Common Fund Flows: Flow Hedging and Factor Pricing

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Abstract

Active mutual funds care about fund size, affected by common fund flows driven by primitive shocks. Funds hedge against common-flow shocks by tilting their portfolios toward low-flow-beta stocks. In equilibrium, common fund flows earn a risk premium, leading to a multi-factor asset-pricing model similar to the ICAPM, even with all agents behaving myopically and using naive asset-pricing models. Empirically, fund flows obey a strong factor structure with the common component earning a risk premium, and fund portfolios are, on average, tilted toward low-flow-beta stocks. This tilt increases in magnitude when flow-hedging motives strengthen following natural disasters and unexpected trade-war announcements.

Keywords: Agency conflicts, Mutual fund flows, Factor models, Heterogeneous agents, Intermediary asset pricing, Uncertainty. (**JEL:** G11, G12, G23)

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1 Introduction

Over the past few decades, delegated asset management such as mutual funds and pension funds have become the dominant player in the United States (US) financial markets (e.g., French, 2008). In 2016, the combination of mutual funds and pension funds held more than 44% of the US equity market. Because the funds charge asset management fees based on their assets under management (AUM), fund managers' incentives are closely related to fund size. Indeed, recent studies have shown that the compensation of active fund managers is significantly and monotonically associated with fund size (e.g., Ibert et al., 2018). Fund size fluctuates not only because of fund returns but also because of fund flows.

We show empirically that fund flows share a significant degree of common time-series variation, consistent with the findings of Ferson and Kim (2012). As a contribution to this area of research, we establish the finding that active equity funds of different asset size groups, age groups, industry concentration levels (Kacperczyk, Sialm and Zheng, 2005), and portfolio liquidity levels (Pástor, Stambaugh and Taylor, 2019) exhibit strong commonality in fund flows at a frequency higher than that of business cycles. The common flow component is closely related to fluctuations in macroeconomic conditions, especially in economic uncertainty faced by investors.

In this paper we develop and test the central theoretical implications of the agency problem between the managers of active mutual funds and fund investors. We show in our model that fund managers tilt their portfolios to hedge against the common component of fund flow fluctuations. By doing so, they raise aggregate demand for stocks with low betas on the common fund flows, thus increasing valuations of such stocks and lowering their expected returns.[1]

This paper addresses an important limitation of standard risk-based explanations of compensated systematic shocks in the cross-section of stock returns, which use Merton's Intertemporal Capital Asset Pricing Model (ICAPM) framework (Merton, 1973) and attribute risk premia on return factors to the intertemporal hedging demand of investors. Many researchers have questioned the core assumption of the ICAPM that investors are able to form accurate long-term expectations and develop sophisticated dynamic investment and consumption plans. An extensive body of the literature provides evidence that many

[1] Our findings illustrate the general insight that institutions have different demand for stock characteristics relative to other investors, which has important implications for stock prices and returns (e.g., Gompers and Metrick, 2001; Koijen and Yogo, 2019).

investors, particularly households, are unsophisticated in their financial decision making.[2]

In our model, stock market investors (and even fund managers) do not need to anticipate and hedge against possible intertemporal changes in their investment environment. Instead, if investors adjust their asset allocation following realizations of a macroeconomic shock, they expose fund managers to aggregate fluctuations in the fund flow. Such macroeconomic shock is then priced in equilibrium because of its endogenous relation with the fund flows.[3]

We introduce a general equilibrium model of delegated asset management. In our model, fund flows fluctuate endogenously with the aggregate state of the economy. Fund managers account for the fund flow risk in their portfolio choice, and their flow-hedging behavior affects stock prices. Our model features an exchange economy populated with investors and active fund managers. Investors allocate their capital between the risk-free asset and multiple stocks. They choose whether to form their portfolio on their own and become "direct investors," or to delegate their investments to the fund managers and become "fund clients." Fund clients pay a fee to the fund managers, proportional to the amount of delegated assets. Fund managers operate active equity funds and consume the net income of these funds.

We use an overlapping-generations (OLG) structure, with all agents living for two periods and behaving myopically. The assumption of myopic behavior is not necessary for the main results, but serves to emphasize that the asset pricing implications of our model do not rely on sophisticated intertemporal optimization by the market participants. Instead, the risk premium on flow shocks in our model arises because of the myopic (single-period) hedging motives of the fund managers, owing to the exposure of the funds' AUM to the flow shocks.

In our model, firm fundamentals are subject to economic uncertainty shocks: conditional volatility of firms' dividends fluctuates with the state variable that captures economic uncertainty. When economic uncertainty rises, fund clients pull their capital out of active equity funds and invest in the safe asset. As a result, they endogenously generate common outflows across active equity funds. Fund managers have an incentive to hedge against (endogenous) fluctuations in common fund flows in order to reduce the volatility of their funds' AUM, which directly affects the volatility of their compensation. They do so by

[2]For example, recent papers by Greenwood and Shleifer (2014), Bordalo et al. (2019), and Bordalo et al. (2020) document financial advisors and professionals form systematically biased expectations, especially for long-term growth. Hirshleifer (2015) discusses how investor overconfidence and limited cognitive processing hamper implementation of strategic plans. Further, empirical evidence has shown that fund managers as investors are often short-sighted in their decision making (e.g., Prat, 2005; Hermalin and Weisbach, 2012).

[3]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) and Kozak, Nagel and Santosh (2018)).

tilting their portfolios away from the stocks with high flow betas, which by definition are the exposures of stock returns to the common fund flow. Because of this hedging demand, market clearing conditions imply that the aggregate stock market portfolio deviates from the mean-variance efficient frontier in equilibrium. In particular, prices of high-flow-beta stocks are reduced by the managers' hedging demand, and their expected returns are elevated relative to their market betas.

Common fund flows bridge the gap between the macroeconomic shocks affecting households and portfolio decisions of self-interested institutions. Because common fund flows are driven by the economic uncertainty shocks in the model, stock betas on common fund flows and their betas on the economic uncertainty shocks are closely related across firms in equilibrium. This means that not only are common fund flow shocks priced in the cross-section of stock returns, but the economic uncertainty shocks are priced as well, even though households themselves do not hedge against uncertainty shocks.

We provide empirical support for the above predictions of our model using detailed data on the returns, asset size, and portfolio holdings of active mutual funds. These empirical results are novel, and represent another contribution of this paper. First, we establish a relation between the common component of fund flows and macroeconomic shocks. Particularly, we find that common fund flows are significantly negatively correlated with fluctuations in the economic policy uncertainty measure proposed by Baker, Bloom and Davis (2016), the (implied) market volatility used by Bloom (2009), and the consumption dispersion measure used by Brav, Constantinides and Geczy (2002), Vissing-Jørgensen (2002), and Jacobs and Wang (2004), suggesting that common fund flows endogenously respond to primitive economic shocks that drive economic uncertainty. Second, we find that stocks with higher flow betas are associated with higher excess returns and higher CAPM alphas. The magnitudes of the flow-beta spreads are both statistically and economically significant.[4] Third, we find that funds tilt their portfolio positions away from the stocks with high flow betas, reducing the covariance of the funds' portfolios with the common fund flow shocks. This finding is robust to defining the tilt relative to the market portfolio or the self-disclosed benchmarks.

To further confirm that the observed portfolio tilts are driven by the flow hedging

[4]We find that capital flows in and out of index funds are not priced in the cross-section of stock returns, which is consistent with the logic of our models: index funds are much more constrained than active funds in their ability to deviate from their benchmark.

motive, we use two quasi-natural experiments to see how funds respond to changes in the magnitude of their outflow risk. In the first experiment, we examine changes of mutual fund holdings following natural disaster shocks in the US. We find that active mutual funds experience an increase in outflow risk in the subsequent quarters when some stocks in their portfolios are negatively affected by natural disaster shocks. The 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 study how mutual funds rebalance their portfolio holdings following the unexpected announcement of a possible US-China trade war made by the Trump administration. The flow betas of China-related stocks increase sharply, relative to China-unrelated stocks, in the aftermath of the unexpected trade war announcement and the resulting heightened trade policy uncertainty. Thus, the unexpected trade war announcement strengthens the flow hedging incentives of the active funds with substantial positions in China-related stocks. Again, consistent with our theory, the exposed mutual funds tilt their China-unrelated holdings toward the low-flow-beta stocks more aggressively after the unexpected trade war announcement.[5]

In addition to its main implications for pricing common fund flow shocks, our model also generates a countercyclical pattern of net fund alphas, which is an important empirical property of active mutual funds.[6] The key model element responsible for this result is the negative relation between the net alpha and the AUM of active funds, which is in turn driven by the funds' convex operating costs. This specification of the funds' investment technology is standard (e.g., Berk and Green, 2004; Berk and van Binsbergen, 2015, 2016*a*). In equilibrium, the net alpha and delegation size are jointly determined by clearing the market for delegation. During periods of heightened uncertainty, fund clients in the model reduce their delegation supply by moving money out of stocks and into the safe asset. This shift in

[5]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 the 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.

[6]See, for example, Moskowitz (2000), Moskowitz (2000), Kosowski (2011), and Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Interestingly, a recent paper by Pástor and Vorsatz (2020) shows that most active funds underperformed passive benchmarks during the 2020 COVID-19 crisis.

the supply curve of delegate investment assets simultaneously reduces the size of the funds' AUM and raises their net alpha.

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 has focused 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). Another strand of the literature has examined the 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 the mutual funds managed by inexperienced managers may contribute to the formation of asset price bubbles. Ben-Rephael, Choi and Goldstein (2019) show that intra-family flow shifts toward high-yield bond mutual funds predict credit spreads. Pástor and Vorsatz (2020) analyze capital flows in and out of active equity mutual funds during the COVID-19 crisis and find that these outflows are rapid during the market crash, outpacing the long-term trend. Similar to our paper, Kim (2020) also studies the asset pricing implications of fund flow betas. The key differences stem from our emphasis on the factor structure of fund flow shocks and the hedging behavior of active mutual funds. 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 flow risk; (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; (iii) we show that mutual fund flows respond to aggregate economic shocks such as shocks to economic policy uncertainty, market volatility, and consumption dispersion; (iv) we use detailed holdings data to document the hedging behavior of mutual funds; and (v) we exploit quasi-natural experiments to study the active hedging behavior of mutual funds.

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, 2019, 2020). We add to this literature by showing that the portfolios of active mutual funds are tilted toward stocks with low flow betas. We show that stock characteristics such as book-to-market ratio are correlated with flow betas in the way such that exploiting the predictive content of these characteristics renders funds more exposed to common fund flow shocks. Koijen and Yogo (2019) construct a characteristics-based demand system that allows for flexible heterogeneity in asset demand across investors and matches institutional and household holdings, including zero holdings and index strategies.

Our paper is closely related to the branch of the literature studying the effect of managers' compensation contracts on institutional portfolio choice. Fraction-of-fund fees are by far the predominant compensation contract in the mutual fund industry (e.g., Hugonnier and Kaniel, 2010; Ibert et al., 2018). However, some funds have a performance component in their compensation contract. Particularly, Grinblatt and Titman (1989), Carpenter (2000), Basak, Pavlova and Shapiro (2007), and Cuoco and Kaniel (2011) study the optimal asset allocation of fund managers receiving relative performance fees. Like us, Hugonnier and Kaniel (2010) focus on fraction-of-fund fees and study how flow hedging motives of managers distort funds' asset allocation decisions. This paper differs in its focus on the hedging motives against the aggregate component of fund flows, and aggregate implications of flow hedging in the capital market.

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; Koijen and Yogo, 2019; Haddad, Huebner and Loualiche, 2021). In a recent paper, Gabaix and Koijen (2021) estimate that flows in and out of the stock market exert a large 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 the 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 costly adjustment of fund clients. Like our work, Vayanos and Woolley (2013) highlight endogenous fund flow risk and its asset pricing implications for return momentum and reversals. We add to this literature by showing that common fund flow shocks play an important role in the financial market; 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 of institutions, as well as its asset pricing implications, to the aggregate shocks affecting (myopic) households.

2 Illutrative Model and Hypotheses

Although the contribution of this paper comes mainly from the empirical results, we develop a simple illustrative model (i.e., a conceptual framework) to explain the basic economics and set up the hypotheses. Despite the simplicity, we need to consider a general-equilibrium model to generate endogenous common fund flows driven by macroeconomic fluctuations and their asset pricing implications. Detailed proofs are in Online Appendix.

2.1 Assets

There are n risky assets in the economy, indexed by $i = 1, \cdots, n$. Their dividends are stacked in a n-dimensional vector $D_t = [D_{1,t}, \cdots, D_{n,t}]^T$, and the log dividends are $d_t = \ln(D_t)$. The data-generating process of the log dividend growth rates is

$$\Delta d_{t+1} = \mu + \sqrt{h_t}\left(Bu_{t+1} + \varepsilon_{t+1}\right), \tag{2.1}$$

where $u_t = [u_{1,t}, \cdots, u_{k,t}]^T$ are k primitive factors distributed as i.i.d. $N(0, I_k)$, and $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]^T$ are residuals distributed as i.i.d. $N(0, I_n)$. The $n \times k$ matrix B captures the loading coefficients of the n log dividend growth rates Δd_{t+1} on the k factors u_{t+1}.

We assume that the number of assets, n, is large, and various cross-sectional averages of idiosyncratic shocks, e.g., $(1/n)\sum_{i=1}^{n} \varepsilon_i$, are approximately equal to 0, which is essentially the assumption of the Arbitrage Pricing Theory (e.g., Ross, 1976).

The time-varying uncertainty is characterized by univariate state variable h_t, which is driven by k aggregate shocks u_t as follows:[7]

$$h_{t+1} = \bar{h} + \rho(h_t - \bar{h}) + \sqrt{h_t}\sigma u_{t+1}, \quad \text{with } \rho \in (0,1) \text{ and } \sigma \in \mathbb{R}^{1\times k}. \tag{2.2}$$

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

Stock i is a claim to dividend stream $D_{i,t}$ for $i = 1, \cdots, n$, and is in unit net supply. Similar to Kozak, Nagel and Santosh (2018), we assume that the supply of the risk-free bond is perfectly elastic, with a constant risk-free rate of $R_f > 1$. Let $r_f = \ln\left(R_f\right)$ denote the log risk-free interest rate. The return of risky asset i is given by $R_{i,t+1} \equiv (P_{i,t+1} + D_{i,t+1})/P_{i,t}$ where $P_{i,t}$ is the price of risky asset i at time t for $i = 1, \cdots, n$. The vector that stacks the risky asset returns is denoted by $R_{t+1} = [R_{1,t+1}, \cdots, R_{n,t+1}]^T$. The conditional mean and covariance matrix of the log return, $r_{t+1} \equiv \ln(R_{t+1})$, are denoted by

$$\mu_t \equiv \mathbb{E}_t\left[r_{t+1}\right] \quad \text{and} \quad \Sigma_t \equiv \text{var}_t\left[r_{t+1}\right], \text{ respectively.} \tag{2.3}$$

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

$$R_{t+1}(\phi) \equiv R_f + \phi^T(R_{t+1} - R_f). \tag{2.4}$$

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

$$r_{t+1}(\phi) \approx r_f + \phi^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi^T\left(v_t - \Sigma_t\phi\right), \tag{2.5}$$

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

2.2 Funds

To focus on common fund flows, we assume that the funds are homogenous. The funds are typically active mutual funds and active pension management, while fund clients are typically individual investors and pension sponsors. Funds can trade all assets and charge an advisory fee from fund clients, which is a constant f fraction of AUM.[8]

Similar to the framework of Berk and Green (2004), we assume the active funds have skillful managers and information advantages to add value by generating expected excess

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

[8] Different from Berk and Green (2004) and Kaniel and Kondor (2013), we assume exogenous constant expense ratio f for simplicity. The expense ratio can be endogenized similar to Kaniel and Kondor (2013).

return relative to passive investment strategies. As argued by the literature (e.g., Vayanos and Woolley, 2013; Berk and van Binsbergen, 2015, 2016*a*; Pedersen, 2018; Leippold and Rueegg, 2020), there are some meaningful ways for active funds to outperform (i.e., add value) as a group.[9] More precisely, the value that a mutual fund extracts from capital markets is essentially a transfer of wealth from passive to active funds in various ways.[10]

Suppose an active fund controls Q_t in AUM. We model the value added by the active fund in reduced form as $\overline{\alpha}Q_t$, which is independent of the fund's portfolio composition. The expected excess return $\overline{\alpha}$ captures the gross alpha of the active fund before expenses and fees. Active funds incur various costs, which we assume to be increasing and convex in the AUM of the fund, as in 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 total wealth of all agents, $q_t = Q_t/W_t$, and

$$\psi(q) \equiv \theta^{-1}q^2. \tag{2.6}$$

Our specification implies decreasing return to scale for the active funds. The expected excess total payout by the active funds to their clients is

$$TP_t = \overbrace{\overline{\alpha}Q_t - \psi(q_t)W_t}^{\text{net gain of funds}} - fQ_t, \tag{2.7}$$

where $\overline{\alpha}Q_t$ is the value added by the active funds, $\psi(q_t)W_t$ is the cost incurred by the active funds to create the gross alpha, and fQ_t is the management fee charged by the active fund.

We define the net alpha as $\alpha_t \equiv TP_t/Q_t$, which is the expected return received by the fund clients in period t in excess of the benchmark return. The relation between the amount of asset management service supplied by funds q_t and the net alpha α_t is

$$q_t = \theta(\overline{\alpha} - \alpha_t) - \theta f. \tag{2.8}$$

[9] The authors show that the argument claiming it to be impossible for the average active fund manager to add value in a fully rational equilibrium (Sharpe, 1991) relies upon extremely strong assumptions.

[10] First, active fund managers act as informed arbitrageurs to make money at the cost of passive funds (especially index funds) as uninformed participants when new price-sensitive information arrives (see, e.g., Grossman and Stiglitz, 1980; García and Vanden, 2009, for the theoretical framework). Second, index funds have to track the benchmark indices closely, thereby making them demand and pay for immediacy. Active fund managers are not subject to the same index-tracking requirements, which in principle allows them to avoid the immediacy costs faced by the index funds and even act as liquidity providers. Third, the benchmark indices do not contain all available assets in the markets such as frontier markets, emerging markets, and private markets. This provides ample scope for active fund managers to diverge from benchmark indices and explore profitable investment opportunities (e.g., Vayanos and Woolley, 2013).

This characterizes the supply curve for active funds' asset management services.

2.3 Agents

Heterogeneous Agents. The economy is populated by agents of three different types: direct investors, fund clients, and fund managers. 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, inactive ETFs, retail investors, and the unregulated money managers, such as hedge funds. Fund clients, labeled by c, have to delegate their investment to professional fund managers.[11] Fund clients can be retail investors or institutions such as pension sponsors and university endowments (e.g., Gerakos, Linnainmaa and Morse, 2020). Fund managers, labeled by m, control the AUM of the active funds and consume the net income of these funds. Direct investors and fund clients own the assets.

All agents live for two periods, and form overlapping generations. Cohort t agents are born at the beginning of period t and die in period $t+1$ after they collect their payoffs. All agents have the same Epstein-Zin-Weil preferences 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

$$U_{i,t} = (1-\beta)\ln\left(C_{i,t}\right) + \beta(1-\gamma)^{-1}\ln \mathbb{E}_t\left[\tilde{W}_{i,t+1}^{1-\gamma}\right], \tag{2.9}$$

where $i \in \{d, c, m\}$, $C_{i,t}$ is cohort t's consumption in period t, and $\tilde{W}_{i,t+1}$ is the wealth of cohort t in period $t+1$.

