66]	[−0.02]	[1.05]

Note: This table explores the cross-sectional heterogeneity of active equity funds. We construct common fund flow shocks from various subsamples of active equity funds and tabulate the CAPM alphas for the stock portfolios sorted on the resulting flow betas. In Panel A, we construct common fund flows from active equity funds with top 80% PST activeness and bottom 20% PST activeness, respectively. In Panel B, we construct common fund flow shocks from active equity funds with top 80% fund expense ratios and bottom 20% fund expense ratios, respectively. In Panel C, we construct common fund flow shocks from active equity funds with top 80% active share and bottom 20% active share, respectively. The mutual fund subsamples are constructed based on their cross-sectional rankings of PST activeness measures, expense ratio measures, and active share measures. We follow Pástor, Stambaugh and Taylor (2020) to measure fund activeness using fund turnover ratio divided by the square root of portfolio liquidity (i.e., the PST activeness measure). We follow Cremers and Petajisto (2009) to measure active share as the absolute weight difference between the fund holdings and the benchmark holdings summed across all stocks. For each mutual fund subsample, we construct fund quintiles sorted based on asset size, and then construct the common fund flow shocks using the approach described in Section 2.1. In June of year t, we sort firms into quintiles based on their average flow betas from January to June of year t. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Our sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We annualize the CAPM alphas by multiplying them by 12. The sample period spans from July 1992 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

hedge against common fund flow shocks by tilting their portfolios toward low-flow-beta stocks and away from the mean-variance efficient portfolio. To test this hypothesis, we construct common fund flow shocks based on various subsamples of active mutual funds sorted on fund activeness and then tabulate CAPM alphas for the stock portfolios sorted on the resulting flow betas.

We start with the measure of fund activeness introduced by Pástor, Stambaugh and Taylor (2020) (PST activeness), which is based on the fund turnover ratio normalized by the square root of portfolio liquidity. As we show in Panel A of Table 10, CAPM alphas of the long-short portfolios sorted on flow betas based on the more active funds (i.e., top 80% activeness) are 8.21% and 8.82% in the CRSP sample and the CRSP-Morningstar intersection sample, respectively. The t-statistics are 2.69 and 2.96, and are higher in magnitude than those in Table 1, in which we use all active equity mutual funds to construct the common fund flow shocks. In contrast, the CAPM alphas of the long-short portfolios sorted on flow betas based on the least active funds (i.e., bottom 20% activeness) are statistically insignificant. In addition to the PST



Note: This figure shows the binned scatter plots between holding tilts ($w^{MF}_{i,t} - w^{mkt}_{i,t}$) and flow betas ($\beta^{flow}_{i,t-1}$) across quintile groups of active equity funds sorted on fund activeness. Specifically, we sort active equity funds into quintiles based on lagged PST activeness in the upper panels. We also sort active equity funds into quintiles based on the lagged fund expense ratio measure as an alternative activeness measure suggested by Pástor, Stambaugh and Taylor (2020) in the middle panels. We lastly sort active equity funds into quintiles based on the lagged active share measure (Cremers and Petajisto, 2009) as a second alternative activeness measure in the bottom panels. $\beta^{flow}_{i,t-1}$ and $w^{MF}_{i,t} - w^{mkt}_{i,t}$ are standardized to have means of 0 and standard deviations of 1. We control for market betas and quarter fixed effects, that is, we regress $\beta^{flow}_{i,t-1}$ and $w^{MF}_{i,t} - w^{mkt}_{i,t}$ separately on both $\beta^{mkt}_{i,t-1}$ and the quarter fixed effects and then plot the two residuals against each other. We use the CRSP-alone sample to compute flow betas in this figure. The pattern is similar in the CRSP-Morningstar intersection sample.

Figure 6: Portfolio tilts vs. flow betas across groups sorted on fund activeness.

activeness measure, we use two alternative measures for fund activeness. The first additional measure is the fund expense ratio — extant studies have shown that more expensive funds are more active on average (e.g., Pástor, Stambaugh and Taylor, 2020). The second additional measure is the active share measure proposed by Cremers and Petajisto (2009), which is the absolute weight difference between fund holdings and benchmark holdings, added across all stocks. We present the corresponding results in Panels B and C of Table 10. We find similar asset-pricing patterns using these two alternative measures, further supporting the core mechanism of our model.

Consistent with the above results, we next show that active equity funds with higher fund activeness levels tilt more aggressively toward low-flow-beta stocks to hedge common fund flow shocks. We separate funds into quintile subgroups by fund activeness measure and