At the beginning of each period, new direct investors and fund clients are born with a unit measure of population. Investors are randomly assigned to be fund clients with probability λ, or direct investors with probability $1-\lambda$. As a result, in period t, 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. The newly-born fund managers have a unit measure of population but zero endowment.

We adopt an OLG framework to avoid tracking the wealth shares as endogenous state variables when characterizing the equilibrium.[12] Moreover, we assume that agents in our

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

[12] Such a simplification assumption is innocuous in the sense that Kaniel and Kondor (2013) show that the

model do not internalize their descendants' utility.[13] As a result, agents are myopic.

Direct Investors. The cohort-t direct investor's wealth is $W_{d,t} = (1-\lambda)W_t$. We denote by $\phi_{d,t}$ the optimal portfolio weights of period t investable wealth. Direct investors choose $\phi_{d,t}$ and the consumption $C_{d,t}$ optimally to maximize the utility in (2.9) subject to the dynamic budget constraint:

$$\tilde{W}_{d,t+1} = (W_{d,t} - C_{d,t} - \overline{\alpha} Q_t) R_{t+1}(\phi_{d,t}), \tag{2.10}$$

where $\overline{\alpha} Q_t$ is the transfer from direct investors to active funds as discussed in Section 2.2.

Proposition 2.1 (Direct investors' holdings)**.** *The optimal consumption of direct investors is*

$$C_{d,t} = (1-\beta)(1-\lambda-\overline{\alpha} q_t) W_t, \tag{2.11}$$

and the optimal portfolio of direct investors is the standard myopic mean-variance efficient portfolio:

$$\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f \mathbf{1} + \frac{1}{2}\nu_t\right), \tag{2.12}$$

where μ_t, Σ_t, and ν_t are defined in (2.3) and (2.5).

Fund Clients. Fund clients decide the amount of wealth to delegate to the funds that actively trade risky assets, denoted by Q_t, and then the fund managers make allocation decisions for the delegated funds. Barber, Huang and Odean (2016) and Berk and van Binsbergen (2016*b*) find evidence that fund clients are not perfectly sophisticated in terms of incorporating the consideration of intertemporal hedging when they assess fund performance and make delegation decisions. To highlight this lack of sophistication, we assume that fund clients care about the net alpha of the active funds relative to the passive benchmark.[14]

The wealth of cohort-t fund clients is $W_{c,t} = \lambda W_t$, and they choose Q_t and the consump-

constant wealth share of fund clients can endogenously arise as an equilibrium outcome.

[13]Seminal works (e.g., Barro, 1974; Abel, 1987) show that an equilibrium in OLG models with operative bequests is formally equivalent to that of a representative infinitely lived age. Our assumption violates the conditions to ensure operative bequests.

[14]While we model the behavior of fund clients to be consistent with the main thrust of the recent literature on mutual fund flow, the precise behavioral assumptions we make are not essential for the key conclusions of our model about mutual fund hedging of common fund flow shocks, and the risk premium the flow-hedging demand generates. The essential element of the fund client's behavior is that they reduce their investment in equity mutual funds in high-uncertainty states when facing heightened economic uncertainty.

tion $C_{c,t}$ optimally to maximize the utility in (2.9) subject to the budget constraint:

$$\tilde{W}_{c,t+1} = (W_{c,t} - C_{c,t} - Q_t)R_f + Q_t\left[R_{t+1}(\phi_{d,t}) + \alpha_t\right]. \tag{2.13}$$

The following proposition characterizes the optimal decisions of fund clients.

Proposition 2.2 (Fund clients' delegation)**.** *If the perceived benefit from active management is sufficiently large 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 this case, the optimal consumption of fund clients is*

$$C_{c,t} = (1-\beta)\lambda W_t, \tag{2.14}$$

and the total amount of asset management service demanded by fund clients satisfies

$$q_t = \beta\lambda\left(1 + \frac{\alpha_t}{\overline{\gamma}h_t}\right), \tag{2.15}$$

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

Fund Managers. The active fund's AUM at the beginning of period t is Q_t and the revenue of the fund is the 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. Similar simplification assumption has been commonly adopted in the literature.[15] We emphasize that the theoretical results remain unchanged as long as the fund manager cares about the fund's AUM, which has been shown by recent empirical findings (e.g., Ibert et al., 2018).[16]

Moreover, we assume that the fund manager cannot invest in risky assets using her private wealth. This simplification assumption has also been widely adopted in the literature (e.g., Berk and Green, 2004; Cuoco and Kaniel, 2011; Kaniel and Kondor, 2013) for technical tractability, which allows us to avoid keeping track of the fund manager's private wealth, and modeling her private investment decisions. We emphasize that the theoretical results remain unchanged as long as the fund manager cannot fully hedge against the flow risk using the

[15] 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).

[16] More precisely, Ibert et al. (2018) find that the compensation of mutual fund managers concavely depends on the mutual fund's AUM, which suffices to ensure the key conclusions of our model about fund managers' flow hedging motives. Our specification basically assumes that the incentives of the fund manager and the fund size are perfectly aligned for simplicity.

money in her own pocket for the reasons such as rational inattention and (relatively) limited private investable wealth.

The fund manager of cohort t chooses the fund portfolio $\phi_{m,t}$ and the consumption $C_{m,t}$ optimally to maximize the utility in (2.9) subject to the budget constraint:

$$\tilde{W}_{m,t+1} = fQ_{t+1} - C_{m,t}R_f, \quad \text{with} \tag{2.16}$$

$$Q_{t+1} = \underbrace{Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t\right]}_{\text{fund returns}} + \underbrace{Q_t flow_{t+1}}_{\text{fund flows}}, \tag{2.17}$$

where Q_t is the delegation characterized in (2.15) given the net alpha α_t and the aggregate state h_t, and $Q_t flow_{t+1}$ is the net fund flow into the fund. Importantly, the fund managers can save and they don't have to consume the fund revenues immediately period by period.

Equation (2.17) essentially gives the definition of the fund flow, denoted by $flow_{t+1}$:

$$flow_{t+1} \equiv \frac{Q_{t+1} - Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t\right]}{Q_t}. \tag{2.18}$$

The dynamic budget constraint in equation (2.17) above 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 the funds. The AUM at the beginning of period $t+1$ is the sum of the fund return and fund flow: $Q_{t+1} = Q_t\left[R_{t+1}(\phi_{m,t}) + \alpha_t + flow_{t+1}\right]$.

We assume that fund managers are myopic to highlight that our equilibrium results do not require any agents in the model to engage in sophisticated dynamic optimization. As a behavioral model, our assumption can be further justified by the fund managers' short-term focus stemming from their career concerns (e.g., Prat, 2005; Hermalin and Weisbach, 2012).

2.4 Equilibrium and Hypotheses to Test

The competitive equilibrium is formally defined in the appendix.

Endogenous Flows. Fund flow $flow_{t+1}$ is endogenous, driven by aggregate shocks in a predictable way in the equilibrium. In Proposition 2.3 below, we show that delegation negatively depends on uncertainty h_t, and thus aggregate fund flows $flow_{t+1}$ are negatively associated with uncertainty shocks Δh_{t+1} in aggregate time series.

Proposition 2.3 (Fund flows and uncertainty)**.** *The equilibrium amount of delegation q_t is a function of uncertainty h_t. When the benefits from active management are large relative to the cost of delegation, i.e., $\overline{\alpha} > \theta^{-1}\beta\lambda + f$, the equilibrium delegation is q_t declines as h_t rises:*

$$\frac{\partial q_t}{\partial h_t} < 0. \tag{2.19}$$

An important hypothesis presented by Proposition 2.3 is that the common fund flow negatively comoves with the fluctuation in economic uncertainty, which has been empirically verified in Tables 1 and 2 and Figure 5 of Section 4.1.

A natural question arising from Proposition 2.3 is which institutional investors that provide delegated management services are the "flow counterparties" of the active funds of risky equities. The common fund flows we study are capital flows across asset classes like in Gabaix and Koijen (2021). Specifically, as another major testable hypothesis, our model implies that, when uncertainty is heightened, fund clients' money flows from the active funds of risky equities to the bond funds of low-risk securities, especially those which mainly invest in investment grade corporate bonds, TIPS bonds, government bonds, and municipal bonds. The bond funds of low-risk securities are the "flow counterparties" of the active funds of risky equities, meaning that, to a large extent, they soak up the fund flows in and out of the active equity funds. There have been extensive empirical evidence in the literature that support this model prediction (e.g., Chen and Qin, 2017; Wang and Young, 2020; Chan and Marsh, 2021).

Returns' Flow Betas. With the characterization of equilibrium delegation q_t, we are now ready to describe flow betas of stock returns in the equilibrium. In Proposition 2.4 below, we show that there could be two primitive sources of determinants behind flow betas of stock returns — not only the flow beta of stock returns depends on the exposure of cash flows to the fundamental shocks in u_t, but also on the exposure of price-dividend ratios to potential non-fundamental shocks in u_t, which reflects the price impact of non-fundamental demand shocks.

Proposition 2.4 (Returns, flows, and flow betas)**.** *The equilibrium log price-dividend ratios z_t can be characterized as*

$$z_t - \mathbb{E}\left[z_t\right] \approx \zeta_h (h_t - \bar{h}), \tag{2.20}$$

where $\zeta_h \in \mathbb{R}^{n\times 1}$ is determined in the equilibrium. The excess log returns and fund flows are

$$r^e_{t+1} - \mathbb{E}_t\left[r^e_{t+1}\right] \approx \sqrt{h_t} K u_{t+1} + \sqrt{h_t}\varepsilon_{t+1}, \tag{2.21}$$

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t} A u_{t+1}, \tag{2.22}$$

where $r^e_{t+1} \equiv r_{t+1} - r_f \mathbf{1}$ with $\mathbf{1} \in \mathbb{R}^{n\times 1}$ denoting a vector of ones, and $K \in \mathbb{R}^{n\times k}$ and $A \in \mathbb{R}^{1\times k}$ capture the respective systematic risk exposures of the stock returns and fund flows:

$$K = L\zeta_h \sigma + B \ \text{ and } \ A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma, \tag{2.23}$$

where B is defined in (2.1), σ is defined in (2.2), and L is a diagonal matrix determined in the equilibrium. Thus, flow betas of stock returns $\mathcal{B}^{flow} \equiv Cov_t\left[r_{t+1}, flow_{t+1}\right]/\mathrm{var}_t\left[flow_{t+1}\right]$ are

$$\mathcal{B}^{flow} \approx \left[\frac{q'(\bar{h})}{q(\bar{h})}\right]^{-1}\left[L\zeta_h + B\sigma^T(\sigma\sigma^T)^{-1}\right]. \tag{2.24}$$

Flow betas $\mathcal{B}^{flow}$ depend on the exposures of cash flows to the fundamental shocks in u_t, captured by the term $B\sigma^T(\sigma\sigma^T)^{-1}$. On the other hand, flow betas $\mathcal{B}^{flow}$ also depend on the exposures of price-dividend ratios to potential non-fundamental shocks in u_t, captured by the term $L\zeta_h$. Particularly, if the kth column of the loading matrix B in (2.1) is zero and the kth element of σ in (2.2) is strictly positive, the factor $u_{k,t}$ tends to be a non-fundamental one (e.g., a sentiment factor or mispricing factor). This is quite intuitive. In principle, factor models can arise in the equilibrium whether expected returns reflect fundamental risk or mispricing due to non-fundamental shocks. Namely, the factors u_t can capture fundamental risk, such as cash flow and discount rate shocks, and they can also capture common sources of mispricing, such as market-wide investor sentiment (e.g., Hirshleifer and Jiang, 2010; Stambaugh and Yuan, 2016; Kozak, Nagel and Santosh, 2018) and common shocks to arbitrageurs (e.g., Shleifer and Vishny, 1997).[17]

We provide a rich set of empirical evidence on the hypothesis that there could be two primitive sources of determinants behind flow betas of stock returns — the price impact of non-fundamental demand shocks and the cash flow loading on fundamental shocks — in Section 4.2.2. Particularly, Table 6 shows that flow betas are positively associated with

[17] Moreover, 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) show that fluctuations in market-wide sentiment of noise traders give rise to a source of systematic risk for which rational traders require compensation.

various price impact measures across stocks, and Table 8 shows that flow betas are also positively associated with cash flow betas across stocks.

Lastly, Proposition 2.4 implies that the covariance matrix of the log returns is

$$\Sigma_t = \Sigma h_t, \quad \text{with } \Sigma = I_n + KK^T. \tag{2.25}$$

Funds' Portfolio Tilts. The great contribution of the CAPM theory is to connect systematic risk to return covariance with the market portfolio return, which can be approximated in the data. Considering the deviation of funds' holdings, $\phi_{m,t}$, and their trading counterparties' holdings (i.e., direct investors' holdings), $\phi_{d,t}$, from the market portfolio holdings, ϕ_t^{mkt}, we can construct useful empirical tests for the fund flow hedging results, summarized in Theorem 1. Particularly, it shows that, relative to the market portfolio, the funds of risky equity tilt their portfolio holdings toward the low-flow-beta stocks, while the direct investors (as the "trading counterparties" of the funds) tilt their portfolio holdings toward the high-flow-beta stocks.

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

$$Cov\left[\mathcal{B}^{flow}, \phi_{m,t} - \phi_t^{mkt}\right] < 0 \quad and \quad Cov\left[\mathcal{B}^{flow}, \phi_{d,t} - \phi_t^{mkt}\right] > 0, \quad for\ each\ t, \tag{2.26}$$

where $\mathcal{B}^{flow}$ is defined in Proposition 2.4.

The result of Theorem 1 sets forth a central hypothesis of our paper, and Section 4.3 provides a rich set of direct evidence to verify the hypothesis. In particular, Table 9 shows that active mutual funds indeed tilt their portfolio holdings farther away from stocks with higher flow betas, relative to the benchmark portfolio. Further, Table 10 shows that the flow hedging behavior is more pronounced among the active mutual funds with higher activeness, smaller size, and younger age. Importantly, Table 12 shows that index funds and retail household investors, as the direct investors, act as the trading counterparties of active equity funds in the economy and gain the risk premium associated with common flow shocks by absorbing the demand for the low-flow-beta stocks from active equity funds.

Endogenous Flow Risk. In equilibrium, common fund flows respond to aggregate economic shocks, and thus risk premia analogous to the hedging term in the ICAPM emerge even in a myopic environment, which is summarized in the following theorem. Theorem 2 is based on Theorem 1 and the market clearing condition of risky assets.

Theorem 2 (Flow risk is priced)**.** *The risk premium of an asset is explained by its covariances with the 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 $\eta_t \equiv q_t/\left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right]$ captures the equilibrium delegation intensity.

Corollary 2.1 (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:*

$$\mathbb{E}_t\left[r_{t+1}\right] - r_f\mathbf{1} + \frac{1}{2}\nu_t \approx \gamma Cov_t\left[r_{t+1},\, r^{mkt}_{t+1}\right]. \tag{2.27}$$

It further implies that the CAPM holds:

$$\mathbb{E}\left[r_{t+1} - r_f\mathbf{1} + \frac{1}{2}\nu_t\right] \approx \beta^T\mathbb{E}\left[r_{t+1} - r_f\mathbf{1} + \frac{1}{2}\nu_t\right], \tag{2.28}$$

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

When there is no fund client in the economy (i.e., $\lambda = 0$), the equilibrium delegation is 0 (i.e., $q_t \equiv 0$) according to Proposition 2.3, leading to $\eta_t \equiv 0$. In this case, every investor consumes $C_t = (1-\beta)W_t$ and holds the mean-variance myopic portfolio $\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f + \frac{1}{2}v_t\right)$.

The result of Theorem 2 sets forth the central asset pricing implication of our paper. It rationalizes the cross-sectional stock return patterns, which initially motivates our study. In Section 4.3, we provide a rich set of direct evidence on the result of Theorem 2.

3 Data

Data on Mutual Fund Returns and Assets. We obtain fund names, monthly returns, monthly total net assets (TNA), investment objectives, and other fund characteristics from the Center for Research in Security Practices (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.[18] We further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data.[19] Because data coverage on the monthly TNAs prior to 1991 is scarce and poor, the sample in our paper spans the period from January 1991 to December 2018.

We use the Morningstar database to cross-check the accuracy of the fund returns and asset size 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 less than 5 basis points, and (ii) the 60th percentile of the absolute value of the difference between the CRSP and Morningstar monthly TNA is less than \$100,000.[20] Around 63% of fund share-month observations in the CRSP panel data are matched with the Morningstar data. Around 2% of share-month observations in the CRSP panel data are not matched with the Morningstar data because of the discrepancies in reported returns and TNA across the two datasets. The remaining 35% of share-month observations in the CRSP panel data are not matched because of no coverage in the Morningstar data. The above summary statistics for

[18]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 insights (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.

[19]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, 2017; Jones and Mo, 2021), we also define a fund as an index fund if its 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.

[20]The cutoffs of 5 basis points and $\$100,000$, as well as the 60th percentile, are the same as those used by Pástor, Stambaugh and Taylor (2015).

the matching percentage are similar to those in Pástor, Stambaugh and Taylor (2015).

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

Data on Mutual Fund Portfolio Holdings and Benchmarks. We obtain the portfolio holdings of mutual funds from the 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 (downloaded from the Morningstar Direct platform). 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 Databases for the United States (SHELDUS). The types of natural disasters 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 (e.g., Barrot and Sauvagnat, 2016; Cortés and Strahan, 2017; Alok, Kumar and Wermers, 2020; Dou, Ji and Wu, 2020). 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.

Data on Firms' Exposure to China. We measure stocks' exposure to China using several datasets. We use Factset Revere data to measure firms' revenue from China. We use Bill of Lading data from US Customs and Border Protection to measure firms' import from China. We also use text-based offshoring network data (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 shocks of market liquidity (Pástor and Stambaugh, 2003) from L'uboš Pástor's website. The economic policy uncertainty index is obtained from Baker, Bloom and Davis (2016). The total macro uncertainty measure is obtained from Jurado, Ludvigson and Ng (2015) and Ludvigson, Ma and Ng (2021). The Standard and Poor's (S&P) 100 volatility index (VXO) and crude oil exchange-traded funds (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 the hedge fund flows based on the Thomson Reuters Lipper Hedge Fund Database (TASS). We obtain institutional (13F) holdings from Thomson Reuters. We obtain holding of 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 during 1991 to 1996.

4 Empirical Analysis

In this section, we test the main predictions of our model. Section 4.1 shows that fund flow shocks share a striking degree of common time-series variation, explains how we construct the common fund flows, and documents the negative relation between common fund flows and economic uncertainty. Section 4.2 shows that flow betas are priced in the cross section. Section 4.3 shows that the hedging behavior of active mutual funds is consistent with the model's predictions.

4.1 Factor Structure of Fund Flow Shocks

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

$$F_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + Ret_{i,t})}{Q_{i,t-1}}, \tag{4.1}$$

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

In order to construct the unpredictable component in fund flows, we control for lagged flows because fund flows are persistent. We also control for the lagged fund performance to account for flow-performance sensitivity.[21] Furthermore, the empirical measure, $F_{i,t}$ defined by (4.1), 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 the contemporaneous fund performance by running a pooled panel regression as follows:[22]

$$F_{i,t} = a + \sum_{k=1}^{2} b_k \times ExRet_{i,t-k+1} + c \times F_{i,t-1} + \theta_t + \varepsilon_{i,t}, \tag{4.2}$$

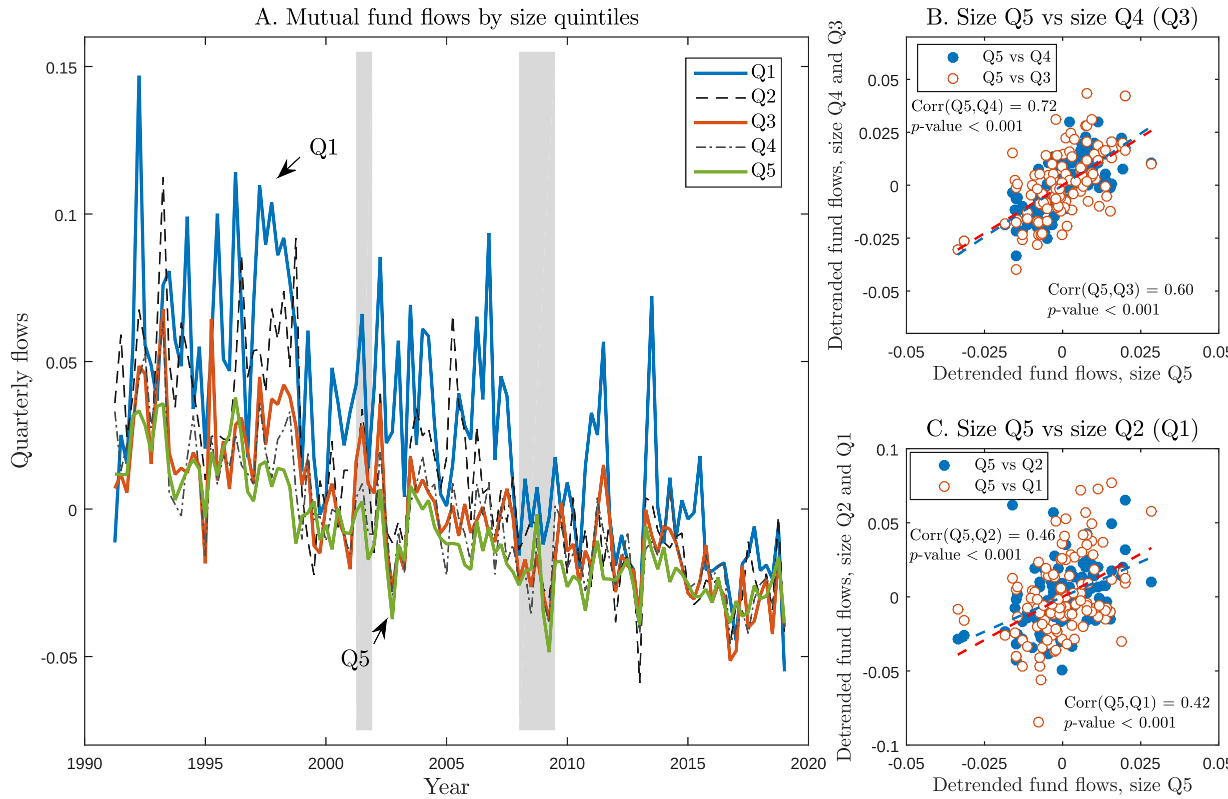
where $ExRet_{i,t}$ is the fund excess return relative to the market return, R_t^M, over month t. $F_{i,t-1}$ represents lagged fund flows and θ_t represents the month fixed effects. We then define the fund flow shock after controlling for the performance-flow sensitivity at the fund level as follows:

$$flow_{i,t} = \theta_t + \varepsilon_{i,t}. \tag{4.3}$$

Construction of Common Fund Flows. Below, we show that there is one dominant common factor that drives much of the common variation of fund flow shocks (i.e., one factor with a

[21] 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), Pástor and Stambaugh (2012), Del Guercio and Reuter (2014), Pástor, Stambaugh and Taylor (2015), Barber, Huang and Odean (2016), Berk and van Binsbergen (2016*b*), Goldstein, Jiang and Ng (2017), Song (2019), and Roussanov, Ruan and Wei (2020).

[22] Lee, Trzcinka and Venkatesan (2019) and Ma, Tang and Gómez (2019) suggest that active fund managers' pay could depend on relative performance even after controlling for fund size in the US, while Ibert et al. (2018) provide strong and clear evidence that managers' pay does not depend on relative performance after controlling for fund size using Swedish data. Our goal is to investigate managers' motives to hedge the aggregate component of fund flows, and their implications.



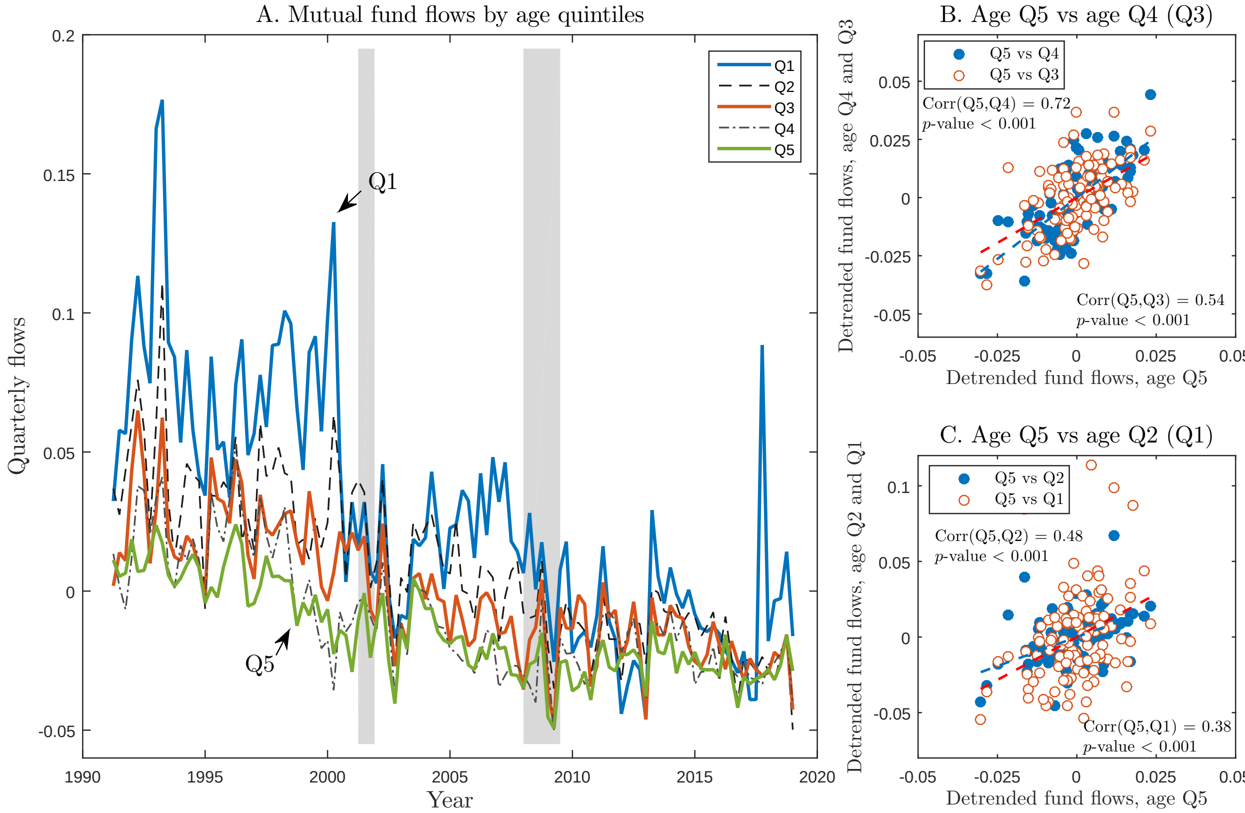
Note: Panel A plots active mutual fund flows by quintiles sorted on fund asset size after removing relative performance. We control for the flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the National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

Figure 1: Mutual fund flows by asset size after removing relative performance.

high eigenvalue).

To extract the common component of fund flow shocks empirically, we sort active funds 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 flow and performance, as extensively studied in the past few decades (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 age, another important characteristic (e.g., Chevalier and Ellison, 1997; Berk and Green, 2004; Pástor, Stambaugh and Taylor, 2015). Consistent with the findings of 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 business cycles.[23]

[23]Besides asset size and age, fund flow shocks sorted on other characteristics also exhibit a high degree of common time-series variation. Figures OA.3 and OA.4 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



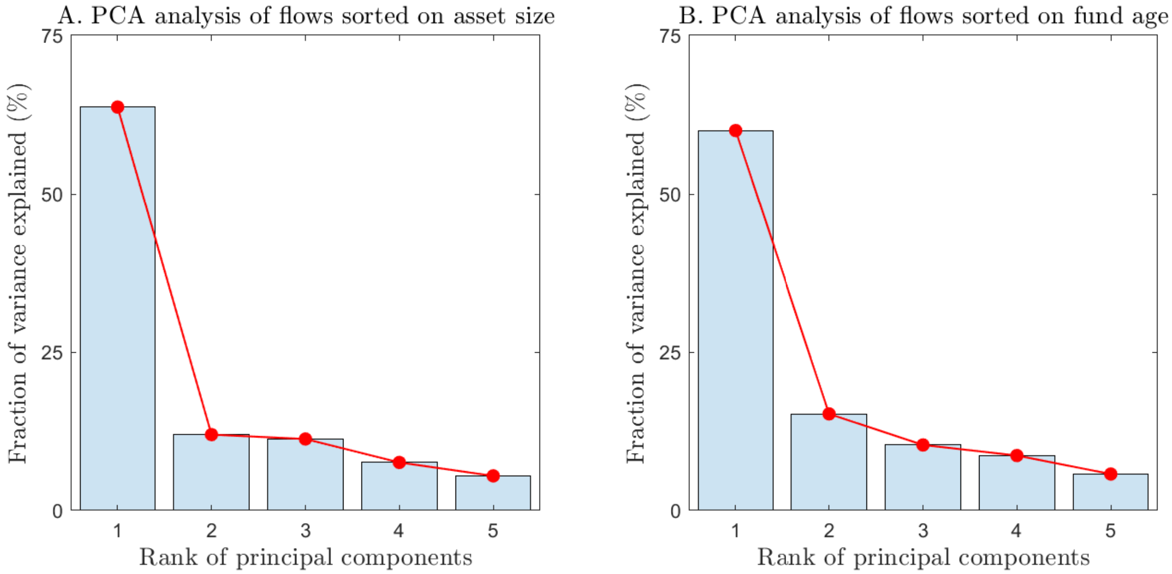
Note: Panel A plots active mutual fund flows by quintiles sorted on the fund age after removing relative performance. We measure fund age by the number of years since the inception dates. We control for the flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund 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 other age groups presented in panel A.

Figure 2: Mutual fund flows by age after removing relative performance.

More precisely, panel A of Figure 1 plots the value-weighted average fund flow shocks after removing relative performance for each quintile of funds sorted on 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 flows of quintile 5 size group against the detrended flows of other size groups presented in panel A. We find that all flow shocks for funds of different sizes exhibit very similar time series patterns. The correlation between mutual fund flow shocks of size quintiles 5 and 4 is 0.72 with p-value < 0.001, and that of size quintiles 5 and 1 is 0.42 with p-value < 0.001.

Similarly, panel A of Figure 2 plots value-weighted fund flow shocks after removing relative performance for each quintile of funds sorted on age. The same high-frequency

by Pástor, Stambaugh and Taylor (2019). 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 the fraction of variance explained by different principal components from the principal component analysis (PCA) of flows sorted on asset size. Panel B plots the fraction of variance explained by different principal components from the PCA of flows sorted on fund age presented in panel A.

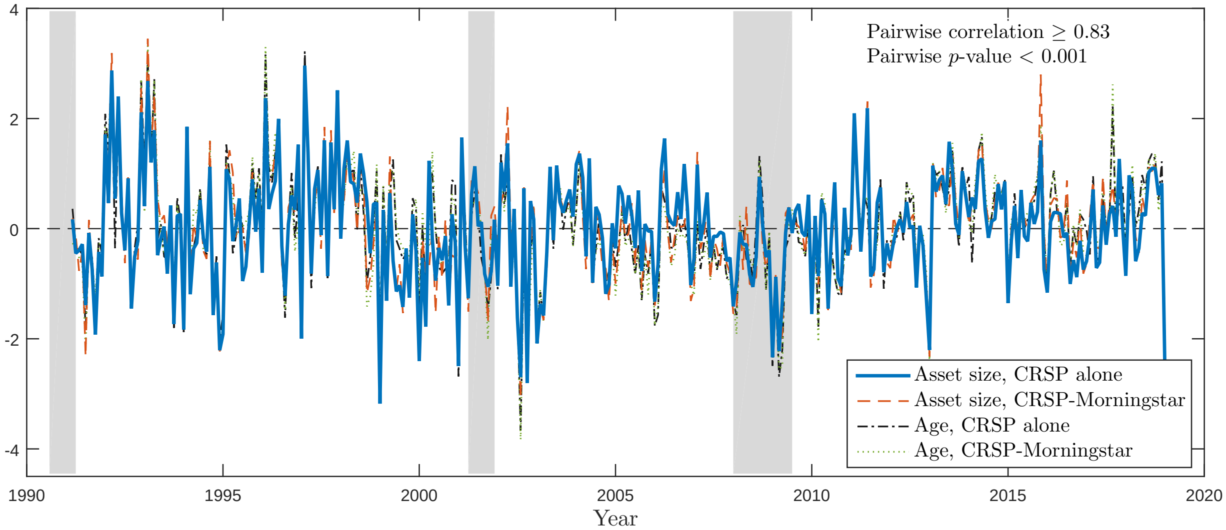
Figure 3: Eigen-decomposition of the covariance matrix of mutual fund flow shocks.

comovement across different groups of fund flow shocks with different ages robustly shows up. Further, panels B and C of Figure 2 plot the detrended flows of quintile 5 age group against the detrended flows of other age groups presented in panel A. The correlation between mutual fund flow shocks of age quintiles 5 and 4 is 0.72 with p-value < 0.001, and that of age quintiles 5 and 1 is 0.38 with p-value $= 0.001$.

To obtain the common fund flow, we extract the first principal component of the fund flows across funds.[24] The eigen-decomposition of the covariance matrix of five groups of fund flow shocks exhibits a dominant highest eigenvalue and fast decay for the rest of the eigenvalues. Figure 3 shows that there is one dominant factor that drives much of the common variation of fund flow shocks — the first principal component (PC1).[25] With no loss of generality, we standardize the first principal component by removing the unconditional mean and normalizing the unconditional standard deviation to 1. We refer to the standardized first principal component as the *common fund flow*. Our construction of the common fund flow using the first principal component across groups of funds is analogous

[24]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 asset size of the mutual fund sector grows over time.

[25]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 existing approaches to determining the number of PCs.



Note: This figure plots the monthly common fund flows constructed based on fund asset size and fund age shares using the 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 4: Common fund flows constructed based on fund asset size and fund age.

to the approach of Herskovic et al. (2016), where they extract the common component in idiosyncratic volatility across groups of stocks.

Figure 4 plots the monthly common fund flows based on asset size and age of funds using the CRSP mutual fund data and CRSP-Morningstar intersection mutual fund data. The four monthly time series are highly correlated with each other, and the correlation ranges from 0.83 to 0.95. In the rest of this paper, we focus on the common fund flow constructed using asset size quintiles, and we show all empirical results on common fund flows not only using the CRSP mutual data, but also using the CRSP-Morningstar intersection mutual fund data.[26]

Alternative Measures of Common Fund Flows. We consider two alternative common flow measures. In the first alternative measure, instead of performing the PCA analysis, we construct the common flow using the AUM-weighted flow shocks after controlling for the

[26]Our results remain robust if we construct the common fund flows based on the quintiles of fund flow shocks sorted using age, industry concentration, or portfolio liquidity. The common fund flows constructed based on size, age, industry concentration, and portfolio liquidity are highly correlated with each other (see Table OA.2 in the online appendix for details). We also verify that the PCA loadings on fund flows of the five fund size quintiles are stable over different subperiods. Particularly, we find that the PCA loadings over the whole sample period (1991 – 2018) are $[0.4002, 0.4123, 0.4807, 0.4788, 0.4578]$, those over 1991 – 2004 are $[0.3988, 0.4057, 0.4821, 0.4764, 0.4658]$, and those over 2005 – 2018 are $[0.4035, 0.4242, 0.4756, 0.4848, 0.4427]$ when using the CRSP mutual fund data. We find similar results when using the CRSP-Morningstar intersection data.

Table 1: Common fund flows are negatively correlated with uncertainty shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone				Panel B. CRSP-Morningstar intersection			
	$flow_t$				$flow_t$			
$MacroUnc\_shock_t$	-0.100^{**}				-0.140^{***}			
	[−1.979]				[−2.795]			
EPU_shock_t		-0.148^{***}				-0.162^{***}		
		[−3.230]				[−3.164]		
VXO_shock_t			-0.236^{***}				-0.292^{***}	
			[−3.560]				[−4.963]	
$MktVol\_shock_t$				-0.160^{***}				-0.238^{***}
				[−2.955]				[−4.035]
$flows_{t-1}$	0.097^{*}	0.081	0.115^{**}	0.089	0.211^{***}	0.199^{***}	0.232^{***}	0.197^{***}
	[1.660]	[1.397]	[2.096]	[1.538]	[3.887]	[3.633]	[4.491]	[3.681]
Observations	334	334	334	334	334	334	334	334
R-squared	0.02	0.03	0.07	0.04	0.07	0.07	0.13	0.10

Note: This table shows the negative relation between the uncertainty shock and the common fund flow, 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) at month t estimated by an AR(6) model. We control for 6 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) at month t estimated by an AR(1) model. VXO_shock_t is the shock to the CBOE S&P 100 volatility index at month t estimated by an AR(1) model. $MktVol\_shock_t$ is the shock to the market volatility at 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 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.

lagged flow and contemporaneous and lagged relative fund performance. Relative to the PCA approach, the AUM-weighted approach assigns more weights to flow shocks of the large funds. We show in Table OA.3 of the online appendix presents that this alternative measure of common fund flows exhibits similar pattern of asset pricing and asset allocation to our main common flow measure.