Table 11: Heterogeneity in activeness across active equity funds and portfolio tilts.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
$Fund\_char_{p,t-1}$:	$Low\_PST\_activeness\_funds_{p,t-1}$		$Low\_fee\_funds_{p,t-1}$		$Low\_active\_share\_funds_{p,t-1}$	
	Panel A: Panel regressions with time FE					
	$w^{MF}_{i,p,t} - w^{mkt}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,p,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.064***	0.038***	0.050***	0.036***	0.070***	0.048***
	[10.326]	[6.764]	[11.275]	[9.263]	[11.193]	[8.651]
$\beta^{flow}_{i,t-1}$	−0.045***	−0.038***	−0.036***	−0.037***	−0.042***	−0.040***
	[−9.013]	[−7.545]	[−8.096]	[−8.173]	[−10.922]	[−10.197]
$Fund\_char_{p,t-1} \times \beta^{mkt}_{i,t-1}$	−0.111***	−0.110***	−0.083***	−0.085***	−0.062***	−0.063***
	[−14.684]	[−14.618]	[−13.500]	[−13.783]	[−8.581]	[−8.552]
$\beta^{mkt}_{i,t-1}$	0.095***	0.098***	0.080***	0.085***	0.059***	0.063***
	[13.531]	[13.644]	[10.938]	[11.242]	[10.876]	[11.675]
$Fund\_char_{p,t-1}$	−0.137***	−0.137***	−0.099***	−0.099***	−0.161***	−0.161***
	[−11.212]	[−11.300]	[−9.819]	[−9.865]	[−11.338]	[−11.367]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1765285	1765285	1748227	1748227	1728512	1728512
R-squared	0.01	0.01	0.01	0.01	0.01	0.01
	Panel B: Fama-MacBeth regressions					
	$w^{MF}_{i,p,t} - w^{mkt}_{i,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.095***	0.055***	0.073***	0.047***	0.105***	0.070***
	[15.696]	[10.865]	[15.348]	[12.726]	[15.163]	[11.547]
$\beta^{flow}_{i,t-1}$	−0.061***	−0.047***	−0.050***	−0.046***	−0.058***	−0.049***
	[−11.137]	[−9.142]	[−9.930]	[−9.989]	[−12.431]	[−11.310]
$Fund\_char_{p,t-1} \times \beta^{mkt}_{i,t-1}$	−0.124***	−0.118***	−0.092***	−0.086***	−0.068***	−0.061***
	[−21.624]	[−20.940]	[−18.741]	[−18.845]	[−17.993]	[−13.868]
$\beta^{mkt}_{i,t-1}$	0.113***	0.114***	0.099***	0.103***	0.075***	0.076***
	[17.297]	[17.215]	[13.948]	[14.399]	[14.975]	[15.308]
$Fund\_char_{p,t-1}$	−0.139***	−0.134***	−0.102***	−0.096***	−0.153***	−0.145***
	[−26.750]	[−31.319]	[−23.087]	[−22.198]	[−26.023]	[−22.565]
Avg. obs./quarter	16498	16498	16339	16339	16154	16154
Avg. R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table investigates the heterogeneity in flow-hedging behaviors for funds with different levels of activeness. We sort active mutual funds into quintiles based on lagged PST activeness in Columns (1) and (2), lagged fund expense ratio as an additional activeness measure suggested by Pástor, Stambaugh and Taylor (2020) in Columns (3) and (4), and lagged active share (Cremers and Petajisto, 2009) as another additional activeness measure in Columns (5) and (6). We perform panel regressions with quarter fixed effects in Panel A, and Fama-MacBeth regressions in Panel B. We compute the weight of the aggregate active mutual fund portfolio for each quintile subgroup of funds. $w^{MF}_{i,p,t}$ is the weight of the aggregate active mutual fund portfolio over the funds in quintile p for stock i in quarter t, and $w^{mkt}_{i,t}$ is the weight of stock i in the market portfolio. $Low\_PST\_activeness\_funds_{p,t-1}$, $Low\_fee\_funds_{p,t-1}$, $Low\_active\_share\_funds_{p,t-1}$ are indicator variables for funds in the bottom PST activeness quintile, the bottom expense ratio quintile, the bottom active share quintile in quarter $t-1$, respectively. We include stocks with zero aggregate mutual fund weight conditional on that these stocks have non-zero aggregate mutual fund weight in any of the quarters in the previous 2 years. $\beta^{flow}_{i,t-1}$, $\beta^{mkt}_{i,t-1}$, and $w^{MF}_{i,p,t} - w^{mkt}_{i,t}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at a quarterly frequency. Standard errors for the panel regressions are double-clustered at the stock and quarter levels. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1992 to 2018.

construct the aggregate mutual fund portfolios for each subgroup of funds. We then define an indicator variable for funds in the bottom quintile sorted on activeness measure and add the indicator variable as an interaction term in the regression of portfolio tilts on flow betas. As we show in Columns (1) and (2) of Table 11, active equity funds with the lowest activeness (bottom activeness quintile) indeed hedge significantly less against common fund flow shocks than other funds. In Columns (3) to (6) of Table 11, we use the fund expense ratio and the active share measure as two additional proxies for fund activeness. Consistently, we find that funds with the lowest expense ratios (bottom fee quintile) and lowest active share (bottom active share quintile) hedge significantly less against common fund flows than other active equity mutual funds.

Figure 6 offers further information using the binned scatter plots between portfolio tilts and flow betas across five groups of active equity mutual funds with different activeness levels. Consistent with the findings in Table 11, active equity funds with high activeness levels tilt their portfolio holdings strongly away from high-flow-beta stocks relative to the market portfolio; in contrast, the strong positive relation between portfolio tilts and flow betas is completely absent for active equity funds with low activeness levels. The evidence above suggests that funds' active flow-hedging behavior is likely to be the driving force behind the relation between portfolio tilt and flow beta presented in Table 3.

4.5 Further Direct Evidence on Flow Hedging of Active Equity Funds

4.5.1 Heterogeneous Flow-Hedging Incentives

In addition to the above analysis of fund activeness (Table 11 and Figure 6), which tests the core mechanism of our intermediary-based asset-pricing theory, we provide further evidence on funds' flow-hedging behaviors by exploring variation in their flow-hedging incentives. We use fund size and fund age as proxies for such incentives. As we show in Figures 1, 2, and OA.2 of the online appendix, larger and older funds are less exposed to the common fund flow shocks than smaller and younger funds and should therefore have weaker incentives to hedge against common fund flow shocks. This is what we find. As we show in Columns (1) and (2) and Columns (3) and (4) of Table 12, active equity mutual funds with the largest fund size (top size quintile) and oldest fund age (top age quintile) hedge significantly less against common fund flow shocks than other funds.