In the second alternative common flow measure, we adopt the flow measure of Berk and Tonks (2007). Specifically, we define fund flows as:

$$F_{i,t} = \frac{Q_{i,t} - Q_{i,t-1} \times (1 + Ret_{i,t})}{Q_{i,t-1} \times (1 + Ret_{i,t})}, \tag{4.4}$$

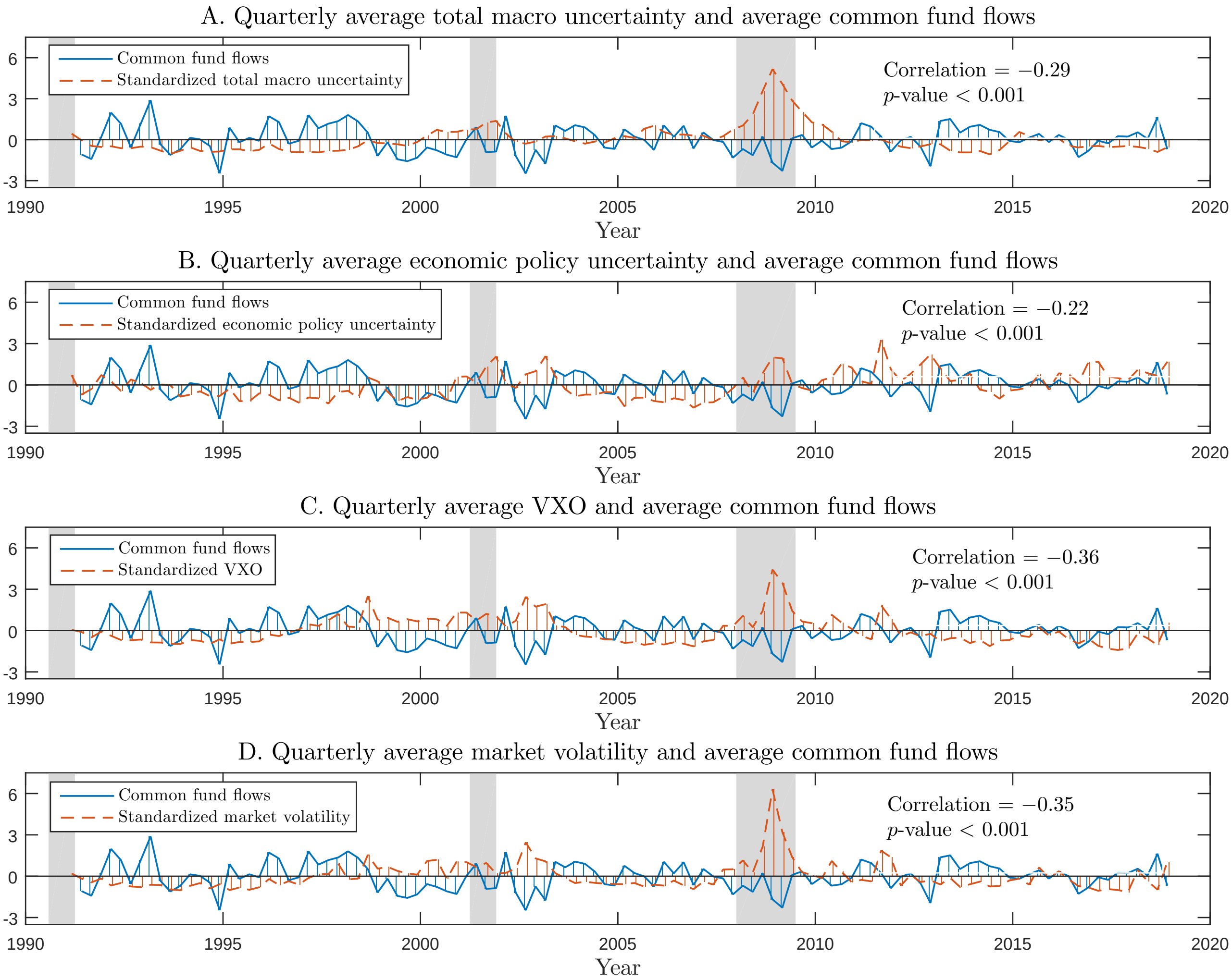
where $Q_{i,t}$ and $Ret_{i,t}$ are, respectively, the TNA and the net return for fund i in month t. This fund flow definition differs from the one in equation (4.1) because the denominator is $Q_{i,t-1} \times (1 + Ret_{i,t})$ instead of $Q_{i,t-1}$. We show in Table OA.4 of the online appendix presents that this alternative measure of common fund flows exhibits similar pattern of asset pricing and asset allocation to our main common flow measure.

Common Fund Flows and Economic Uncertainty. We now examine the relation between common fund flows and economic uncertainty. Particularly, we show that common fund flows are negatively related to economic policy uncertainty, market volatility, and idiosyncratic consumption dispersion, consistent with our model's prediction (Proposition 1.5). We are by no means advocating economic uncertainty as the only primitive driver of common fund flows. Rather, we emphasize that economic uncertainty is one of the major primitive forces causing common fund flows in equilibrium. 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) examine retail stock sales from 2008 to 2009 using population tax return data, and show that volatility-driven sales were prevalent across sectors; especially, mutual fund sales by retail investors responded more strongly to increased volatility than stock sales.

We first perform regression analysis to examine the relation between common fund flows and economic uncertainty shocks. Specifically, we regress common fund flows on the contemporaneous shocks to various economic uncertainty measures, which are estimated as the residuals of autoregression models. As shown in panel A of Table 1, active mutual funds experience outflows when economic uncertainty rises. The 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 is 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.

Furthermore, Figure 5 plots the quarterly average common fund flow (level) against the quarterly average economic uncertainty (level). It is clear that the quarterly average common fund flow (level) comoves negatively with both the quarterly average economic uncertainty (level) and average market volatility (level).

We next examine the relation between the common fund flows and the shocks to the idiosyncratic consumption dispersion, which is measured by the dispersion of consumption growth rates (e.g., Brav, Constantinides and Geczy, 2002; Vissing-Jørgensen, 2002; Jacobs and Wang, 2004). Table 2 shows that mutual funds experience outflows when there is an increase



Note: Panel A shows the quarterly average common fund flow and the quarterly average total macro uncertainty measure, which is based on the monthly total macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021). Panel B shows the quarterly average common fund flow and the quarterly average economic policy uncertainty index, which is based on the monthly news based policy uncertainty index (Baker, Bloom and Davis, 2016). Panel C shows the quarterly average common fund flow and the quarterly average VXO index, which is based on the CBOE S&P 100 monthly volatility index. Panel D shows the quarterly average common fund flow and the quarterly average market volatility, which is based on the standard deviation of the daily returns of the S&P 500 index each month. All time series are standardized to have means of 0 and standard deviations of 1. The quarterly average common fund flow is constructed from the monthly fund flow shocks based on the CRSP mutual fund data and asset size groups. Gray areas represent the NBER recession periods.

Figure 5: Average common fund flows and economic uncertainty.

in idiosyncratic consumption dispersion.

Lastly, we emphasize that economic uncertainty is by no means the only primitive force behind common fund flows. Rather, it is one of the major underlying shocks that affect fund clients' delegation decisions. Exploring which economic shocks cause fund clients to move their capital in and out of active funds is an important question for future research. As a

Table 2: Consumption dispersion shocks and common fund flows.

	(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^M		0.319***		0.365***
		[5.286]		[6.653]
Ret_{t-1}^M		−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 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^M 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 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.

partial step toward this goal, we show that common fund flows comove negatively with shocks to the aggregate discount rates in Table OA.5 in Online Appendix. In the same table, we also show that common fund flows comove positively with shocks to sentiment, although this relation is statistically insignificant.

4.2 Flow Betas Are Priced

In this section, we test one of the main predictions of our model: the exposure to common fund flows is priced in the cross-section of stock returns (Theorem 2).

4.2.1 Portfolio Sorting Analyses

Portfolio Sorting Analyses. We first perform portfolio sorting analyses. 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 non-missing observations are available):

$$ret_{i,t-\tau} = a_{i,t} + \beta_{i,t}^{flow} \times flow_{t-\tau} + \varepsilon_{i,t-\tau}, \quad \text{with } \tau = 0, 1, \cdots, 35, \tag{4.5}$$

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.

In June of each year, we sort firms into quintiles based on their flow betas. Table 3

Table 3: Excess returns and CAPM alphas of portfolios sorted on flow betas.

	Panel A. CRSP mutual funds alone		Panel B. CRSP-Morningstar intersection	
β_i^{flow} quintiles	Excess returns	CAPM α	Excess returns	CAPM α
Q1	5.22	-5.51^{**}	4.84	-4.90^{**}
	[1.22]	[−2.56]	[1.26]	[−2.58]
Q2	7.17^{**}	−0.97	7.75^{***}	0.51
	[2.34]	[−0.79]	[2.87]	[0.49]
Q3	8.18^{***}	0.57	7.93^{***}	0.03
	[2.88]	[0.52]	[2.77]	[0.03]
Q4	9.27^{***}	1.05	10.72^{***}	1.79
	[3.13]	[1.20]	[3.24]	[1.44]
Q5	12.02^{***}	2.10	13.34^{***}	1.80
	[3.02]	[1.02]	[2.83]	[0.70]
Q5 − Q1	6.81^{**}	7.62^{**}	8.50^{**}	6.70^{**}
	[2.19]	[2.42]	[2.56]	[2.02]

Note: This table shows the value-weighted average excess returns and CAPM alphas for stock portfolios sorted on flow betas. 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 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. 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.

shows average excess returns and CAPM alphas of the long-short portfolios sorted on the flow betas. 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 3), the spread in average excess returns between the stocks 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 to the equity premium and the value premium. We find a similar pattern when constructing common fund flows based on the CRSP-Morningstar intersection sample (see panel B of Table 3). Figure 6 plots the annualized value-weighted excess returns of the portfolios sorted on flow betas. We find that higher flow betas predict higher excess returns cross portfolios persistently in the 12 month window after portfolio formation.

Fama-MacBeth Regressions. We perform Fama-MacBeth tests by regressing monthly stock returns on flow betas. As Table 4 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 4, 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 data choices in computing flow betas (i.e., CRSP alone vs. CRSP-

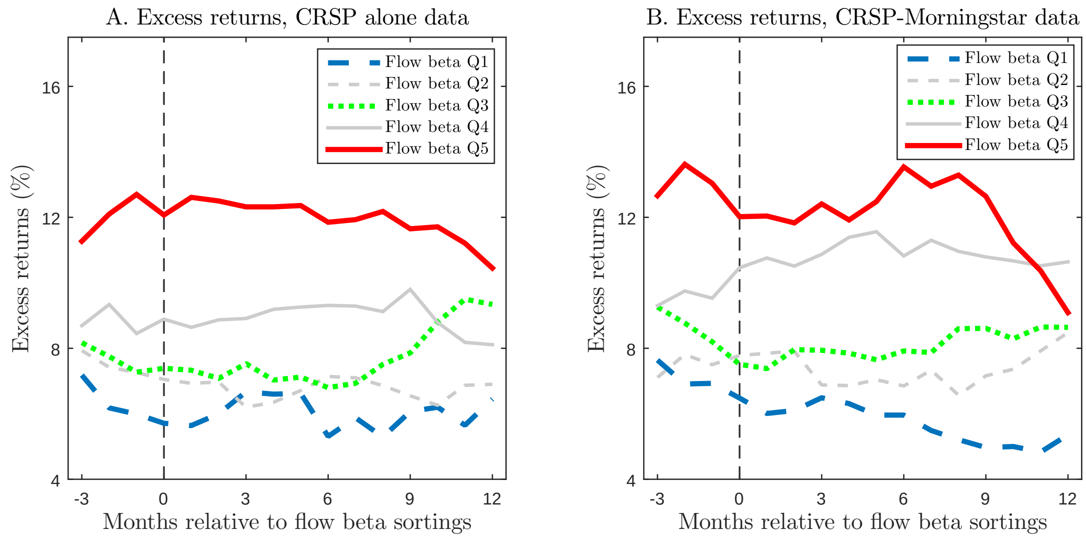


Figure 6: Excess returns after portfolio sorting based on quintiles of flow betas.

Morningstar intersection). The result is also robust after we exclude microcap stocks. Specifically, we drop stocks with market cap smaller than the bottom size decile of the NYSE sample and find similar results (see columns (7) through (12) in Table 4).

We then add stock characteristics as control variables into the Fama-MacBeth regressions. Specifically, we control for the betas to the macro uncertainty index (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).[27] We also control for other stock characteristics including market betas, market cap, book-to-market ratio, momentum, short-term and long-term reversal, historical liquidity betas, and Amihud illiquidity. Although the coefficient of the flow beta reduces substantially after controlling for the uncertainty betas and other stock characteristics, it remains statistically and economically significant, suggesting that the relation between flow betas and returns is not fully subsumed by these stock characteristics.

Evidence Exploiting the Heterogeneity in Fund Activeness. We further explore cross-sectional heterogeneity of active mutual funds. In particular, we focus on the cross-sectional

[27] In Table OA.6 of the online appendix, we perform the Fama-MacBeth tests which regress stock returns on the betas to the various economic uncertainty measures, including the macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021), the 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 4: 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]
$\beta^{M}_{i,t-1}$		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 flow betas ($\beta^{flow}_{i,t-1}$) and a set of control variables, which include betas to the shock to the macro uncertainty measure ($\beta^{MacroUnc}_{i,t-1}$), market betas ($\beta^{M}_{i,t-1}$), natural log of market cap ($Lnsize_{i,t-1}$), 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 ($LT\_Reversal_{i,t-1}$), historical 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 market returns, size and value factors (Fama and French, 1993), momentum factor (Carhart, 1997), liquidity factor (Pástor and Stambaugh, 2003), investment and profitability factors (Fama and French, 2015; Hou, Xue and Zhang, 2015). The sample in panel A 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. In panel B, we further exclude stocks with market cap smaller than the bottom size decile of the NYSE sample. We compute standard errors using the Newey-West estimator with 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.

variation of funds' activeness. According to our model, the common fund flows from more active mutual funds should have stronger asset pricing implications. To test this hypothesis, we construct common fund flows from various subsamples of active mutual funds sorted on fund activeness, and then tabulate the CAPM alphas for the stock portfolios sorted on the resulting flow betas. We follow Pástor, Stambaugh and Taylor (2019) to measure fund activeness using fund turnover ratio divided by the square root of portfolio liquidity (see equation 37 of their paper).

Table 5: Heterogeneity across active mutual funds.

Subsamples	Panel A: Fund activeness				Panel B: Fund expense ratios				Panel C: Active share			
	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 cross-sectional heterogeneity of active mutual funds. We construct common fund flows from various subsamples of active mutual 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 mutual funds with top 80% fund activeness and bottom 20% fund activeness, respectively. In panel B, we construct common fund flows from active mutual funds with top 80% fund expense ratios and bottom 20% fund expense ratios, respectively. In panel C, we construct common fund flows from active mutual 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 fund activeness, expense ratio, and active share. We follow Pástor, Stambaugh and Taylor (2019) to measure fund activeness using fund turnover ratio divided by the square root of portfolio liquidity. 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 the asset size, and then construct the common fund flows using the approach description in Section 4.1. 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.

As shown in panel A of Table 5, the spread of CAPM alphas for flow betas constructed from the more active funds (i.e., top 80% activeness) is 8.21% and 8.82% in the CRSP alone and the CRSP-Morningstar intersection sample, respectively. The t-statistics are 2.69 and 2.96. The magnitude of the t-statistics is larger than those in Table 3, in which we use all active mutual funds to construct the common flows. On the other hand, the spread of CAPM alphas for flow betas constructed from the least active funds (i.e., bottom 20% activeness) is statistically insignificant. Besides the fund activeness measure, we also use two additional measures for fund activeness. The first addtional measure is the fund expense ratio because past studies have shown that more expensive funds are on average more active (e.g., Pástor, Stambaugh and Taylor, 2019). The second addtional measure is the active share measure proposed by Cremers and Petajisto (2009), which is the absolute weight difference between the fund holdings and the benchmark holdings summed across all stocks. We find similar asset pricing patterns using these two alternative measures (see panels B and C of Table 5).

These evidence from the cross section of mutual funds further supports our model.

Index Fund Flows and Hedge Fund Flows. Our theory in Section 2 suggests that the common fund flows of active equity mutual funds are priced in the cross section of stock returns, because they are open-end funds featuring (i) daily redemption obligations, (ii) an explicit AUM-based fee structure, and (iii) full asset allocation discretion. By contrast, index funds have no allocation discretion and simply mimic a given index, and hedge funds have an explicit performance-based fee structure with limited redemption rights granted to their investors.[28] In fact, both index funds and hedge funds are classified as direct investors in our simple model.

In Online Appendix 3, we examine the pricing of the betas to common flows of index funds and hedge funds. As we show in Table OA.7 and OA.8 of the online appendix, the long-short portfolios sorted on both the betas to common flows of index funds and those to common flows of hedge funds have insignificant average (risk-adjusted) returns. This is consistent with our theoretical model, where the common fund flows are priced because of the flow hedging behavior of active equity mutual funds. The common flows of index funds fail to share the same properties because index fund managers have little allocation discretion to actively hedge against their fund flow risk, so do the common flows of hedge funds because hedge fund managers care mainly about their relative performance rather than their asset size.

4.2.2 Primitive Sources behind Flow Betas

Flow Betas and Price Impact. As shown by Proposition 2.4, there could be two primitive sources behind the flow beta. Besides the loadings of stock returns on fundamental shocks, flow betas may also capture the price impact of non-fundamental demand shocks (i.e., liquidity shocks), which is only reflected in the variation of price-dividend ratios.

We first study the relation between the flow beta and the price impact of trading caused by different types of investors (e.g., mutual funds, households, investor advisors, and pension funds). We obtain the price impact measures from Koijen and Yogo (2019), who estimate the price impact based on an asset pricing model with flexible heterogeneity in asset demand across different types of investors. Columns (6) to (9) of Table 6 show that flow betas are

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

Table 6: Relation between flow betas and price impact measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Panel A: CRSP mutual funds alone								
	$Lnsize_{i,t}$	$LnBEME_{i,t}$	$AIM_{i,t}$	$Liqbeta_{i,t}$	$FIT_{i,t-1}$	$PI\_MF_{i,t}$	$PI\_HH_{i,t}$	$PI\_IA_{i,t}$	$PI\_PF_{i,t}$
$\beta^{flow}_{i,t}$	-0.057^{***}	0.055^{***}	0.045^{***}	0.179^{***}	-0.003	0.001	0.066^{***}	0.013^{**}	0.010^{*}
	[-9.917]	[8.227]	[8.231]	[12.871]	[-0.490]	[0.183]	[6.498]	[2.267]	[1.701]
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1785679	1433429	1779558	1795592	1010251	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								
	$Lnsize_{i,t}$	$LnBEME_{i,t}$	$AIM_{i,t}$	$Liqbeta_{i,t}$	$FIT_{i,t-1}$	$PI\_MF_{i,t}$	$PI\_HH_{i,t}$	$PI\_IA_{i,t}$	$PI\_PF_{i,t}$
$\beta^{flow}_{i,t}$	-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]	[-0.890]	[1.916]	[8.975]	[4.237]	[4.958]
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1785679	1433429	1779558	1795592	1010251	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 ($LnBEME_{i,t}$), historical liquidity betas ($Liqbeta_{i,t}$), Amihud illiquidity ($AIM_{i,t}$), flow-induced trading pressure ($FIT_{i,t-1}$), 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 the price impact measures from Koijen and Yogo (2019). The analysis is performed at the 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. Sample period spans from 1992 to 2018.

positively correlated with the price impact measures in the cross section of stocks.[29] We then examine the asset pricing implications of flow betas by double sorting on the price impact measures. As shown in Panel A of Table 7, the flow betas remain significantly priced in the cross section of stock returns after controlling for the price impact measures, suggesting that the asset pricing implications of flow betas cannot be entirely explained by price impact.