4.5.2 Evidence from Portfolio Tilts and Between-Style Flow Betas

We have shown above that active equity funds tilt away from stocks with high flow betas. A salient feature of the delegated asset management industry is that it offers different styles of investing such as value and growth. Active equity funds should also have incentives to hedge against the risk associated with between-style flows (e.g., fund flows from growth to value

Table 12: Heterogeneity in flow hedging incentives and portfolio tilts.

	(1) CRSP	(2) CRSP-MS	(3) CRSP	(4) CRSP-MS
$Fund\_char_{p,t-1}$:	$Large\_funds_{p,t-1}$		$Old\_funds_{p,t-1}$	
	Panel A: Panel regressions with time FE			
	$w^{MF}_{i,p,t} - w^{mkt}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,p,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.045***	0.031***	0.025***	0.013***
	[10.420]	[7.447]	[5.024]	[2.888]
$\beta^{flow}_{i,t-1}$	−0.047***	−0.048***	−0.024***	−0.029***
	[−9.522]	[−9.207]	[−4.420]	[−4.966]
$Fund\_char_{p,t-1} \times \beta^{mkt}_{i,t-1}$	−0.036***	−0.037***	−0.035***	−0.033***
	[−6.501]	[−6.604]	[−6.299]	[−5.984]
$\beta^{mkt}_{i,t-1}$	0.071***	0.077***	0.055***	0059***
	[10.903]	[11.604]	[7.456]	[7.573]
$Fund\_char_{p,t-1}$	−0.114***	−0.114***	−0.074***	−0.074***
	[−11.745]	[−11.720]	[−8.055]	[−8.141]
Quarter FE	Yes	Yes	Yes	Yes
Observations	1773870	1773870	1768854	1768854
R-squared	0.01	0.01	0.01	0.01
	Panel B: Fama-MacBeth regressions			
	$w^{MF}_{i,p,t} - w^{mkt}_{i,t}$		$w^{MF}_{i,p,t} - w^{mkt}_{i,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.059***	0.038***	0.046***	0.029***
	[15.682]	[10.491]	[8.514]	[6.132]
$\beta^{flow}_{i,t-1}$	−0.063***	−0.058***	−0.038***	−0.040***
	[−10.724]	[−10.676]	[−6.038]	[−6.788]
$Fund\_char_{p,t-1} \times \beta^{mkt}_{i,t-1}$	−0.043***	−0.037***	−0.031***	−0.027***
	[−10.584]	[−8.940]	[−10.213]	[−7.605]
$\beta^{mkt}_{i,t-1}$	0.092***	0.094***	0.073***	0.078***
	[15.872]	[16.089]	[10.074]	[10.368]
$Fund\_char_{p,t-1}$	−0.110***	−0.103***	−0.074***	−0.068***
	[−25.377]	[−24.213]	[−15.903]	[−16.182]
Avg. obs./quarter	16578	16578	16531	16531
Avg. R-squared	0.01	0.01	0.01	0.01

Note: This table investigates the heterogeneity across funds for their flow-hedging behaviors. We sort active mutual funds into quintiles based on lagged asset size in Columns (1) and (2), and fund age in Columns (3) and (4). We perform panel regressions with quarter fixed effects in Panel A, and Fama-MacBeth regressions in Panel B. We compute the weight of the aggregate active mutual fund portfolio for each quintile subgroup of funds. $w^{MF}_{i,p,t}$ is the weight of the aggregate active mutual fund portfolio over the funds in quintile p for stock i in quarter t, and $w^{mkt}_{i,t}$ is the weight of stock i in the market portfolio. $Large\_funds_{p,t-1}$ and $Old\_funds_{p,t-1}$ are indicator variables for funds in the top size quintile and the top age quintile in quarter $t-1$, respectively. We include stocks with zero aggregate mutual fund weight conditional on that these stocks have non-zero aggregate mutual fund weight in any of the quarters in the previous 2 years. $\beta^{flow}_{i,t-1}$, $\beta^{mkt}_{i,t-1}$, and $w^{MF}_{i,p,t} - w^{mkt}_{i,t}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at a quarterly frequency. Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1992 to 2018.

funds). For example, we expect value equity funds to tilt their holdings away from stocks that perform poorly when clients direct funds from value to growth funds; on the contrary, we expect growth equity funds to tilt their holdings toward such stocks. In contrast to the betas on common fund flows, we do not expect between-style betas to be priced in the cross-section of stocks because value and growth funds tilt their holdings in the opposite directions for stocks with high between-style betas. In Online Appendix 4.12, we examine the holdings of value funds and growth funds and find evidence supporting our predictions.

4.5.3 Evidence from Quasi-Natural Experiments

We use quasi-natural experiments to analyze time variations in the hedging behaviors of active equity funds against common flow shocks. Our goal in this subsection is to show that active equity funds hedge against the common fund flow shock more aggressively in response to an increase in the level of fund-specific outflow risk. Specifically, we examine how active equity funds rebalance their portfolio holdings around unexpected local natural disaster shocks in the US. We also conduct a similar quasi-natural experiment using the unexpected announcement of the possible US-China trade war in Online Appendix 5.2. The former experiment utilizes many idiosyncratic shocks across different quarters and US counties, while the latter experiment exploits a one-time aggregate shift.[40]

Let $Outflow\_Risk_{f,t}$ denote fund f's (ex-ante) outflow risk in period t, meaning that higher $Outflow\_Risk_{f,t}$ predicts greater net outflows from fund f in the following period $t+1$. Here, we study whether an increase in the outflow risk of fund f, denoted by $\Delta Outflow\_Risk_{f,t}$, leads to fund f's portfolio rebalancing further toward low-flow-beta stocks. There are at least two empirical challenges: first, the correlation (if any) between $\Delta Outflow\_Risk_{f,t}$ and fund f's portfolio change in period t may be driven by other common economic forces and second, the (ex-ante) outflow risk $Outflow\_Risk_{f,t}$ is latent; it is not directly observable.

To tackle the first challenge, we explore natural disasters in the US as a driver of fund-level variations in outflow risk. Natural disasters have significant short-term effects on the returns of affected stocks, which in turn affects a fund's relative performance, with the degree of impact depending on the fraction of the fund's portfolio hit by natural disaster. We essentially instrument for changes in fund f's (ex-ante) outflow risk, denoted by $\Delta Outflow\_Risk_{f,t}$, using fund f's exposure to natural disaster in period t, $ND_{f,t}$, which captures the extent to which fund f is affected by natural disaster in period t.[41] More precisely, we compute $ND_{f,t}$ as the

[40] In the online appendix, we also examine changes of mutual fund holdings after the unexpected announcement made by the Organization of the Petroleum Exporting Countries (OPEC) in 2014 (e.g., Gilje, Ready and Roussanov, 2016). In the announcement, the member countries decided not to cut their oil supply in response to increased supply from non-OPEC countries and falling prices. The 2014 OPEC announcement substantially increased the uncertainty betas and flow betas for "oil-related" stocks relative to "oil-unrelated" stocks. In response, mutual funds increased the tilt of their oil-unrelated positions toward low-flow-beta stocks.

[41] Natural disaster shocks have been used as a source of exogenous variation in firm-level economic variables in a number of prior papers, including those of Morse (2011), Barrot and Sauvagnat (2016), Cortés and Strahan (2017), Dessaint and Matray (2017), Alok, Kumar and Wermers (2020), and Dou, Ji and Wu (2020).

portfolio share of the stocks held by fund f in period t, whose headquarters are located in a county hit by natural disaster in period t. Following Barrot and Sauvagnat (2016), we define a stock as being negatively affected by natural disaster in a given quarter if it is a non-financial firm and the county of its headquarters experiences property losses due to natural disaster during that quarter.[42] Data on property losses of each county are from SHELDUS. We obtain information on the headquarters of companies from textual analysis of EDGAR filings.

Funds affected by natural disaster may experience changes in outflow risk for at least two reasons. First, poor relative performance of fund f may lead to higher outflow risk $Outflow\_Risk_{f,t}$.[43] Contemporaneous returns of active mutual funds are, not surprisingly, negatively associated with $ND_{f,t}$: we find that a one-standard-deviation increase in mutual funds' exposure to natural disaster is associated with a 1.36-percentage-point reduction in annualized performance relative to market return.[44] Second, uncertainty about the fund's performance tends to increase more when the fund is hit more heavily by natural disaster (e.g., Kruttli, Roth Tran and Watugala, 2020). Higher dispersion in future performance would then translate into higher dispersion in fund flows and a higher likelihood that investors may pull their money out of the fund.

Panel A of Table 13 confirms that an increase in fund exposure to natural disaster leads to a contemporaneous increase in outflow risk. Specifically, we regress the abnormal fund flows, defined as the difference between fund-level flows and the asset-size-weighted average flows of the entire active US equity mutual fund sector, on fund exposure to natural disaster $ND_{f,t}$ as follows:

$$Abflow_{f,t+k} = a + b \times ND_{f,t} + \varepsilon_{f,t+k}, \quad \text{with } k = 0, 1, 2, 3. \tag{4.3}$$

The coefficient on $ND_{f,t}$ is significantly negative for abnormal fund flows in the contemporaneous quarters and for the two subsequent quarters, suggesting that mutual funds whose stocks are hit by natural disaster experience more outflows in the near future. In Panel B of Table 13, we find that abnormal flows for funds with higher natural disaster exposure exhibit a significantly more negative left tail and more dispersion. Thus, outflow risk increases significantly following natural disaster shock.

[42]In Table OA.16 of the online appendix, we use establishment-level data from Infogroup to map firms to counties. We define a stock as being negatively affected by natural disaster if it is a non-financial firm and at least one of its main establishments (i.e., those with more than 5% of firm-level sales) experiences property losses due to natural disaster. Our findings remain robust in this test.

[43]The performance-flow relationship of active mutual funds has been widely documented (e.g., Brown, Harlow and Starks, 1996; Chevalier and Ellison, 1997; Lynch and Musto, 2003; Goldstein, Jiang and Ng, 2017).

[44]See Table OA.17 of the online appendix for the regression results.

Table 13: Outflow risk increases following natural disaster shocks.

Panel A: Abnormal fund flows following natural disaster shocks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone				CRSP-Morningstar intersection			
	$Abflow_{f,t}$	$Abflow_{f,t+1}$	$Abflow_{f,t+2}$	$Abflow_{f,t+3}$	$Abflow_{f,t}$	$Abflow_{f,t+1}$	$Abflow_{f,t+2}$	$Abflow_{f,t+3}$
$ND_{f,t}$	-0.034^{***}	-0.025^{***}	-0.019^{***}	-0.008	-0.024^{***}	-0.017^{**}	-0.012^{*}	0.001
	[−5.246]	[−3.884]	[−2.949]	[−1.338]	[−3.369]	[−2.368]	[−1.746]	[0.078]
Observations	174984	170928	166856	162733	141530	137756	134611	131575
R-squared	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001

Panel B: Left tail and dispersion of abnormal fund flows across funds with different natural disaster exposure