Next, we study the relation between the flow beta and the flow-induced trading pressure (FIT). Existing literature has documented that aggregate fund flows can exert a 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). Because flow betas are estimated based on the 36-month rolling windows, it is possible that different flow betas simply reflect that the stocks have experienced different flow-induced trading pressures or they are at different stages in the flow-induced trading-pressure cycles. To address the concern, we construct the FIT measure following Lou (2012) and examine its relation with flow betas. Column (5) of Table 6 shows insignificant cross-sectional association between

[29] The results are especially strong for the price impact caused by households and investment advisors. Households are direct retail investors and investment advisors are mainly hedge funds, which are classified as the direct investors in our model. The positive relation between flow betas and price impact caused by mutual funds and pension funds is slightly weaker, probably 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 7: Double-sort analysis.

First-sort measures	Panel A: Price impact				Panel B: Flow-induced trading				Panel C: Cash flow betas			
	CRSP alone		CRSP-Morningstar		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	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^{**}	5.52	-5.31^{***}	5.53	-3.64^{**}
	[1.24]	[−2.59]	[1.47]	[−2.69]	[1.67]	[−2.34]	[1.64]	[−2.19]	[1.30]	[−2.88]	[1.60]	[−2.12]
Q2	6.56^{*}	−1.42	6.86^{**}	−0.23	6.76^{*}	−1.55	7.18^{*}	−0.27	6.87^{**}	−1.08	6.93^{**}	−0.46
	[1.88]	[−0.77]	[2.23]	[−0.23]	[1.83]	[−0.78]	[1.95]	[−0.20]	[2.02]	[−0.62]	[2.04]	[−0.43]
Q3	7.96^{**}	0.14	7.67^{**}	−0.14	7.43^{*}	−0.55	7.76^{***}	−0.08	7.62^{**}	−0.11	8.09^{***}	0.27
	[2.12]	[0.09]	[2.35]	[−0.14]	[1.95]	[−0.32]	[2.64]	[−0.10]	[2.05]	[−0.07]	[2.62]	[0.30]
Q4	9.93^{***}	1.37	10.93^{***}	2.13	9.61^{***}	1.80	11.12^{***}	2.33^{*}	9.81^{***}	1.74	11.42^{***}	2.68^{**}
	[3.39]	[1.17]	[3.54]	[1.63]	[3.31]	[1.48]	[3.68]	[1.69]	[3.42]	[1.27]	[3.92]	[2.17]
Q5	11.63^{***}	2.22	12.33^{***}	1.55	11.83^{***}	2.47	11.99^{***}	1.16	11.52^{***}	1.93	12.13^{***}	0.91
	[3.61]	[1.24]	[3.30]	[0.71]	[4.03]	[1.33]	[3.07]	[0.53]	[3.63]	[0.98]	[3.08]	[0.38]
Q5 − Q1	6.29^{***}	7.63^{**}	7.04^{***}	5.80^{**}	5.22^{**}	6.51^{**}	6.35^{***}	4.96^{*}	6.00^{***}	7.24^{***}	6.59^{***}	4.55^{*}
	[2.74]	[2.58]	[3.13]	[2.04]	[2.46]	[2.54]	[2.91]	[1.94]	[2.66]	[2.73]	[2.72]	[1.75]

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), flow-induced trading pressure (panel B), and cash flow betas (panel C). Next, we sort stocks within each group into quintiles based on their average flow betas from January of year t to June of year t. 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). The flow-induced trading 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.

the flow beta and the lagged FIT measure. Moreover, as shown in Table OA.11 of Online Appendix, the flow beta has insignificant cross-sectional correlation with the more lagged FIT measure and the FIT measure accumulated across different time horizons (i.e., past two quarters, one year, two years, and three years). Given such weak associations, it is not surprising that the flow betas remain significantly priced in the cross section of stock returns after controlling for the FIT measure (see panel B of Table 7). Taken together, the asset pricing implications of the flow betas are unlikely to be a side effect of different stages in the flow-induced trading-pressure cycles.

Flow Betas and Cash Flow Loadings. Our model (Proposition 2.4) implies that flow betas should capture cash flow loadings on the common fund flow. To test whether this is true empirically, we follow Cohen, Polk and Vuolteenaho (2003, 2009) and Campbell, Polk and Vuolteenaho (2010) to use 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 the cash flow loadings at the firm level year by year, running expanding window regressions for each stock. One caveat of this approach is that the estimation of cash flow loadings can be noisy because the cash flow fundamentals are measured at yearly frequency over a relatively short sample period (1992 – 2018). We use two alternative approaches to alleviate this concern. First, we examine the cash flow loadings of stock portfolios sorted on flow betas. Specifically, we sort stocks into quintiles based on flow betas, 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. Panel A of Table 8 tabulates the cash flow loadings of the portfolios sorted on flow betas, showing that the 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:

$$\sum_{j=0}^{2} \rho^j ROE_{i,t+j} = a_0 + Predicted\_\beta_{i,t-1}^{CF} \times Common\_flow_t + \varepsilon_{i,t}, \quad \text{where} \tag{4.6}$$

$$Predicted\_\beta_{i,t-1}^{CF} = a_1 + a_2 \times \beta_{i,t-1}^{flow} + a_3 \times FIT_{i,t-1}. \tag{4.7}$$

As shown in panel B of Table 8, the coefficient $\hat{a}_2$ is positive and statistically significant, suggesting that the cash flows of the stocks with higher flow betas load significantly more positively on common fund flows. Moreover, not surprisingly, the flow-induced trading pressure (FIT) does not affect stock returns and their dynamics through a fundamental channel of firms' cash flows.

Further, we perform double sort analysis by using the cash flow loading as the first-sort measure. As shown in panel C of Table 7, flow betas remain significantly priced in the cross section of stock returns after controlling for cash flow loadings, showing that the cash flow loading β^{CF} cannot fully explain the asset pricing implications of the flow beta β^{flow}, although the cash flow loading is a primitive determinant of the flow beta as our illustrative model suggests.

Table 8: Relation between common flow betas and cash flow betas.

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
	$\sum_{j=0}^{2} \rho^j ROE_{p,t+j}$						$\sum_{j=0}^{2} \rho^j ROE_{p,t+j}$					
$Common\_flow_t$	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	
	$\sum_{j=0}^{2} \rho^j ROE_{i,t+j}$		$\sum_{j=0}^{2} \rho^j ROE_{i,t+j}$	
$Common\_flow_t \times \beta_{i,t-1}^{flow}$	0.008***	0.011***	0.006**	0.010***
	[3.070]	[3.659]	[2.395]	[3.435]
$Common\_flow_t \times FIT_{i,t-1}$		0.004		0.006
		[1.112]		[1.492]
$Common\_flow_t$	0.027***	0.005	0.024***	−0.001
	[6.565]	[1.196]	[5.176]	[−0.221]
Observations	85459	54123	85459	54123
R-squared	0.001	0.001	0.001	0.001

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 flow-induced trading pressure at year $t-1$. The time series $Common\_flow_t$, $\beta_{i,t-1}^{flow}$, and $FIT_{i,t-1}$ are all standardized to have means of 0 and standard deviations of 1. Sample period spans from 1992 to 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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 6 shows, stocks with high flow betas tend to be small, value, illiquid, and high-liquidity-risk stocks. In Table OA.9 of the online appendix, we show that the mean values of the stock characteristics across the stock quintile portfolios sorted on flow betas. Consistent with Table 6, we find that stocks with higher flow betas tend to have higher book-to-market ratio, higher historical liquidity betas, and higher Amihud illiquidity. Previous studies have shown that these characteristics are priced in the cross section of stock returns, although there is no consensus on the theoretical mechanisms that account for their return premia. The relation between these stock characteristics and flow betas suggests that such characteristics may be partially priced through flow betas.

Although our model has no prediction over the alphas of multifactor models controlling for additional empirical risk factors, such as SMB, HML, and the liquidity factor, it is empirically interesting to test whether controlling for these additional risk factors can explain the asset pricing implications of flow betas. Table OA.10 of the online appendix presents the alplas of various multifactor models for the long-short portfolio sorted on flow betas. We find that although the alpha of the long-short portfolio reduces after controlling for additional empirical risk factors, the alpha remains economically and statistically significant.

Predicted Flow Betas. Because flow betas are closely associated with stock characteristics, we further strengthen our asset pricing results using the predicted beta approach following the literature[30] In particular, we use lagged market caps, lagged book-to-market ratios, lagged historical liquidity betas, lagged Amihud illiquidity measures, lagged price impact measures, lagged cash flow betas, and lagged flow betas to predict flow betas. The predicted flow betas are negatively associated with market caps and positively correlated with book-to-market ratios, historical liquidity betas, Amihud illiquidity measures, price impact measures, and cash flow betas (see Table OA.12 of the online appendix). Using the Fama-MacBeth regressions, we show that the predicted flow betas are also positively priced in the cross section (see panel A of Table OA.13 in the online appendix).

4.3 Common Fund Flows Are Hedged

In this subsection, we provide a rich set of evidence showing that active mutual funds hedge against common fund flows. Using a panel regression approach, we first show that active mutual funds tilt their portfolios away from stocks with high flow betas. We then exploit two quasi-natural experiments to examine the hedging behaviors of active mutual funds. In the first setting, we study the portfolio rebalancing behavior of active mutual funds after the stocks of their existing portfolios experience natural disaster shocks. We find that active mutual funds face an increase in outflow risk that lasts for a few quarters resulting from natural disaster shocks. In response to the increased outflow risk, the magnitude of the portfolio tilt of active mutual funds increases among the stocks that are unaffected by natural disasters. In the second setting, we examine the portfolio rebalancing behavior of active mutual funds after the unexpected announcement of a possible US-China trade war which sharply increases the flow beta of the China-related stocks. We find that active mutual funds

[30] See, e.g., Pástor and Stambaugh (2003), Kogan and Papanikolaou (2013), and Dittmar and Lundblad (2017).

Table 9: Active mutual 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					
	$w^{MF}_{i,t} - w^{M}_{i,t}$		$w^{MF}_{i,t} - w^{Benchmark}_{i,t}$		$w^{MF}_{i,t} - w^{Benchmark}_{i,t}$	
$\beta^{flow}_{i,t-1}$	-0.017^{***}	-0.033^{***}	-0.121^{***}	-0.078^{**}	-0.076^{***}	-0.074^{***}
	[−3.253]	[−5.884]	[−3.496]	[−2.416]	[−3.407]	[−3.327]
$\beta^{M}_{i,t-1}$	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					
	$w^{MF}_{i,t} - w^{M}_{i,t}$		$w^{MF}_{i,t} - w^{Benchmark}_{i,t}$		$w^{MF}_{i,t} - w^{Benchmark}_{i,t}$	
$\beta^{flow}_{i,t-1}$	-0.026^{***}	-0.040^{***}	-0.116^{***}	-0.066^{***}	-0.118^{***}	-0.112^{***}
	[−5.157]	[−7.541]	[−7.650]	[−3.803]	[−7.685]	[−7.839]
$\beta^{M}_{i,t-1}$	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 investigates the relation between flow betas $\beta^{flow}_{i,t-1}$ and the deviation of the weight of the aggregate active mutual fund portfolio from the benchmark portfolio. We control for market betas $\beta^{M}_{i,t-1}$ 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 $w^{MF}_{i,t}$ and $w^{M}_{i,t}$ are defined in equation (4.8). The difference $w^{MF}_{i,t} - w^{M}_{i,t}$ represents the deviation of the aggregate active mutual fund portfolio from the market portfolio. For a given quarter t, we exclude the stocks with zero aggregate mutual fund holdings in current quarter t and 8 preceding quarters (i.e., quarter $t-8$ to quarter $t-1$) from our analysis; namely, 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. In columns (3) and (4), we focus on funds that use 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 mutual fund holdings with the corresponding self-declared benchmarks; specifically, the variable $w^{MF}_{i,t}$ is the weight of the aggregate portfolio of active mutual funds with a given self-declared benchmark for stock i in quarter t, and the variable $w^{Benchmark}_{i,t}$ is the weight for 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 $\beta^{flow}_{i,t-1}$, $\beta^{M}_{i,t-1}$, $w^{MF}_{i,t} - w^{M}_{i,t}$, and $w^{MF}_{i,t} - w^{Benchmark}_{i,t}$ is standardized to have mean of zero and standard deviation of one. The analysis in this table is performed at quarterly frequency. 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 in Table OA.14 of the online appendix by rescaling the stock weights in the aggregate mutual fund portfolio and the market portfolio to make sure the sum of the weights for the stocks included in the analysis is 1 in each quarter, and the results here remain robust to the usage of the rescaled portfolio weights.

tilt their holdings of the China-unrelated stocks farther away from stocks with high flow betas after the onset of the trade war announcement.

4.3.1 Evidence from Portfolio Tilts and Flow Betas

Our model (Theorem 1) predicts that active mutual funds tilt their portfolio holdings farther away from stocks with higher flow betas, relative to the benchmark portfolio. To test this prediction, we run the following regression:

$$w_{i,t}^{MF} - w_{i,t}^{M} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{M} + \varepsilon_{i,t}, \tag{4.8}$$

where $\beta_{i,t}^{flow}$, $\beta_{i,t}^{M}$, $w_{i,t}^{MF}$, and $w_{i,t}^{M}$ are the flow beta, the market beta, the weight of the aggregate active mutual fund portfolio, and the weight of the market portfolio for stock i in quarter t, respectively. The term, $w_{i,t}^{MF} - w_{i,t}^{M}$, represents the deviation of the weight of the aggregate active mutual fund portfolio from that of the market portfolio for stock i in quarter t.

Columns (1) and (2) of Table 9 show the regression results. We perform panel regressions with quarter fixed effects in panel A, and Fama-MacBeth regressions in panel B. Both regression settings allow us to test the cross-sectional relation between the portfolio tilts of active mutual funds and the flow betas of stocks. We find that the estimated coefficient $\hat{b}_1$ is significantly negative, suggesting that active mutual funds tilt their portfolio holdings away from the high-flow-beta stocks relative to the market portfolio. The finding is robust in both the CRSP alone sample and the CRSP-Morningstar intersection sample.

One may argue that mutual funds have different benchmarks, and thus, it can be problematic to use the market portfolio as the universal benchmark portfolio. To address this concern, we use the self-declared benchmarks of active mutual funds to compute the portfolio weight deviation. In particular, we focus on several most frequently used benchmarks, including S&P 500 TR and Russell 1000 Growth TR.[31] We first aggregate the portfolio holdings of active mutual funds with the same self-declared benchmark over the stocks in this benchmark, then run the following regression separately for each benchmark:

$$w_{i,t}^{MF} - w_{i,t}^{Benchmark} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{M} + \varepsilon_{i,t}, \tag{4.9}$$

where $w_{i,t}^{MF}$ is the weight of the aggregate portfolio holdings of active mutual funds with a given self-declared benchmark for stock i in this benchmark in quarter t, and $w_{i,t}^{Benchmark}$ is the weight for stock i in the self-declared benchmark portfolio in quarter t. As shown in columns (3) – (6) of Table 9, the estimated coefficient $\hat{b}_1$ is significantly negative across

[31] Our data source is the Morningstar Direct platform, which only keeps the latest self-declared benchmarks. According to Evans and Sun (2020) who have access to several snapshots of historical data, the changes of the self-declared benchmarks are rare (about 2% per year). Thus, we backfill the benchmark data for 15 years to 2004 and perform our analysis in columns (3) – (6) of Table 9. 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, Russell Mid Cap TR.

different benchmarks, further strengthening the result that active mutual funds tilt their portfolio holdings farther away from stocks with higher flow betas relative to their own benchmarks.

One potential alternative explanation for our findings in Table 9 is that mutual 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 6). To address this potential concern, we emphasize that we only consider stocks that are included in these benchmark portfolios, which are mostly large-cap stocks, for the analyses presented in columns (3) – (6) of Table 9. The fact that active mutual funds tilt away from the high-flow-beta stocks within the stocks included in the S&P 500 index and those in the Russell 1000 growth index suggests that our findings in Table 6 are not likely driven by small-cap stocks through the potential alternative channel.

One point that worths discussing is that the estimated coefficient $\hat{b}_2$ is significantly positive for the market portfolio and two additional self-declared benchmark portfolios. This empirical result 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. For example, high-beta stocks tend to outperform in up markets and mutual fund clients chase returns across funds, making the highest-performing funds capture the largest fraction of the aggregate inflows into the mutual fund sector, and consequently, active mutual funds tilt their portfolios toward high-market-beta stocks to compete for inflows (e.g., Karceski, 2002). Moreover, active mutual funds tilt toward high-market-beta stocks to increase their exposures to systematic risk because of their risk shifting incentives arising from agency conflicts (e.g., Huang, Sialm and Zhang, 2011) and because of their incentives to implicitly leverage up in the presence of financial leverage constraints (Frazzini and Pedersen, 2014). Incorporating those mechanisms goes beyond the scope of this paper which seeks to address how funds handle aggregate fund flow risk and how their flow hedging behaviors affect asset prices. The illustrative model in Section 2 is designed to be the simplest yet sufficient to explain the flow hedging behavior of mutual funds and its asset pricing implications in an economy populated with naive myopic agents.

Moreover, another point that worths discussing is that our findings shed light on some of the puzzling patterns found by Lettau, Ludvigson and Manoel (2018), who show that active 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, the book-to-market ratio and the flow beta are positively correlated in the cross-section of stocks (see column 2 of Table 6). Taken together with This suggests that a simple tilt based solely on the book-to-market ratio would expose funds to elevated flow risk.

We perform two robustness tests for active mutual funds' flow hedging behavior implied by Theorem 1. First, we examine the relation between the portfolio tilt and the predicted flow beta constructed in the same way as in Section 4.2.2. Consistent with the predictions of Theorem 1 and the results of Table 9, we find that active mutual funds tilt their holdings farther away from stocks with higher predicted flow betas relative to their benchmarks (see panel B of Table OA.13 of the online appendix). Second, we examine the relation between the observed portfolio tilt and the model-implied portfolio tilt (i.e, $-\Sigma_t^{-1}\beta_t^{flow}$ as illustrated in Theorem 1). We first estimate the variance-covariance matrix of stock returns Σ_t from the data, then use it to compute the model-implied portfolio tilt (see Section 3 of the online appendix for details). We find that the model-implied portfolio tilt is significantly negatively correlated with the flow beta with a correlation of -0.70 in the CRSP mutual fund data and a correlation of -0.69 in the CRSP-Morningstar intersection data. Moreover, we rerun the regression specification in (4.8) using the lagged model-implied portfolio tilt as the independent variable. Consistent with Theorem 1 and Table 9, we find that the observed portfolio tilt is significantly positively correlated with the model-implied portfolio tilt (see Table OA.15 of the online appendix).