	Left tails of abnormal fund flows				Dispersion of abnormal fund flows			
	p5	p10	p20	p25	p95 − p5	p90 − p10	p80 − p20	p75 − p25
	$Abflow_{f,t+1}$ (unstandardized)				$Abflow_{f,t+1}$ (unstandardized)			
Q1 of $ND_{f,t}$	-0.146^{***}	-0.089^{***}	-0.054^{***}	-0.044^{***}	0.379^{***}	0.219^{***}	0.109^{***}	0.081^{***}
	[−35.638]	[−42.088]	[−36.028]	[−33.472]	[38.942]	[32.841]	[30.726]	[30.030]
Q5 of $ND_{f,t}$	-0.162^{***}	-0.100^{***}	-0.061^{***}	-0.049^{***}	0.398^{***}	0.232^{***}	0.115^{***}	0.084^{***}
	[−41.596]	[−39.117]	[−32.518]	[−30.036]	[36.065]	[34.448]	[33.428]	[31.956]
Q5 − Q1	-0.016^{***}	-0.011^{***}	-0.006^{***}	-0.005^{***}	0.019^{**}	0.013^{***}	0.006^{**}	0.004^{**}
	[−3.072]	[−4.561]	[−4.001]	[−3.422]	[1.999]	[2.628]	[2.493]	[2.404]
	$Abflow_{f,t+2}$ (unstandardized)				$Abflow_{f,t+2}$ (unstandardized)			
Q1 of $ND_{f,t}$	-0.151^{***}	-0.092^{***}	-0.055^{***}	-0.045^{***}	0.371^{***}	0.212^{***}	0.105^{***}	0.078^{***}
	[−31.903]	[−44.030]	[−37.245]	[−34.691]	[33.764]	[32.018]	[29.726]	[29.266]
Q5 of $ND_{f,t}$	-0.163^{***}	-0.100^{***}	-0.060^{***}	-0.050^{***}	0.381^{***}	0.223^{***}	0.112^{***}	0.083^{***}
	[−41.848]	[−36.764]	[−31.426]	[−28.276]	[39.257]	[37.896]	[35.910]	[34.221]
Q5 − Q1	-0.013^{**}	-0.009^{***}	-0.006^{***}	-0.005^{***}	0.010	0.011^{**}	0.006^{**}	0.005^{**}
	[−2.376]	[−3.498]	[−3.491]	[−3.073]	[1.011]	[2.219]	[2.294]	[2.358]

Note: This table examines the changes of outflow risk after natural disaster shocks. In Panel A, the dependent variable is the quarterly abnormal flows of individual funds, defined as the fund-level flows minus the asset-size-weighted aggregate flows of the entire active US equity mutual fund sector. Independent variable $ND_{f,t}$ is the portfolio weight of the stocks affected by natural disasters in fund f. We standardize both the dependent variable and the independent variable. We cluster standard errors at both the fund level and at the quarter level. In Panel B, we tabulate the left tail and dispersion of abnormal fund flows across funds with different natural disaster exposures. Specifically, we sort funds into quintiles each quarter based on their exposure to natural disasters. We measure the left tail of abnormal fund flows using the 5th, 10th, 20th, and 25th percentiles (denoted by p5, p10, p20, and p25, respectively). We measure the dispersion of abnormal fund flows using distance between various percentiles, including p95 − p5, p90 − p10, p80 − p20, and p75 − p25. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1994 to 2018.

To tackle the second challenge of unobserved $Outflow\_Risk_{f,t}$ as the explanatory variable, we follow the design of the reduced-form regression of dependent variables on instruments (see Angrist and Pischke, 2009, Chapter 4). Specifically, we bypass the unobserved endogenous explanatory variable – outflow risk – and directly regress changes in mutual fund portfolio weight deviations from the market portfolio on fund exposure to natural disaster. We run our regression on the stocks not affected by natural disaster to mitigate the concern that stock properties are affected by the same shock that shifts the outflow risk of the fund:

$$\Delta(w_{i,f,t} - w_{i,t}^{mkt}) = b_1 \times \beta_{i,t-1}^{flow} \times ND_{f,t} + b_2 \times \beta_{i,t-1}^{flow} + b_3 \times \beta_{i,t-1}^{mkt} \times ND_{f,t} + b_4 \times \beta_{i,t-1}^{mkt}$$
$$+ b_5 \times ND_{f,t} + a_i + a_f + a_t + \varepsilon_{i,f,t}, \tag{4.4}$$

Table 14: Mutual fund rebalancing of stocks unaffected by natural disaster following natural disaster shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone				Panel B. CRSP-Morningstar intersection			
	$\Delta(w_{i,f,t} - w^{mkt}_{i,t})$ $(\times 10^3)$				$\Delta(w_{i,f,t} - w^{mkt}_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-0.031^{***}	-0.033^{***}	-0.035^{***}	-0.039^{***}	-0.023^{**}	-0.026^{**}	-0.030^{***}	-0.033^{***}
	[−3.323]	[−3.332]	[−3.548]	[−3.734]	[−2.394]	[−2.383]	[−2.852]	[−2.869]
$\beta^{flow}_{i,t-1}$	0.039^{***}	0.062^{***}	0.061^{***}	0.090^{***}	0.022^{***}	0.044^{***}	0.045^{***}	0.065^{***}
	[5.523]	[7.680]	[6.775]	[8.391]	[3.228]	[5.123]	[5.105]	[5.744]
$\beta^{mkt}_{i,t-1} \times ND_{f,t}$	0.022^{**}	0.033^{***}	0.027^{**}	0.037^{***}	0.024^{**}	0.036^{***}	0.030^{***}	0.040^{***}
	[2.244]	[3.377]	[2.537]	[3.451]	[2.310]	[3.337]	[2.645]	[3.428]
$\beta^{mkt}_{i,t-1}$	0.007	-0.012^{**}	0.053^{***}	0.024^{**}	0.007	-0.015^{**}	0.051^{***}	0.022^{**}
	[1.082]	[−1.985]	[5.308]	[2.236]	[1.087]	[−2.356]	[5.162]	[2.014]
$ND_{f,t}$	-0.053^{***}	-0.259^{***}	-0.093^{***}	-0.258^{***}	-0.055^{***}	-0.260^{***}	-0.095^{***}	-0.260^{***}
	[−5.324]	[−15.161]	[−8.384]	[−15.478]	[−5.520]	[−15.225]	[−8.608]	[−15.578]
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9477152	9477152	9476833	9476833	9477152	9477152	9476833	9476833
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disaster after natural disaster shocks. The dependent variable is the quarterly change of stock weights in mutual funds in excess of the quarterly change of stock weights of the market portfolio. $\Delta(w_{i,f,t} - w^{mkt}_{i,t}) = (w_{i,f,t} - w_{i,f,t-1}) - (w^{mkt}_{i,t} - w^{mkt}_{i,t-1})$, where $w_{i,f,t}$ represents the weight of stock i in fund f in quarter t and $w^{mkt}_{i,t}$ represents the weight of stock i in the market portfolio in quarter t. β^{flow}_i is the flow beta for stock i, β^{mkt}_i is the market beta for stock i, and $ND_{f,t}$ is the portfolio weight of the stocks affected by natural disaster in fund f. β^{flow}_i, β^{mkt}_i, and $ND_{f,t}$ are standardized to have means of 0 and standard deviations of 1. Standard errors are clustered at the stock level. Results remain robust if we double-cluster standard errors at the stock and quarter levels. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1994 to 2018.

where $\Delta(w_{i,f,t} - w^{mkt}_{i,t})$ is the portfolio weight changes of fund f in stock i (in excess of the weight change in the market portfolio) from quarter $t-1$ to t, $\beta^{flow}_{i,t-1}$ is the flow beta of stock i, and $ND_{f,t}$ is fund f's exposure to natural disaster. Here, $w_{i,f,t}$ is the portfolio weight of stock i in the holdings of fund f in period t, and $w^{mkt}_{i,t}$ is the market portfolio weight of stock i in period t. Fixed effects a_i, a_f, and a_t correspond to the stock, the fund, and the observation period, respectively. As we show in Table 14, coefficient b_1 is significantly negative across all specifications. This shows that, relative to other funds, active mutual funds with heavy exposure to natural disaster shocks tilt their holdings of unaffected stocks toward low-flow-beta stocks. The rebalancing patterns we show above support our theoretical prediction that elevated exposure to outflow risk strengthens the incentive of an active fund to hedge against common fund flow shocks.

Fund exposure to natural disaster $ND_{f,t}$ is a useful source of variation in outflow risk because time-series variation in $ND_{f,t}$ is largely unpredictable (e.g., Dessaint and Matray, 2017).[45] The main challenge in interpreting our results above is that exposure to natural

[45] In Table OA.20 of the online appendix we address the possibility that natural disasters may be somewhat predictable by portfolio characteristics correlated with future portfolio changes.

disaster may affect other properties of a fund's portfolio, leading the fund to rebalance for reasons other than its elevated outflow risk. To mitigate this concern, we focus our analysis on the weight changes of stocks not directly affected by disaster shocks. One may argue that some of these stocks may still experience a spill-over effect through supplier-customer linkages (e.g., Barrot and Sauvagnat, 2016). While it is unclear how the spill-over of firm-level shocks affects the relation between stocks' flow betas $\beta_{i,t}^{flow}$ and portfolio weight changes $\Delta(w_{i,f,t} - w_{i,t}^{mkt})$, we address this potential issue empirically by excluding the suppliers and customers of firms affected by natural disaster from our analysis. We show in Table OA.18 of the online appendix that our findings remain robust.

Another potential concern is that mutual funds may tilt their portfolios following natural disaster because of how they rebalance stocks with different liquidity — e.g., funds experiencing outflows because of disaster shocks may reduce their holdings of more liquid stocks on impact. To mitigate this concern, we control for stock liquidity and its interaction with flow betas in Table OA.19 of the online appendix. Our results remain robust.

We find that active mutual funds lower their exposure to common fund flow shocks at the expense of their performance, showing that they must perceive a benefit from tilting toward low-flow-beta stocks on dimensions other than expected fund return. Specifically, in each quarter t, we consider a counterfactual world in which active mutual funds keep the relative portfolio weights across the stocks unaffected by natural disaster the same as those in quarter $t-1$.[46] Compared to this counterfactual world, we find that mutual funds on average lose 63 basis points ($p < 0.001$) in annualized returns by changing the relative weights of the stocks that are unaffected by natural disasters (see Table OA.21 of the online appendix).[47] This loss in performance is more significant for funds with higher exposure to natural disaster shock. Specifically, when we consider the fund-quarters with a higher-than-median exposure to natural disaster, the loss in annualized fund returns increases to 99 basis points ($p < 0.001$).

[46]Note that the hedging expense would be 0 in our estimation if funds simply adjust their holdings of the stocks unaffected by natural disaster as a whole without changing the relative weights of these stocks. The natural disaster setting allows us to compare the fund performance with that in the counterfactual world because natural disaster shocks take place through out our sample period from 1994 to 2018.