We next consider different proxies for funds' activeness to capture the incentive or capacity to hedge against aggregate fund flow shocks. The prior literature suggests that several fund characteristics reflect the activeness of mutual funds. For example, Pástor, Stambaugh and Taylor (2019) propose a measure for fund activeness using the fund turnover ratio divided by the square root of portfolio liquidity, and show that cheaper funds are less active based on the proposed measure of activeness, which is quite intuitive. Cremers and Petajisto (2009) measure fund activeness using the active share measure which is the absolute weight difference between the fund holdings and the benchmark holdings summed across all stocks. Our model suggests that mutual funds that are less active have lower incentive or lower capacity to actively hedge against fund flow risk and thus should exhibit a less aggressive tilt away from the high-flow-beta stocks. This sets forth an informative testable prediction on the heterogeneity in the behavior of funds' tilting away from stocks

Table 10: Heterogeneity in the behavior of tilting away from stocks with high flow betas across funds with different levels of activeness.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
$Fund\_char_{p,t-1}$:	$Low\_activeness\_funds_{p,t-1}$		$Low\_fee\_funds_{p,t-1}$		$Low\_active\_share\_funds_{p,t-1}$	
	Panel A: Panel regressions with time FE					
	$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	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]
$Fund\_char_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.111***	−0.110***	−0.083***	−0.085***	−0.062***	−0.063***
	[−14.684]	[−14.618]	[−13.500]	[−13.783]	[−8.581]	[−8.552]
$\beta^{M}_{i,t-1}$	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					
	$w^{MF}_{i,p,t} - w^{M}_{i,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	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]
$Fund\_char_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.124***	−0.118***	−0.092***	−0.086***	−0.068***	−0.061***
	[−21.624]	[−20.940]	[−18.741]	[−18.845]	[−17.993]	[−13.868]
$\beta^{M}_{i,t-1}$	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 across funds with different levels of activeness for their flow-hedging behaviors. We sort active mutual funds into quintiles based on lagged fund activeness measure proposed by Pástor, Stambaugh and Taylor (2019) in columns (1) and (2), lagged fund expense ratio as an additional activeness measure suggested by Pástor, Stambaugh and Taylor (2019) 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 $w^{M}_{i,t}$ is the weight of stock i in the market portfolio. $Low\_activeness\_funds_{p,t-1}$, $Low\_fee\_funds_{p,t-1}$, $Low\_active\_share\_funds_{p,t-1}$ are indicator variables for funds in the bottom 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. $\beta^{flow}_{i,t-1}$, $\beta^{M}_{i,t-1}$, and $w^{MF}_{i,p,t} - w^{M}_{i,t}$ 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.

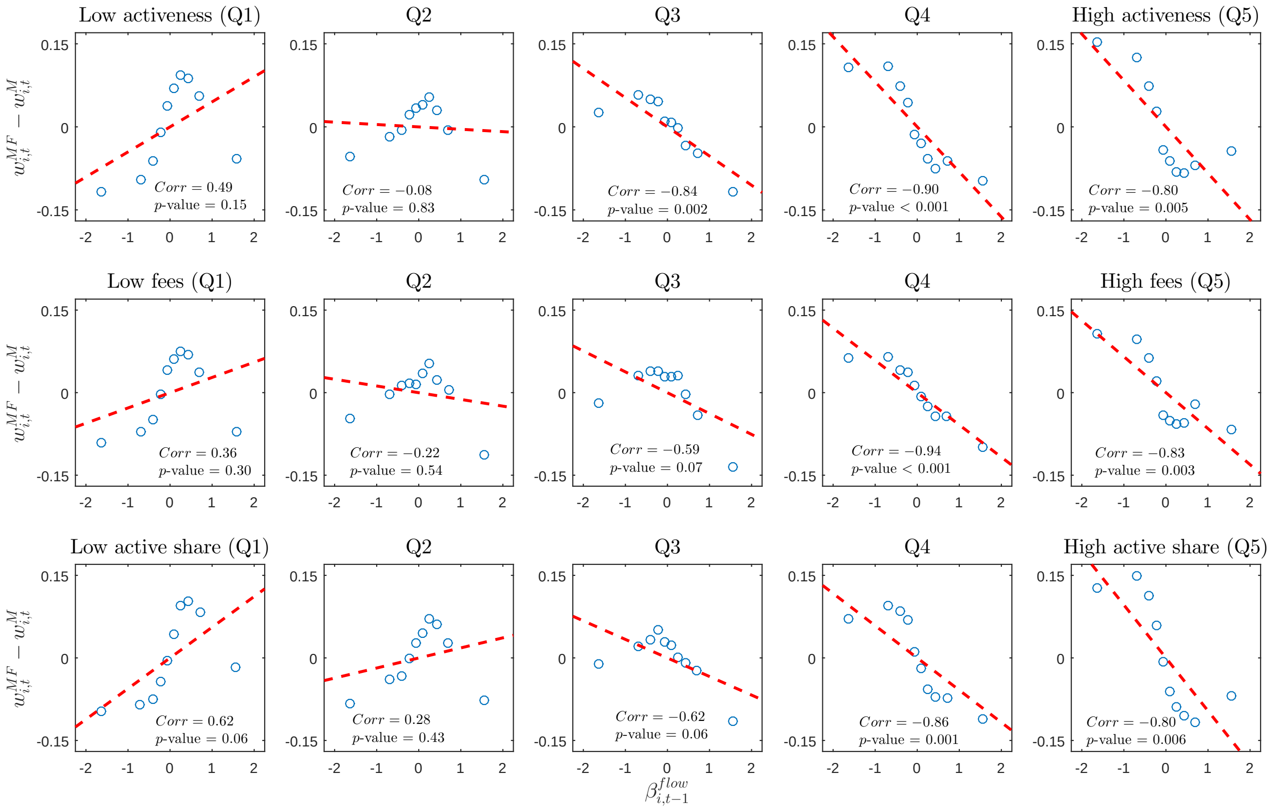
with high flow betas. We separate funds into quintile subgroups by these fund activeness measures and construct the aggregate mutual fund portfolios for each subgroup of funds.

We then define an indicator variable for funds in the bottom quintile sorted based on the activeness measure and add the indicator variable as an interaction term in the regression of portfolio tilts on flow betas. As shown in columns (1) and (2) of Table 10, active mutual funds with lowest activeness (bottom activeness quintile) indeed hedge significantly less against common fund flows than other funds. In columns (3) to (6) of Table 10, we use the fund expense ratio and the active share measure as two additional proxies that reflect 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 funds. This evidence suggests that funds' active flow hedging behaviors are likely to be a force behind the relation between the portfolio tilt and the flow beta presented in Table 9. Furthermore, Figure 7 shows the binned scatter plots between portfolio tilts and flow betas across five groups of mutual funds with different activeness. Consistent with the findings in Table 10, mutual funds with high activeness tilt their portfolio holdings strongly away from the high-flow-beta stocks relative to the market portfolio; in contrast, the strong positive relationship between portfolio tilts and flow betas is totally absent for mutual funds with low activeness.

Besides fund activeness, we also explore the variation in fund size and fund age. As we show in Figure OA.2 of the online appendix, the systematic component of fund flow shocks faced by larger funds or older funds is much less volatile than that faced by smaller funds or younger funds, respectively. Our model suggests that large funds and old funds have weaker incentives to hedge against common fund flows. This is what we find in the data. As shown in columns (1) – (2) and columns (3) – (4) of Table 11, active mutual funds with the largest fund size (top size quintile) or the oldest fund age (top age quintile) hedge significantly less against common fund flows than other funds.[32]

In columns (5) – (6) of Table 11, we further explore the funds' heterogeneity in their fund families; specifically, we construct an equity-concentration measure for a fund family by calculating the equity-to-total-AUM ratio — the fraction of its total asset under management invested in active equity funds. When a fund family invests a larger fraction of its total asset under management in active equity funds (i.e., a fund family has a higher equity-concentration level), the equity fund manager should have stronger incentives to hedge the flow risks, because it is less likely for the flows of other parts of the fund family (such as its

[32]Intuitively, Tables 10 and 11 also show that active mutual funds with lower activeness, larger size, or older age tilt significantly less toward stocks with higher market betas.



Note: This figure shows the binned scatter plots between holding tilt ($w^{MF}_{i,t} - w^{M}_{i,t}$) and flow betas ($\beta^{flow}_{i,t-1}$) across mutual fund quintile portfolios sorted on activeness. We sort active mutual funds into quintiles based on lagged fund activeness measure proposed by Pástor, Stambaugh and Taylor (2019) in the upper panels. We sort active mutual funds into quintiles based on lagged fund expense ratio as an alternative activeness measure suggested by Pástor, Stambaugh and Taylor (2019) in the middle panels. We sort active mutual funds into quintiles based on lagged active share (Cremers and Petajisto, 2009) as another alternative activeness measure in the bottom panels. $\beta^{flow}_{i,t-1}$ and $w^{MF}_{i,t} - w^{M}_{i,t}$ are standardized to have means of 0 and standard deviations of 1. We control for market betas and quarter fixed effects. Specifically, we regress $\beta^{flow}_{i,t-1}$ and $w^{MF}_{i,t} - w^{M}_{i,t}$ separately on both $\beta^{M}_{i,t-1}$ and the quarter fixed effects and then plot the two residuals against each other. We use the CRSP alone sample to compute common flow betas in this figure. The pattern is similar in the CRSP-Morningstar intersection sample.

Figure 7: Relation between holding tilt and flow betas across mutual fund quintile portfolios sorted on activeness.

bond funds) to offset the flow risk of its equity funds. In both the panel regressions and the Fama-MacBeth regressions, we find that active mutual funds with the lowest equity-to-total-AUM ratio (bottom quintile) hedge significantly less against common fund flows than other funds.

Last but not least, there must be some participants in the economy must absorb active equity funds' demand for hedging. Our model (Theorem 1) suggests that the participants who absorb the demand for low-flow-beta stocks are the direct investors (i.e., the "trading counterparties" of the active equity funds), and to persuade the direct investors to hold additional high-flow-beta stocks, the market clearing condition makes the high-flow-beta

Table 11: Heterogeneity in the behavior of tilting away from stocks with high flow betas across funds with different size, age, and levels of equity-to-total-AUM ratio.

	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
$Fund\_char_{p,t-1}$:	$Large\_funds_{p,t-1}$		$Old\_funds_{p,t-1}$		$Low\_equity\_weight_{p,t-1}$	
	Panel A: Panel regressions with time FE					
	$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,p,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.045***	0.031***	0.025***	0.013***	0.013***	0.011***
	[10.420]	[7.447]	[5.024]	[2.888]	[3.415]	[3.273]
$\beta^{flow}_{i,t-1}$	−0.047***	−0.048***	−0.024***	−0.029***	−0.015***	−0.025***
	[−9.522]	[−9.207]	[−4.420]	[−4.966]	[−3.692]	[−5.388]
$Fund\_char_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.036***	−0.037***	−0.035***	−0.033***	−0.020***	−0.021***
	[−6.501]	[−6.604]	[−6.299]	[−5.984]	[−3.795]	[−3.959]
$\beta^{M}_{i,t-1}$	0.071***	0.077***	0.055***	0059***	0.043***	0.047***
	[10.903]	[11.604]	[7.456]	[7.573]	[6.786]	[7.261]
$Fund\_char_{p,t-1}$	−0.114***	−0.114***	−0.074***	−0.074***	−0.053***	−0.053***
	[−11.745]	[−11.720]	[−8.055]	[−8.141]	[−7.740]	[−7.748]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1773870	1773870	1768854	1768854	1726814	1726814
R-squared	0.01	0.01	0.01	0.01	0.01	0.01
	Panel B: Fama-MacBeth regressions					
	$w^{MF}_{i,p,t} - w^{M}_{i,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,t}$		$w^{MF}_{i,p,t} - w^{M}_{i,t}$	
$Fund\_char_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.059***	0.038***	0.046***	0.029***	0.016***	0.014***
	[15.682]	[10.491]	[8.514]	[6.132]	[5.854]	[5.428]
$\beta^{flow}_{i,t-1}$	−0.063***	−0.058***	−0.038***	−0.040***	−0.024***	−0.032***
	[−10.724]	[−10.676]	[−6.038]	[−6.788]	[−5.266]	[−7.135]
$Fund\_char_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.043***	−0.037***	−0.031***	−0.027***	−0.024***	−0.024***
	[−10.584]	[−8.940]	[−10.213]	[−7.605]	[−7.894]	[−7.392]
$\beta^{M}_{i,t-1}$	0.092***	0.094***	0.073***	0.078***	0.064***	0.070***
	[15.872]	[16.089]	[10.074]	[10.368]	[10.354]	[11.042]
$Fund\_char_{p,t-1}$	−0.110***	−0.103***	−0.074***	−0.068***	−0.053***	−0.052***
	[−25.377]	[−24.213]	[−15.903]	[−16.182]	[−19.347]	[−20.018]
Avg. obs./quarter	16578	16578	16531	16531	16138	16138
Avg. R-squared	0.01	0.01	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), fund age in columns (3) and (4), and the lagged equity-to-total-AUM ratio in columns (5) and (6). The equity-to-total-AUM ratio is the fraction of assets of the fund family invested in active equity funds. 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 $w^{M}_{i,t}$ is the weight of stock i in the market portfolio. $Large\_funds_{p,t-1}$, $Old\_funds_{p,t-1}$, and $Low\_equity\_weight_{p,t-1}$ are indicator variables for funds in the top size quintile, the top age quintile, and the bottom equity-to-total-AUM ratio 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. $\beta^{flow}_{i,t-1}$, $\beta^{M}_{i,t-1}$, and $w^{MF}_{i,p,t} - w^{M}_{i,t}$ 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.

stocks pay higher expected returns to ensure that the direct investor's (mean-variance) optimal portfolio agrees with the additional holdings of high-flow-beta stocks. To test this important hypothesis, we examine the holdings of index funds and households. Columns (1)

Table 12: Index funds and households tilt holdings toward stocks with high flow betas.

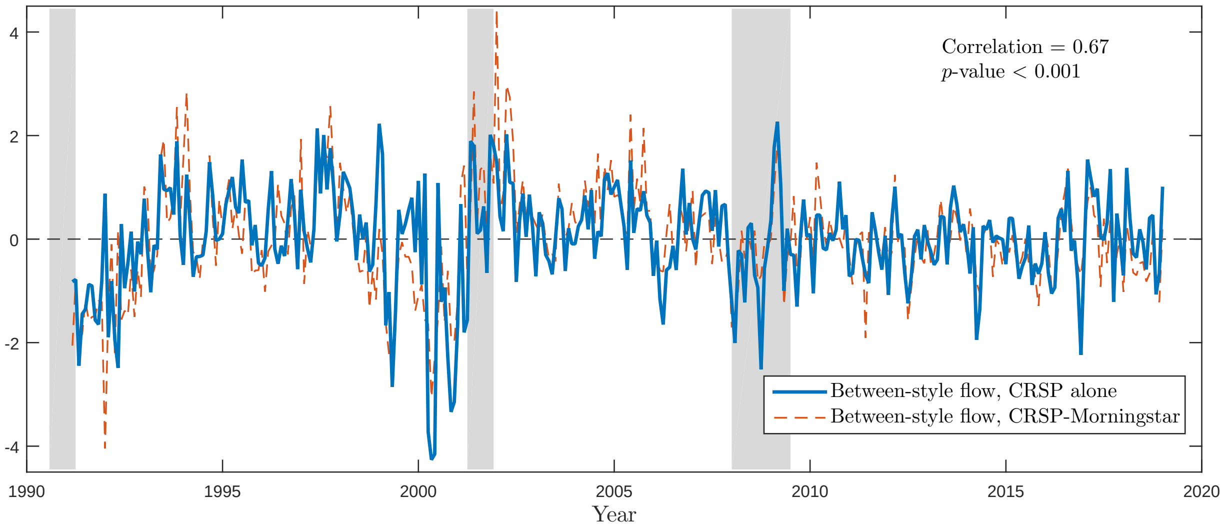
	(1) CRSP	(2) CRSP-MS	(3) CRSP	(4) CRSP-MS	(5) CRSP	(6) CRSP-MS
	Panel A: Panel regressions with time FE					
	$w^{IF}_{i,t} - w^M_{i,t}$		$w^{NI}_{i,t} - w^M_{i,t}$		$w^H_{i,t} - w^M_{i,t}$	
$\beta^{flow}_{i,t-1}$	0.027***	0.015*	0.010**	0.021***	0.031**	0.071***
	[5.253]	[1.947]	[2.145]	[4.378]	[2.119]	[6.014]
$\beta^M_{i,t-1}$	−0.025***	−0.020***	−0.079***	−0.084***	−0.043***	−0.051***
	[−3.839]	[−3.054]	[−12.301]	[−13.429]	[−4.233]	[−5.031]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	395294	395294	582332	582332	60091	60091
R-squared	0.01	0.01	0.01	0.01	0.02	0.02
	Panel B: Fama-MacBeth regressions					
	$w^{IF}_{i,t} - w^M_{i,t}$		$w^{NI}_{i,t} - w^M_{i,t}$		$w^H_{i,t} - w^M_{i,t}$	
$\beta^{flow}_{i,t-1}$	0.035***	0.012*	0.013***	0.019***	0.042***	0.077***
	[9.622]	[1.836]	[3.837]	[5.313]	[3.235]	[7.485]
$\beta^M_{i,t-1}$	−0.017***	−0.008**	−0.091***	−0.094***	−0.054***	−0.061***
	[−5.404]	[−2.505]	[−22.896]	[−24.304]	[−8.106]	[−8.557]
Avg. obs./quarter	3694	3694	5442	5442	3163	3163
Avg. R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table investigates the relation between the flow beta $\beta^{flow}_{i,t-1}$ and the portfolio tilt of the index funds, the non-institutional investors, and the retail household investors, relative to the market portfolio. We control for the market beta $\beta^M_{i,t-1}$ in the regressions. We perform panel regressions with quarter fixed effects in panel A and Fama-MacBeth regressions in panel B. $w^{IF}_{i,t}$, $w^{NI}_{i,t}$, and $w^H_{i,t}$ are the portfolio weights for stock i in the aggregate portfolio holdings of index funds, non-institutional investors, and retail household investors in quarter t, respectively. $w^M_{i,t}$ is the weight for stock i in the market portfolio. We measure 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 holding of 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 during 1991 to 1996. $w^{IF}_{i,t} - w^M_{i,t}$, $w^{NI}_{i,t} - w^M_{i,t}$, $w^H_{i,t} - w^M_{i,t}$, $\beta^{flow}_{i,t-1}$, and $\beta^M_{i,t-1}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at quarterly frequency. Sample period spans from 1992 to 2018 in columns (1) – (4), and spans from 1992 to 1996 in columns (5) and (6). 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.

and (2) of Table 12 show that index funds tilt their holdings significantly toward stocks with high flow betas. For robustness, we measure the holdings of households using two different approaches. In columns (3) and (4) of Table 12, we follow Koijen and Yogo (2019) to measure household holdings by non-institutional holdings, and in columns (5) and (6) of Table 12, we measure household holdings based on Barber and Odean's retail investor data (e.g., Barber and Odean, 2000). We find that households tilt their holdings significantly toward stocks with high flow betas.

4.3.2 Evidence from Portfolio Tilts and Between-Style Flow Betas

We have shown that mutual fund managers tilt away from stocks with high common flow betas due to flow-hedging motives. In theory, mutual fund managers should have incentives to hedge the fund-specific flow risk as well. A salient feature of the mutual fund



Note: This figure plots the monthly between-style flows (from growth funds to value funds) constructed using the CRSP mutual fund data and CRSP-Morningstar intersection mutual fund data. The between-style flows are standardized to have means of 0 and standard deviations of 1. Gray areas represent the NBER recession periods.