[47]Theoretically, it is possible that the costs of hedging are driven by price impact. Suppose that mutual funds hit by disaster shocks aggressively sell stocks unaffected by the natural disaster and thus drive down their prices temporarily. These mutual funds will experience underperformance when the prices of the unaffected stocks bounce back. We show that this alternative explanation is inconsistent with what we find in the data. The unaffected stocks held by the mutual funds hit by disaster shocks have past returns similar to the market after adjusting for characteristics. Specifically, the size and book-to-market adjusted abnormal returns for the unaffected stocks held by the affected mutual funds is 0.04% in the quarters of natural disasters, with a t-statistic of 0.37. In other words, we find no evidence that these stocks are aggressively sold and thus experience negative price impact.

This loss stands in contrast to the generally positive effect of rebalancing on fund performance. In particular, we show in Table OA.21 of the online appendix that the annualized fund return estimated based on all positions (instead of the positions of the unaffected stocks only) of mutual funds is 49 basis points ($p < 0.001$) higher than that in the counterfactual world.

5 Conclusion

In this paper we develop the idea that endogenous aggregate fund flows induce hedging demand from active equity fund managers, which in turn implies that aggregate fund flow shocks earn a risk premium in equilibrium. Our empirical results support the main implications of the model. Importantly, not only are aggregate flow shocks priced in the cross-section of stock returns, but we also find that mutual fund managers tilt their portfolios in a way that helps protect them against common fund flow shocks. Our results may be seen as an "invisible hand" argument, which helps explain how macroeconomic shocks are priced in an environment where agents do not engage in intertemporal hedging because of their limited sophistication or short-term focus. Our model thus suggests an alternative mechanism for some of the predictions of dynamic general-equilibrium models, where households, in particular, are assumed to develop complex multi-period investment-consumption plans. We are exploring quantitatively the link between our model and traditional institution-free dynamic equilibrium models in ongoing work.

The framework of this paper can be extended in several directions. While we find that aggregate uncertainty shocks contribute to common fund flows, it would be useful to understand what other primitive economic shocks drive fund flows. Moreover, it would be interesting to examine the economic mechanisms behind the empirical relations between firm characteristics and fund flow betas in greater depth. Another promising direction for future work is to integrate liquidity considerations explicitly into the fund managers' problem, as stock liquidity naturally interacts with fund flow shocks.

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Appendix

A Competitive Equilibrium

Now we formally state the definition of the equilibrium. We focus on the symmetric competitive equilibrium with atomistic homogeneous fund managers, fund clients, and direct investors. Formally speaking, we are looking for a stationary symmetric competitive equilibrium defined as follows.

Definition A.1 (Competitive equilibrium)**.** *A competitive equilibrium is a price process, P_t, for the risky assets, a risk-free rate, R_f, a net alpha process for active funds, α_t, offered by the active funds, consumption processes $\{C_{c,t}, C_{d,t}, C_{m,t}\}$, and portfolio processes $\{\phi_{d,t}, \phi_{m,t}, q_t\}$ such that*

(i) given the equilibrium prices, fund's excess return, and aggregate allocations,

(i.a) each direct investor's consumption $C_{d,t}$ and portfolio strategy $\phi_{d,t}$ are optimal in terms of maximizing the utility in Equation (3.7) subject to Equation (3.8);

(i.b) each fund client's consumption $C_{c,t}$ and delegation decision q_t are optimal in terms of maximizing the utility in Equation (3.7) subject to Equation (3.10);

(i.c) each fund manager's consumption $C_{m,t}$ and portfolio strategy $\phi_{m,t}$ are optimal in terms of maximizing the utility in Equation (3.7) subject to Equations (3.12) and (3.13);

(ii) prices P_t, risk-free rate R_f, and fund's net alpha α_t clear goods, assets, and delegation markets:

(ii.a) goods market: $\sum_{i=1}^{n} D_{i,t} = C_{d,t} + C_{c,t} + C_{m,t} + \psi(q_t)W_t$;

(ii.b) delegation market: $\theta(\overline{\alpha} - \alpha_t - f) = q_t$;

(ii.c) assets market: $Q_t\phi_{m,t} + [W_{d,t} - C_{d,t} - \overline{\alpha}Q_t]\,\phi_{d,t} = [W_{d,t} - C_{d,t} + (1-\overline{\alpha})Q_t]\,\phi_t^{mkt}$, where ϕ_t^{mkt} is the market portfolio.

The market clearing condition (ii.a) reflects that the total goods, $\sum_{i=1}^{n} D_{i,t}$ are either consumed by the agents (i.e., $C_{d,t} + C_{c,t} + C_{m,t}$) or used by the active fund managers to create gross alphas (i.e., $\psi(q_t)W_t$). The market clearing condition (ii.b) is essentially the supply curve for active funds' asset management services (Equation (3.6)), and the demand curve for active funds' asset management services (Equation (3.11)) results from the optimization condition (i.b). The market clearing condition (ii.c) effectively characterizes the market portfolio in the economy, and the market clearing condition for risky assets plays an essential role in generating equilibrium relations among the market portfolio, the myopic portfolio, and the active fund portfolio, summarized in Theorem 1.

B Classification of Active and Index Funds

Similar to prior studies (e.g., Kacperczyk, Sialm and Zheng, 2008; Huang, Sialm and Zhang, 2011), we identify actively managed US equity mutual funds based on their objective codes and disclosed asset compositions. We first select funds with the following Lipper objectives: CA, CG, CS, EI, FS, G, GI, H, ID, LCCE, LCGE, LCVE, MC, MCCE, MCGE, MCVE, MLCE, MLGE, MLVE, MR, NR, S, SCCE, SCGE, SCVE, SG, SP, TK, TL, UT. If a fund does not have any of the above objectives, we select funds with the following strategic insight (SI) objectives: AGG, ENV, FIN, GMC, GRI, GRO, HLT, ING, NTR, SCG, SEC, TEC, UTI, GLD, RLE. If a fund has neither the Lipper nor the SI objective, then we use the Wiesenberger fund type code to select funds with the following objectives: G, G-I, G-S, GCI, IEQ, ENR, FIN, GRI, HLT, LTG, MCG, SCG, TCH, UTL, GPM. If none of these objectives is available and the fund holds more than 80% of its value in common shares, then the fund will be included.