Figure 8: Between-style fund flows.

industry is that it offers different styles of investing such as value and growth. According to the framework of our model, fund managers should hedge the risk associated with the between-style flow (e.g., fund flows from growth funds to value funds) as well. For example, we expect managers of value funds to tilt their holdings away from stocks that have bad performance when money flows from value funds to growth funds. On the other hand, we expect that managers of growth funds to tilt their holdings toward these stocks. The key difference between the between-style flows and common fund flows lies in their asset pricing implications. Unlike the common fund flows, we do not expect that the between-style flow shocks to be priced in the cross section of stocks, because different mutual funds tilt their portfolios in opposite directions and thus do not generate a risk premium associated with the between-style flow shocks. In this subsection, we test the predictions on the portfolio tilts and asset pricing implications related to the between-style flows to further support the economic mechanism illustrated by our model.

To construct the between-style fund flows, we estimate the fund-level flow shock of value funds and growth funds using regression specifications (4.2) and (4.3). We then sort the value funds and growth funds into five groups separately based on asset size and compute the value-weighted average fund flow shocks for each group.[33] To make sure the between-style

[33]Following Lettau, Ludvigson and Manoel (2018), we classify active mutual funds into growth, value, and

fund flows capture flows between fund styles within the mutual fund sector rather than the flows in and out of the mutual fund sector, we regress the fund flow shocks of the ten fund groups on the common fund flows and take the residuals. Finally, we extract the PC1 of the residuals of the ten fund groups. The PCA loadings of the PC1 are positive for all five groups of value funds and are negative for all five groups of growth funds. Specifically, when using the CRSP alone data, the PCA loadings for the five groups of value funds are $[0.2359, 0.1248, 0.3607, 0.3956, 0.4210]$ from the smallest asset size group to the largest asset size group, while the PCA loadings for the five groups of growth funds are $[-0.1114, -0.3101, -0.2533, -0.4157, -0.3454]$. We find similar pattern for the PCA loadings when using the CRSP-Morningstar intersection data. We define the PC1 as the between-style fund flow and it reflects the flows from growth funds to value funds. Figure 8 plots the monthly between-style fund flows constructed using the CRSP alone and CRSP-Morningstar intersection data. The two monthly time series are highly correlated with the correlation of 0.67 (p-value < 0.001). The between-style fund flows are negative during the dot-com bubble period and are positive after the subsequent bust, suggesting that money flows into growth funds during the dot-com bubble period and then flows out after the bust.

We expect that value funds tilt holdings away from stocks with high between-style betas. This is because value fund managers dislike stocks that have bad performance when money flows from value funds to growth funds (i.e., negative between-style fund flows). On the other hand, we expect that growth funds to show the opposite tilt. To test this hypothesis, we estimate the between-style flow beta of each stock using regression specification (4.5) by replacing the common flows with the between-style flows on the right-hand side. We then examine the relation between the between-style flow beta and the portfolio tilt of the value funds and growth funds relative to the market portfolio in Table 13. Consistent with our hypotheses, we find that value funds indeed tilt their holdings away from stocks with high between-style betas (Columns 1 to 6), while growth funds do the opposite (Columns 7 to 12). These findings are robust after controlling for the book-to-market ratios and the HML betas of the stocks to account for the difference in investment style. The findings are also robust to the choice of the data samples we use to construct the between-style betas (i.e., CRSP alone and CRSP-Morningstar intersection) and the regression specifications (i.e., panel regressions and Fama-MacBeth regressions).

other funds based on fund names. We use the CRSP, Lipper, Wiesenberger, and Strategic Insight objective codes to further classify mutual funds that cannot be identified by their names.

Table 13: Value funds tilt holdings away from stocks with high between-style betas while growth funds tilt holdings toward these stocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		CRSP			CRSP-MS			CRSP			CRSP-MS	
	Panel A: Panel regressions with time FE											
		$w^V_{i,t} - w^M_{i,t}$			$w^V_{i,t} - w^M_{i,t}$			$w^G_{i,t} - w^M_{i,t}$			$w^G_{i,t} - w^M_{i,t}$	
$\beta^{G\to V}_{i,t-1}$	-0.094^{***}	-0.092^{***}	-0.053^{***}	-0.045^{***}	-0.045^{***}	-0.030^{***}	0.065^{***}	0.060^{***}	0.037^{***}	0.026^{***}	0.022^{***}	0.017^{**}
	[−11.766]	[−10.959]	[−7.896]	[−8.078]	[−7.500]	[−6.045]	[8.805]	[7.520]	[5.063]	[3.451]	[2.764]	[2.548]
$\beta^{M}_{i,t-1}$	0.005	0.005	0.008	-0.025^{***}	-0.025^{***}	−0.005	0.069^{***}	0.058^{***}	0.065^{***}	0.090^{***}	0.078^{***}	0.073^{***}
	[0.668]	[0.701]	[1.065]	[−3.351]	[−3.163]	[−0.619]	[8.351]	[6.359]	[7.899]	[10.575]	[8.389]	[8.827]
$LnBEME_{i,t-1}$		0.049^{***}			0.054^{***}			-0.150^{***}			-0.154^{***}	
		[5.161]			[5.662]			[−13.791]			[−14.006]	
$\beta^{HML}_{i,t-1}$			0.089^{***}			0.113^{***}			-0.066^{***}			-0.083^{***}
			[9.920]			[12.517]			[−8.141]			[−9.991]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	335910	305276	335910	335910	305276	335910	336657	301087	336657	336657	301087	336657
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.04	0.02	0.02	0.03	0.02
	Panel B: Fama-MacBeth regressions											
		$w^V_{i,t} - w^M_{i,t}$			$w^V_{i,t} - w^M_{i,t}$			$w^G_{i,t} - w^M_{i,t}$			$w^G_{i,t} - w^M_{i,t}$	
$\beta^{G\to V}_{i,t-1}$	-0.122^{***}	-0.124^{***}	-0.082^{***}	-0.043^{***}	-0.047^{***}	-0.043^{***}	0.050^{***}	0.046^{***}	0.027^{***}	0.017^{**}	0.016^{**}	0.014^{*}
	[−12.955]	[−11.884]	[−12.806]	[−7.985]	[−8.134]	[−9.057]	[5.689]	[5.125]	[3.199]	[2.308]	[2.163]	[1.945]
$\beta^{M}_{i,t-1}$	0.029^{***}	0.035^{***}	0.062^{***}	-0.016^{***}	-0.014^{**}	0.043^{***}	0.100^{***}	0.092^{***}	0.092^{***}	0.110^{***}	0.103^{***}	0.109^{***}
	[5.127]	[5.404]	[9.170]	[−2.944]	[−2.394]	[5.626]	[11.536]	[9.609]	[10.803]	[13.584]	[10.945]	[13.583]
$LnBEME_{i,t-1}$		0.057^{***}			0.061^{***}			-0.144^{***}			-0.146^{***}	
		[12.887]			[14.109]			[−32.876]			[−34.905]	
$\beta^{HML}_{i,t-1}$			0.107^{***}			0.167^{***}			-0.058^{***}			-0.065^{***}
			[11.459]			[14.635]			[−9.463]			[−8.157]
Avg. obs/quarter	3139	2853	3139	3139	2853	3139	3146	2814	3146	3146	2814	3146
Avg. R-squared	0.01	0.02	0.02	0.01	0.01	0.02	0.02	0.04	0.02	0.02	0.04	0.02

Note: This table investigates the relation between the between-style flow beta $\beta^{G\to V}_{i,t-1}$ and the portfolio tilt of the value funds and growth funds, relative to the market portfolio. We control for the market beta $\beta^{M}_{i,t-1}$ in the regressions. We also control for the book-to-market ratio $LnBEME_{i,t-1}$ and the HML beta $\beta^{HML}_{i,t-1}$ of the stocks. We perform panel regressions with quarter fixed effects in panel A and Fama-MacBeth regressions in panel B. $w^V_{i,t}$ and $w^G_{i,t}$ are the portfolio weights for stock i in the aggregate portfolio holdings of value funds and growth funds in quarter t, respectively. $w^M_{i,t}$ is the weight for stock i in the market portfolio. $w^V_{i,t} - w^M_{i,t}$, $w^G_{i,t} - w^M_{i,t}$, $\beta^{G\to V}_{i,t-1}$, $\beta^{M}_{i,t-1}$, $LnBEME_{i,t-1}$, and $\beta^{HML}_{i,t-1}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at quarterly frequency. Sample period spans from 1992 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.

Because value and growth funds tilt their holdings in the opposite directions for stocks with high between-style betas, we do not expect that the between-style betas to be priced in the cross section of stocks. To test this hypothesis, we perform portfolio sorting analyses. Table 14 shows the average excess returns and alphas of the long-short portfolios sorted on the between-style flow betas. Unlike the common flow betas, we find that stocks with higher between-style flow betas are not associated with significantly higher excess returns or risk-adjusted alphas.

Table 14: Excess returns and alphas of portfolios sorted on between-style flow betas.

	Panel A. CRSP mutual funds alone			Panel B. CRSP-Morningstar intersection		
$\beta_i^{G\to V}$ quintiles	Excess returns	CAPM α	FF3F α	Excess returns	CAPM α	FF3F α
Q1	9.83***	2.93*	2.08	8.01**	−1.65	−0.76
	[3.46]	[1.86]	[1.36]	[2.15]	[−0.98]	[−0.47]
Q2	9.07***	2.61**	2.13**	8.27***	0.68	0.94
	[3.66]	[2.38]	[2.23]	[2.98]	[0.72]	[1.01]
Q3	9.76***	2.05**	2.11**	8.44***	0.67	0.62
	[3.47]	[2.16]	[2.18]	[3.02]	[0.83]	[0.78]
Q4	8.06**	−2.29	−1.38	8.34**	−0.14	−0.24
	[2.08]	[−1.50]	[−1.03]	[2.56]	[−0.09]	[−0.16]
Q5	10.69**	−2.32	0.15	12.80***	2.38	3.11
	[2.04]	[−0.84]	[0.07]	[2.91]	[0.92]	[1.58]
Q5 − Q1	0.86	−5.25	−1.92	4.79	4.03	3.87
	[0.20]	[−1.41]	[−0.66]	[1.59]	[1.32]	[1.39]

Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on between-style flow betas. In June of year t, we sort firms into quintiles based on their average between-style 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 $t+1$. We estimate the portfolio alphas using both the CAPM model and the Fama-French three-factor model. 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 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.

4.3.3 Evidence from Two Quasi-Natural Experiments

We use two quasi-natural experiments to gain further insight into the hedging behavior of active mutual funds. Our goal in this subsection is to establish evidence on how mutual funds rebalance their portfolios when their incentives to hedge common flow shocks change. Specifically, we examine how active mutual funds rebalance their portfolio holdings around the unexpected (local) natural disaster shocks in the US and the unexpected announcements on the possible US-China trade war.[34] The former experiment utilizes many idiosyncratic shocks across different quarters and US counties, while the latter experiment exploits a one-time aggregate shift.

Unexpected Natural Disaster Shocks. 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 outflow risk of fund f, denoted by $\Delta Outflow\_Risk_{f,t}$, leads to fund f's portfolio rebalancing further toward the 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

[34] In Online Appendix 3, we also study the hedging behavior of active mutual funds by exploiting a quasi-natural experiment setting in which oil-related industries experience an exogenous increase in their flow betas around the unexpected price war announcement out of the 166th OPEC meeting on November 28, 2014.

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 the outflow risk. Natural disasters have significant short-term effect 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 disasters. 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 disasters in period t, $ND_{f,t}$, which captures the extent to which fund f is affected by natural disasters in period t.[35] More precisely, we compute $ND_{f,t}$ as the portfolio share of the stocks held by fund f in period t, whose headquarters are located in the counties hit by natural disasters in period t. Following Barrot and Sauvagnat (2016), we define a stock as being negatively affected by natural disasters in a given quarter if it is a non-financial firm and the county of its headquarters experiences property losses due to natural disasters during that quarter.[36] 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 disasters may experience a change in their outflow risk for at least two reasons. First, poor relative performance of fund f may lead to higher outflow risk $Outflow\_Risk_{f,t}$.[37] 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 disasters is associated with a 1.36-percentage-point reduction in the annualized performance relative to the market return.[38] Second, uncertainty about the fund's performance tends to increase more when the fund is hit more heavily by natural disasters (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.

[35] Natural disaster shocks have been used as a source of exogenous variation in firm-level economic variables in a number of prior papers, including 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).

[36] 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 disasters if it is a non-financial firm and at least one of its main establishments (i.e., the establishments with more than 5% of firm-level sales) experiences property losses due to natural disasters. Our findings remain robust in this test.

[37] 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).

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

Panel A of Table 15 confirms that an increase in funds' exposure to natural disasters leads to a contemporaneous increase in outflow risk. Specifically, we regress the abnormal fund flows, defined as the fund-level flows net of the asset-size-weighted average flows of the entire active US equity mutual fund sector, on the funds' exposure to natural disasters $ND_{f,t}$ as follows:

$$Abflow_{f,t+k} = a + b \times ND_{f,t} + \varepsilon_{f,t+k}, \quad \text{with } k = 0, 1, 2, 3. \tag{4.10}$$

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 disasters experience a larger amount of outflows in the near future. In Panel B of Table 15, we find that the 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 shocks.

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 the fund's exposure to natural disasters. We run our regression on the stocks not affected by natural disasters to mitigate the concern that the properties of the stocks are affected by the same shock that shifts the outflow risk of the fund:

$$\begin{aligned}\Delta(w_{i,f,t} - w^M_{i,t}) = b_1 \times \beta^{flow}_{i,t-1} \times ND_{f,t} + b_2 \times \beta^{flow}_{i,t-1} + b_3 \times \beta^M_{i,t-1} \times ND_{f,t} + b_4 \times \beta^M_{i,t-1} \\ + b_5 \times ND_{f,t} + a_i + a_f + a_t + \varepsilon_{i,f,t},\end{aligned} \tag{4.11}$$

where $\Delta(w_{i,f,t} - w^M_{i,t})$ is the portfolio weight changes of fund f in stock i (in excess of the weight changes 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 disasters. Here, $w_{i,f,t}$ is the portfolio weight of stock i in the holdings of fund f in period t, and $w^M_{i,t}$ 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 16, 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 the unaffected

Table 15: 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.

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 flow shocks.

The fund's exposure to natural disasters $ND_{f,t}$ 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).[39] The main challenge in interpreting our results above is that exposure to natural disasters may affect other properties of the funds' portfolio, leading the fund to rebalance for reasons other than its elevated outflow risk. To mitigate this concern, we focus our

[39] 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.

Table 16: Mutual funds' rebalancing of the stocks unaffected by natural disasters following the natural disaster shocks.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone				Panel B. CRSP-Morningstar intersection			
	$\Delta(w_{i,f,t}-w^M_{i,t})$ $(\times 10^3)$				$\Delta(w_{i,f,t}-w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-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]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	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]
$\beta^{M}_{i,t-1}$	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 disasters after the natural disaster shocks. The dependent variable is the quarterly changes of stock weights in mutual funds in excess of the quarterly changes of stock weights of the market portfolio. $\Delta(w_{i,f,t}-w^M_{i,t}) = (w_{i,f,t}-w_{i,f,t-1}) - (w^M_{i,t}-w^M_{i,t-1})$, where $w_{i,f,t}$ represents the weight of stock i in fund f in quarter t and $w^M_{i,t}$ represents the weight of stock i in the market portfolio in quarter t. β^{flow}_i is the flow beta for stock i, β^M_i is the market beta for stock i, and $ND_{f,t}$ is the portfolio weight of the stocks affected by natural disasters in fund f. β^{flow}_i, β^M_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.

analysis on the weight changes of the stocks not directly affected by the disaster shocks. One may argue that some of these stocks may still experience a spill-over effect through the supplier-customer linkages (e.g., Barrot and Sauvagnat, 2016). While it is unclear how the spill-over of firm-level shocks should affect the relation between stocks' flow betas $\beta^{flow}_{i,t}$ and portfolio weight changes $\Delta(w_{i,f,t}-w^M_{i,t})$, we address this potential issue empirically by excluding the suppliers and customers of the firms affected by natural disasters 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 disasters because of how they rebalance stocks with different liquidity – e.g., funds experiencing outflows because of the 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 flow shocks at the expense of their performance, which shows that they must perceive a benefit from tilting toward the low-flow-beta stocks on dimensions other than the 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 disasters the same as those in quarter $t-1$.[40] 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).[41] This loss in performance is larger for funds with higher exposure to natural disaster shocks. Specifically, when we consider the fund-quarters with a higher-than-median exposure to natural disasters, the loss in the annualized fund returns increases to 99 basis points ($p < 0.001$). 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.

Unexpected Announcement of a Possible US-China Trade War. As another test of our theory, we examine how active mutual funds rebalance their portfolio holdings in response to changes in the flow beta of a specific subgroup of stocks. The main empirical challenge is that the changes in flow betas and the rebalancing behavior of active mutual funds may be simultaneously driven by other primitive economic forces. To alleviate this concern, we aim to isolate an instance of exogenous change in the flow beta for a specific subgroup of stocks, and then investigate the portfolio rebalancing behavior of active mutual funds across other stocks in their portfolios.

We exploit the unexpected announcement of a possible US-China trade war, leading to a sharp increase in the flow beta of China-related stocks compared to China-unrelated

[40] Note that the hedging expense would be 0 in our estimation if funds simply adjust their holdings of the stocks unaffected by natural disasters 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.

[41] 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 disasters, 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 the natural disasters, with a t-statistic of 0.37. In other words, we find no evidence that these stocks are aggressively dumped and thus experience negative price impact.

Table 17: Changes in uncertainty betas and flow betas following the unexpected announcement of the possible US-China trade war.