After finishing the procedure described above, we further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data. CRSP mutual fund data provide a variable "index fund flag" to identify index funds. We define a fund as an index fund if its index fund flag is B (index-based fund), D (pure index fund), or E (index fund enhanced). Similar to previous studies (e.g., Busse and Tong, 2012; Ferson and Lin, 2014; Busse, Jiang and Tang, 2021; Jones and Mo, 2021), we also define a fund as an index fund if its

Table A.1: Alternative flow measures.

Panel A: Portfolio sorting analysis								
	AUM-weighted flow measure				Flow measure of Berk and Tonks (2007)			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
β_i^{flow} quintiles	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α
Q1	5.49	-5.30^{**}	5.74	-3.75^{**}	4.87	-4.16^{**}	6.99^{*}	-2.73
	[1.28]	[-2.48]	[1.55]	[-2.10]	[1.38]	[-2.44]	[1.79]	[-1.33]
Q2	7.32^{**}	-0.65	7.20^{**}	-0.66	6.98^{**}	-0.30	6.44^{**}	-1.30
	[2.40]	[-0.49]	[2.44]	[-0.56]	[2.59]	[-0.31]	[2.23]	[-1.17]
Q3	9.32^{***}	1.65^{*}	9.85^{***}	2.29^{**}	8.52^{***}	0.21	6.95^{**}	-0.57
	[3.32]	[1.71]	[3.58]	[2.58]	[2.84]	[0.24]	[2.52]	[-0.60]
Q4	9.42^{***}	1.32	9.99^{***}	1.32	10.85^{***}	1.96	11.38^{***}	2.40^{**}
	[3.14]	[1.19]	[3.08]	[1.03]	[3.27]	[1.50]	[3.45]	[2.06]
Q5	12.68^{***}	1.86	12.24^{**}	1.62	15.09^{***}	3.43	13.34^{***}	2.52
	[2.85]	[0.76]	[2.51]	[1.16]	[3.14]	[1.29]	[2.92]	[1.55]
Q5 − Q1	7.20^{**}	7.16^{**}	6.51^{**}	5.38^{**}	10.21^{***}	7.59^{**}	6.35^{**}	5.25^{*}
	[2.16]	[2.12]	[2.24]	[2.17]	[2.96]	[2.24]	[2.02]	[1.93]

Panel B: Holdings analysis									
	(1)	(2)	(3)	(4)		(5)	(6)	(7)	(8)
	Panel regressions with time FE					Fama-MacBeth regressions			
	AUM-weighted		Berk and Tonks (2007)			AUM-weighted		Berk and Tonks (2007)	
	CRSP	CRSP-MS	CRSP	CRSP-MS		CRSP	CRSP-MS	CRSP	CRSP-MS
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{mkt}$			$w_{i,t}^{MF} - w_{i,t}^{mkt}$		$w_{i,t}^{MF} - w_{i,t}^{mkt}$	
$\beta_{i,t-1}^{flow}$	-0.021^{***}	-0.033^{***}	-0.019^{***}	-0.012^{**}	$\beta_{i,t-1}^{flow}$	-0.041^{***}	-0.043^{***}	-0.026^{***}	-0.022^{***}
	[-3.746]	[-5.748]	[-3.398]	[-2.288]		[-6.759]	[-7.207]	[-5.865]	[-5.344]
$\beta_{i,t-1}^{mkt}$	0.062^{***}	0.066^{***}	0.063^{***}	0.060^{***}	$\beta_{i,t-1}^{mkt}$	0.091^{***}	0.093^{***}	0.087^{***}	0.085^{***}
	[7.385]	[7.810]	[7.810]	[7.622]		[11.153]	[11.297]	[10.953]	[10.767]
Quarter FE	Yes	Yes	Yes	Yes					
Observations	413321	413321	413321	413321	Avg. obs./quarter	3863	3863	3863	3863
R-squared	0.01	0.01	0.01	0.01	Avg. R-squared	0.01	0.01	0.01	0.01

Note: We consider two alternative measures of common fund flow shocks in this table. The first measure is based on AUM-weighted fund flow shocks. The second measure is based on the fund flow measure of Berk and Tonks (2007). Panel A of this table shows the value-weighted average excess returns and alphas for stock portfolios sorted on flow beta. Panel B of this table studies the relation between flow betas ($\beta_{i,t-1}^{flow}$) and active equity mutual funds' weight deviation from the benchmark portfolios. We perform panel regressions with quarter fixed effects in Columns (1) to (4), and Fama-MacBeth regressions in Columns (5) to (8). Standard errors for the panel regressions are double clustered at the stock and quarter levels. We include t-statistics in brackets. FE is fixed effects. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

name contains any of the following text strings: Index, Inde, Indx, Inx, Idx, Exchange-traded, Exchange traded, ETF, DFA, Dow Jones, iShare, S&P, S &P, S& P, S & P, 500, Wilshire, Russell, Russ, MSCI.

C Alternative Measures for Common Fund Flows

We consider two more alternative measures of common fund flow shocks. First, instead of performing PCA, we construct the common fund flow shock using AUM-weighted fund flow shocks. Second, we construct the common fund flow shock based on PCA but using the method of Berk and Tonks (2007) to measure fund flows. As shown in Table A.1, the asset pricing implications and the portfolio tilt results remain robust using these two alternative measures of common fund flow shocks.