	Panel A: Changes in trade policy uncertainty betas			
	(1)	(2)	(3)	(4)
China-related measure:	Export and import		Offshore activities	
	$-1 \times \beta_{i,t}^{uncertainty}$	$-1 \times \beta_{i,t}^{uncertainty}$	$-1 \times \beta_{i,t}^{uncertainty}$	$-1 \times \beta_{i,t}^{uncertainty}$
$China\_related_i \times \mathbf{1}_{\{t>March\_2018\}}$	0.065***	0.065***	0.074***	0.075***
	[2.880]	[2.879]	[3.561]	[3.570]
$China\_related_i$	−0.150***	−0.150***	−0.166***	−0.166***
	[−4.817]	[−4.811]	[−5.119]	[−5.114]
$\mathbf{1}_{\{t>March\_2018\}}$	−0.022		−0.015	
	[−1.443]		[−1.057]	
Month FE	No	Yes	No	Yes
Observations	141352	141352	141352	141352
R-squared	0.003	0.004	0.004	0.005

	Panel B: Changes in flow betas							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$	
$China\_related_i \times \mathbf{1}_{\{t>March\_2018\}}$	0.087***	0.086***	0.073***	0.072***	0.115***	0.113***	0.084***	0.082***
	[4.137]	[4.053]	[4.039]	[3.928]	[4.444]	[4.352]	[4.369]	[4.174]
$China\_related_i$	−0.117***	−0.116***	−0.078**	−0.078**	−0.200***	−0.200***	−0.172***	−0.172***
	[−4.173]	[−4.158]	[−2.827]	[−2.829]	[−6.470]	[−6.450]	[−5.686]	[−5.688]
$\mathbf{1}_{\{t>March\_2018\}}$	−0.148***		−0.135**		−0.147***		−0.131***	
	[−3.643]		[−2.947]		[−3.947]		[−2.880]	
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	141353	141353	141353	141353	141353	141353	141353	141353
R-squared	0.01	0.01	0.01	0.01	0.01	0.02	0.01	0.02

Note: This table shows the changes in stocks' trade policy uncertainty betas ($\beta_{i,t}^{uncertainty}$ in panel A) and flow betas ($\beta_{i,t}^{flow}$ in panel B) following the unexpected announcement of the possible US-China trade war in March 2018. The sample period spans from January 2017 to December 2018. $China\_related_i$ is an indicator variable that equals one for China-related stocks. $\mathbf{1}_{\{t>March\_2018\}}$ is an indicator variable that equals one for time periods after March 2018. $\beta_{i,t}^{uncertainty}$ and $\beta_{i,t}^{flow}$ are standardized to have means of zero and standard deviations of one. Because stock prices tend to react negatively to increases in economic uncertainty, we multiply the trade policy uncertainty betas with -1 so that higher values of the outcome variable in panel A represent higher sensitivity of stock returns to uncertainty. The analysis is performed at a monthly frequency. Standard errors are double clustered at the stock and month levels. Results remain robust if standard errors are clustered at the stock level. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

stocks. We then examine how active mutual funds change their portfolio holdings of the China-unrelated stocks in response to the increase in their exposure to the common fund flows through their holdings of China-related stocks. We focus on funds' trading behavior of China-unrelated stocks because properties of these securities are less affected by the announcement of a possible US-China trade war.

The first public announcement of a possible US-China trade war shocked the market because it was from an unexpected personal Twitter post by the US president on March 2, 2018. A few days later, on March 22, the Trump administration issued a presidential memorandum proposing 25% tariffs on more than \$50 billion worth of Chinese imports. Right after the unexpected announcement of the US-China trade war (i.e., March 2018), the monthly trade policy uncertainty index (Baker, Bloom and Davis, 2016) skyrocketed (see panel A of Figure 9). To justify the use of the trade-war announcement as a shifter of the flow beta of China-related stocks, we show that such stocks become significantly more sensitive to both economic uncertainty and common fund flows following the announcement. Specifically, we run the following regression to examine changes in stocks' uncertainty betas at a monthly frequency:

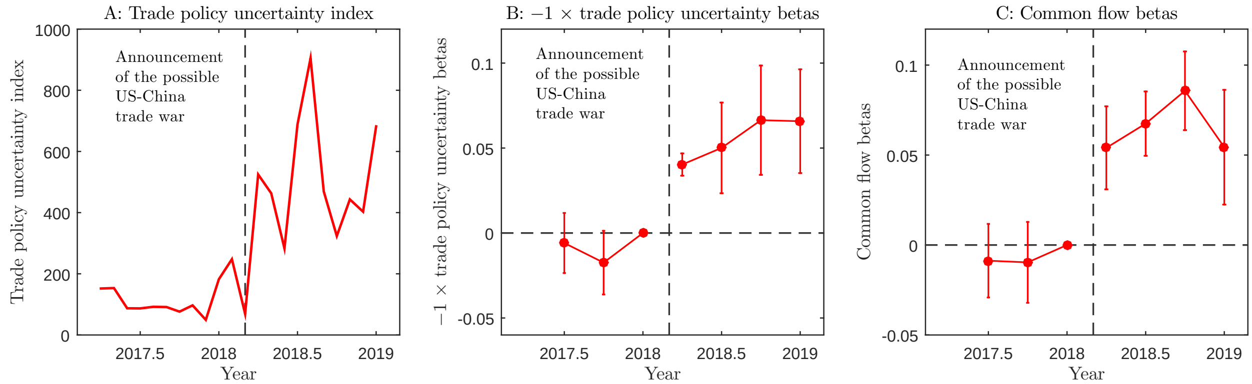
$$
\begin{aligned}
-1 \times \beta_{i,t}^{uncertainty} = {} & b_1 \times China\_related_i \times \mathbf{1}_{\{t>March\_2018\}} \\
& + b_2 \times China\_related_i + b_3 \times \mathbf{1}_{\{t>March\_2018\}} + a_t + \varepsilon_{i,t}.
\end{aligned} \tag{4.12}
$$

Here, $\beta_{i,t}^{uncertainty}$ is the sensitivity of stock i's returns to trade policy uncertainty index in month t, estimated using the stock returns from month $t-36$ to $t-1$. The trade policy uncertainty index is from Baker, Bloom and Davis (2016). Because stock prices tend to react negatively to increases in economic uncertainty,[42] we multiply the trade policy uncertainty betas with -1 so that higher values of the left-hand side variable in specification (4.12) represent higher sensitivity of stock returns to uncertainty. Variable $China\_related_i$ is an indicator variable that is defined using two methods. Under the first method, China-related stocks are defined as the firms that have either positive revenue or positive import from China in 2016. Firms' revenue from China comes from Factset Revere data. Firms' imports from China come from US Customs and Border Protection's Bill of Lading data. Under the second method, China-related stocks are defined as firms that sell goods to or purchase inputs from China from 2011 to 2015 according to the text-based offshoring network data (e.g., Hoberg and Moon, 2017, 2019).[43] Under both methods, we define $China\_related_i$ based on information prior to the first announcement of a possible trade war to ensure that the categorization of stocks is not affected by firms' endogenous response to the trade war or its announcement. Indicator $\mathbf{1}_{\{t>March\_2018\}}$ is a dummy variable that equals 1 for the time period after March 2018.

As we show in panel A of Table 17, coefficient b_1 is positive and statistically significant,

[42]e.g., Bloom (2009), Pástor and Veronesi (2012), Pástor and Veronesi (2013), Baker, Bloom and Davis (2016), Kelly, Pástor and Veronesi (2016), and Dou (2017).

[43]The text-based offshoring network data cover the period from 1997 to 2015. The data are constructed based on textual analysis of firms' 10-K forms. Because China-related firms may not mention information about China in their 10-Ks every year, we use a 5-year time window to define the $China\_related_i$ variable.



Note: Panel A plots the trade policy uncertainty index around the unexpected announcement of a possible US-China trade war (i.e., March 2018). Panel B plots the trade policy uncertainty betas around the unexpected announcement of a possible US-China trade war for China-related stocks relative to China-unrelated stocks. Because stock prices tend to react negatively to increases in economic uncertainty, we multiply the trade policy uncertainty betas with -1 so that higher values of the outcome variable in panel B represent higher sensitivity of stock returns to uncertainty. China-related stocks are firms that have either positive revenue or positive import from China in 2016. Firms' revenue from China comes from Factset Revere data. Firms' import from China comes from US Customs and Border Protection's Bill of Lading data. Panel C plots the flow beta around the announcement of a possible US-China trade war for China-related stocks relative to China-unrelated stocks. The trade policy uncertainty betas and the common fund flow betas are standardized to have means of zero and standard deviations of one.

Figure 9: Uncertainty betas and flow betas of China-related stocks around the unexpected announcement of a possible US-China trade war.

suggesting that China-related stocks become more sensitive to economic uncertainty relative to China-unrelated stocks following the unexpected trade war announcement. Moreover, we also examine the dynamic impact of the announcement of a possible trade war. We consider the quarterly regression specification as follows:

$$
\begin{aligned}
-1 \times \beta_{i,t}^{uncertainty} &= a + \sum_{\tau=-3}^{3} b_{1,\tau} \times China\_related_i \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} \\
&\quad + b_2 \times China\_related_i + \sum_{\tau=-3}^{3} b_{3,\tau} \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} + \varepsilon_{i,t}, \qquad (4.13)
\end{aligned}
$$

where $\mathbf{1}_{\{t-\tau=Q1\_2018\}}$ is an indicator variable equal to 1 if and only if $t-\tau$ is the first quarter of 2018 — the time of the announcement by the Trump adminstration about a possible US-China trade war. When running the regression, we impose $b_{1,-1} = b_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the quarter right before the announcement quarter, namely the fourth quarter of 2017, as the benchmark. The sample period is from the second quarter of 2017 to the fourth quarter of 2018. We plot estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \cdots, 3$, as well as their 95% confidence bands, in panel B of Figure 9.

We find that the treatment effect emerges only after the announcement of a possible US-China trade war (see panel B of Figure 9). There is no significant change in the uncertainty betas prior to the trade war, which provides evidence supporting the parallel trend assumption for the difference-in-differences (DID) analysis. We also find that changes in the uncertainty betas for China-related stocks are persistent and remain robustly high in the 1 year window after the first announcement of a possible US-China trade war.[44]

Because common fund flows are strongly related to economic uncertainty fluctuations, we expect that the sensitivity of China-related stocks to common fund flows (i.e., flow betas) should also increase after the first announcement of a possible US-China trade war. We again use the DID approach to examine the changes of flow betas of China-related stocks relative. As shown in panel B of Table 17, the flow beta of China-related stocks indeed increase significantly relative to those of China-unrelated stocks after the onset of the trade war. Importantly, similar to the relative increase in the uncertainty betas of China-related stocks, the relative increase in the flow beta of China-related stocks is also persistent (see panel C of Figure 9).

Our model predicts that the persistent increase in the fund flow betas for the China-related stocks strengthens hedging demands for active mutual funds. This hedging demand is sustained by a related empirical fact: active mutual funds do not reduce their holdings of China-related stocks following the unexpected trade war announcement.[45] Because China-related stocks experience an increase in their flow betas and active mutual funds hold on to these stocks, we expect active mutual funds to tilt their holdings of China-unrelated stocks further toward low-flow-beta stocks in order to hedge their increased exposure to common fund flows. To test this hypothesis, we regress the changes in the portfolio weight of stock i in fund f relative to the market portfolio weight of stock i after the onset of the trade war, $\Delta(w_{i,f} - w_i^M)$, on the stock's flow beta prior to the trade war, $\beta^{flow}_{i,Dec2016}$. Specifically, we run the following quarterly regression:

$$\Delta(w_{i,f} - w_i^M) = b_1 \times \beta^{flow}_{i,Dec2016} + b_2 \times \beta^{M}_{i,Dec2016} + \alpha_{ind} + \alpha_f + \alpha_t + \varepsilon_{i,f}, \tag{4.14}$$

[44]There are several potential reasons why the announcement of a possible US-China trade war leads to relatively high uncertainty betas for China-related stocks. Economic fundamentals of China-related firms are likely to be more negatively affected by trade-war shocks, which also contribute to aggregate uncertainty during this period. In addition, investors may be reacting more aggressively to news about China-related stocks, which became more volatile and more connected to changing aggregate economic conditions following the start of the trade war (e.g., Mondria, 2010; Maćkowiak and Wiederholt, 2015; Kacperczyk, Van Nieuwerburgh and Veldkamp, 2016; Peng and Xiong, 2006; Kacperczyk, Nosal and Stevens, 2019).

[45]See Table OA.22 of the online appendix for summary statistics of the changes in portfolio weights for both the China-related stocks and China-unrelated stocks after the first announcement of a possible US-China trade war in March 2018.

Table 18: Mutual funds' rebalancing of the China-unrelated stocks following the unexpected announcement of a possible US-China trade war.

Panel A: Changes in portfolio weights after the unexpected trade war announcement

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)	
$\beta_{i,Dec2016}^{flow}$	−0.031***	−0.042**	−0.031***	−0.045**	−0.041***	−0.043**	−0.037**	−0.047***
	[−2.711]	[−2.298]	[−3.196]	[−2.463]	[−2.648]	[−2.472]	[−2.403]	[−2.592]
$\beta_{i,Dec2016}^{M}$	−0.054**	−0.074***	−0.057**	−0.076***	−0.057***	−0.048***	−0.061***	−0.051***
	[−2.166]	[−3.712]	[−2.339]	[−3.926]	[−3.411]	[−2.681]	[−3.937]	[−2.871]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110563	110063	110563	110063	156051	155156	156051	155156
R-squared	0.04	0.04	0.04	0.04	0.02	0.03	0.02	0.03

Panel B: Changes in portfolio weights assuming no price changes

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)	
$\beta_{i,Dec2016}^{flow}$	−0.027**	−0.051***	−0.029***	−0.059***	−0.030*	−0.033**	−0.033**	−0.043**
	[−2.280]	[−2.590]	[−2.866]	[−2.986]	[−1.918]	[−1.978]	[−2.071]	[−2.375]
$\beta_{i,Dec2016}^{M}$	−0.003	−0.042**	−0.006	−0.045**	−0.016	−0.044**	−0.020	−0.046**
	[−0.126]	[−2.117]	[−0.237]	[−2.312]	[−0.986]	[−2.352]	[−1.289]	[−2.487]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114054	113552	114054	113552	160608	159712	160608	159712
R-squared	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04

Note: This table shows how active mutual funds rebalance their China-unrelated portfolios after the unexpected announcement of a possible US-China trade war. In panel A, the dependent variable is the changes of portfolio weights in mutual funds after the unexpected trade war announcement in excess of the changes in the portfolio weights in the market portfolio. $\Delta(w_{i,f}-w_i^M) \equiv (w_{i,f,Dec2018}-w_{i,Dec2018}^M)-(w_{i,f,Dec2017}-w_{i,Dec2017}^M)$. Variable $w_{i,f,Dec2017}$ represents the weight of stock i in fund f in December 2017 (i.e., the quarter end prior to the announcement of a possible US-China trade war). Variable $w_{i,f,Dec2018}$ represents the weight of stock i in fund f in December 2018. Variable $w_{i,Dec2017}^M$ and $w_{i,Dec2018}^M$ represent the weight of stock i in the market portfolio in December 2017 and 2018, respectively. $\beta_{i,Dec2016}^{flow}$ is the standardized flow beta for stock i in December 2016 with a mean of 0 and a standard deviation of 1. We intentionally choose to use the flow beta in 2016 so that the cross-sectional variation in the flow beta is not related to the unexpected trade war announcement in March 2018. $\beta_{i,Dec2016}^{M}$ is the standardized market beta for stock i in December 2016 with a mean of 0 and a standard deviation of 1. In panel B, the dependent variable is the changes of portfolio weights in mutual funds after the unexpected trade war announcement, assuming stock prices are held constant at the levels of December 2017. $\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M) \equiv (\tilde{w}_{i,f,Dec2018}-w_{i,Dec2017}^M)-(w_{i,f,Dec2017}-w_{i,Dec2017}^M)$ where $\tilde{w}_{i,f,Dec2018}$ is the hypothetical portfolio weight of stock i held by fund f in December 2018 if stock prices are kept constant at the levels of December 2017. Standard errors are clustered at the fund level. Results remain robust if standard errors are clustered at the stock level, or double-clustered at both the fund level and the stock level. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

where $\Delta(w_{i,f}-w_i^M) \equiv (w_{i,f,Dec2018}-w_{i,Dec2018}^M)-(w_{i,f,Dec2017}-w_{i,Dec2017}^M)$, variable α_{ind} captures industry fixed effect, α_f represents fund-level fixed effect, and α_t is the time fixed effect. Further, $w_{i,f,Dec2017}$ and $w_{i,f,Dec2018}$ are stock i's weights in fund f's portfolio in December 2017 and 2018, respectively, and $w_{i,Dec2017}^M$ and $w_{i,Dec2018}^M$ are stock i's weights in the market portfolio in December 2017 and 2018, respectively.

As we show in panel A of Table 18, the coefficient of the flow beta, b_1, is significantly negative, which means that the weight of the China-unrelated high-flow-beta stocks decreases significantly relative to that of the China-unrelated low-flow-beta stocks. This result remains robust after we rule out the possibility that the portfolio weight adjustment is the result of certain industries becoming less attractive in the fear of the US-China trade war (using industry fixed effects).[46]

We focus on the set of China-unrelated stocks to mitigate the concern that portfolio rebalancing responds to the change in firm fundamentals as a result of the shock, and not to the change in the funds' exposures to the common flow shocks. One potential concern is that our definition does not adequately capture the set of China-related stocks because of the spill-over effect across the supplier-customer linkage. While it is unclear how the spill-over would affect the relation between the flow betas of China-unrelated stocks (i.e., $\beta_{i,t}^{flow}$) and their portfolio weight changes (i.e., $\Delta(w_{i,f,t} - w_{i,t}^{M})$), we address this issue empirically by excluding the suppliers and customers of the China-related firms from our analysis. As we show in Table OA.23 in the online appendix, our findings remain robust.

5 Conclusion

In this paper we develop the idea that endogenous aggregate fund flows induce hedging demand from active mutual 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

[46]To highlight that changes in portfolio weights result from funds' actions, and do not follow mechanically from changes in stock prices, while funds hold on to their original positions, we compute an alternative measure of portfolio weight variations by holding stock prices constant at the level of December 2017. Using this alternative measure, we again find that active mutual funds adjust their holdings of China-unrelated stocks toward the stocks with lower flow betas in response to the unexpected announcement of a possible US-China trade war (see panel B of Table 18).

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 understand the economic mechanisms behind the empirical relations between firm characteristics and fund flow betas. 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 stocks, a risk-free rate, R_f, a fund's net alpha process, α_t, offered by the fund, 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 (2.9) subject to (2.10);

(i.b) each fund client's consumption $C_{c,t}$ and delegation decision (portfolio strategy) q_t are optimal in terms of maximizing the utility in (2.9) subject to (2.13);

(i.c) each fund manager's consumption $C_{m,t}$ and portfolio strategy $\phi_{m,t}$ is optimal in terms of maximizing the utility in (2.9) subject to (2.17);

(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: $\psi^{-1}(\overline{\alpha} - \alpha_t - f) = q_t$;

(ii.c) assets market: $Q_t\phi_{m,t} + [W_{d,t} - C_{d,t} - \overline{\alpha}Q_t]\,\phi_{d,t} \;=\; [W_{d,t} - C_{d,t} + (1-\overline{\alpha})Q_t]\,\phi_{M,t}$*, where* $\phi_{M,t}$ *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 demand curve of delegation (2.8), and the supply curve of delegation (2.15) results from the optimization condition (i.b). The market clearing condition (ii.c) effectively characterizes the market portfolio in the economy, leading to the relation among the market portfolio, the myopic portfolio, and the active fund's portfolio, summarized in Theorem 1.

Log-Linear Approximation. We use a log-linear approximation to characterize the equilibrium relation among consumption, portfolio holdings, and asset prices analytically. The log return vector, $r_{t+1} \equiv \log(R_{t+1})$, can be expressed as

$$r_{t+1} \approx L z_{t+1} - z_t + \Delta d_{t+1} + \ell, \tag{A.1}$$

where $z_t = \ln(P_t/D_t)$ is the $n \times 1$ vector of log price-dividend ratios with elements $z_{i,t} = \ln(P_{i,t}/D_{i,t})$. The matrix L in (A.1) is a $n \times n$ diagonal matrix with the ith diagonal element equal to $L_i = e^{\overline{z}_i}/(1+e^{\overline{z}_i}) \in (0,1)$, where $\overline{z}_i$ is the long-run average of the log price-dividend ratio for asset i. The vector ℓ in (A.1) is a $n \times 1$ vector with the ith element equal to $\ell_i = -\ln(L_i) + (1-L_i)\ln(1/L_i - 1)$.