Common Fund Flows:
Flow Hedging and Factor Pricing

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Abstract

Active mutual fund managers care about fund size, which is affected by common fund flows driven by macroeconomic shocks. Fund managers hedge against common flow shocks by tilting their portfolios toward low-flow-beta stocks. In equilibrium, common flow shocks earn a risk premium. A multi-factor asset pricing model similar to the ICAPM arises, even with all agents behaving myopically. 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: Mutual fund flow, Factor model, Heterogeneous agents, Financial Intermediaries, Natural disasters, 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 tilting

[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)).

their portfolios away from the stocks with high flow betas. 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 common 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 motive, we use two quasi-natural experiments to see how funds respond to changes in the

[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.

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 common 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 the supply curve of delegate investment assets simultaneously reduces the size of the funds'

[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.

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 common 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). In a recent paper, Gabaix and Koijen (2020) 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 The Model

We introduce fund managers and delegated investment management into a discrete-time, infinite-horizon, overlapping-generations (OLG) exchange economy with multiple risky assets, one risk-free asset, and a single perishable consumption good. Instead of deriving the optimal compensation contracts to fund managers in our general equilibrium framework, we postulate a simple specification of compensation contracts, which is strongly supported in the data. In particular, we specify the compensation structure of fund managers based on the estimation of Ibert et al. (2018). Our model is set up based on the framework of portfolio choice and asset pricing, and we use a loglinear approximation to derive analytical results (e.g., Campbell, 1993; Campbell and Viceira, 1999, 2001).[7] In what follows, we introduce our simple model, define the equilibrium concept, and derive the theoretical properties.

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 risky assets can be viewed

[7] Also see, e.g., Campbell and Shiller (1988), Cochrane (1992), and Engsted, Pedersen and Tanggaard (2012).

as n Lucas trees that produce fruits $D_t = [D_{1,t}, \cdots, D_{n,t}]^T$ in period t.

We assume that the number of assets in this economy is large, and assume that 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). In particular, the number of assets is much larger than the number of primitive factors, i.e., $1 \leq k \ll n$. The $n \times k$ matrix B captures the loading coefficients of log dividend growth Δd_{t+1} on factors u_{t+1}. By postulating distributional structure (2.1) for log dividend growth, we assume that the covariance matrix of assets' cash flows is mainly captured by that of a few dominant factors, similar to many other multi-asset portfolio choice and asset pricing models (e.g., Kozak, Nagel and Santosh, 2018; Koijen and Yogo, 2019). This assumption is consistent with the empirical evidence documented by Ball, Sadka and Sadka (2009), who show that there is a strong factor structure in firms' fundamentals.

The time-varying uncertainty is characterized by univariate state variable h_t, which is driven by k aggregate shocks u_t as follows:[8]

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

Without loss of generality, we assume that k-dimensional vector σ has positive elements.

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 $R_f > 1$.[9] 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 $R_{t+1} = [R_{1,t+1}, \cdots, R_{n,t+1}]^T$.

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

$$r_{t+1} \approx L z_{t+1} - z_t + \Delta d_{t+1} + \ell, \tag{2.3}$$

[8] We assume that the variances follow AR(1) processes. We do this to simplify exposition. h_t may become negative, although this happens rarely under reasonable calibrations. In the simulation, we impose a small positive lower bound on h_t, as in the works of Bansal and Yaron (2004) and Chen, Dou and Kogan (2019).

[9] We fix the risk-free rate in the model for tractability. This assumption is not unreasonable for the US market, where US Treasuries are largely held and traded by foreign investors, and the risk-free rate is not determined entirely by domestic demand (e.g., Gourinchas and Rey, 2007; Caballero, Farhi and Gourinchas, 2008; Dou and Verdelhan, 2017).

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

We conjecture that the log price-dividend ratio is an affine function of the aggregate state variable h_t:

$$z_t \approx \zeta + \zeta_h(h_t - \bar{h}), \tag{2.4}$$

where $\zeta, \zeta_h \in \mathbb{R}^n$ are constant vectors to be determined in equilibrium.

Based on the representation of log returns in (2.3) and the equilibrium log price-dividend ratio in (2.4), equilibrium log returns r_{t+1} can thus be characterized as follows. The proof is in Online Appendix 1.1.

Proposition 2.1 (Log returns of risky assets)**.** *The equilibrium log stock returns are*

$$r_{t+1} \approx \mu_t + \sqrt{h_t}\left(Ku_{t+1} + \varepsilon_{t+1}\right), \tag{2.5}$$

where $\mu_t \in \mathbb{R}^n$ is the conditional expected log return given the information set up to time t, and $K \in \mathbb{R}^{n\times k}$ captures stock returns' systematic risk exposure:

$$\mu_t = [\mu + \ell + (L - I_n)\zeta] + (\rho L - I_n)\zeta_h(h_t - \bar{h}) \ \text{ and } \ K = L\zeta_h\sigma + B, \tag{2.6}$$

where μ and B are defined in (2.1), ρ and σ are defined in (2.2), ℓ and L are defined in (2.3), and ζ and ζ_h are defined in (2.4). The variance-covariance matrix of the log returns is

$$\Sigma_t = h_t\Sigma, \ \text{ with } \ \Sigma = I_n + KK^T. \tag{2.7}$$

Next, we approximate the portfolio's log return. Let $r_f = \ln\left(R_f\right)$ denote the log risk-free interest rate and $r_{t+1}(\phi) = \ln\left[R_{t+1}(\phi)\right]$ denote the log return of the portfolio with weights $\phi \in \mathbb{R}^{n\times 1}$. Then, we approximate the portfolio's log return as

$$r_{t+1}(\phi) \approx r_f + \phi^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi^T\left(v_t - \Sigma_t\phi\right), \tag{2.8}$$

where $v_t \equiv \mathrm{diag}(\Sigma_t)$ is the vector that contains the diagonal elements of Σ_t, and $\mathbf{1} \in \mathbb{R}^{n\times 1}$ is a vector on ones.

A Non-Arbitrage Condition. If $h_t = 0$, all assets are risk-free during period t. Thus, the conditional expected returns in μ_t all equal risk-free rate r_f. Therefore, according to (2.6), the log risk-free rate must satisfy

$$r_f = [\mu + \ell + (L - I_n)\zeta] - (\rho L - I_n)\zeta_h \bar{h}. \tag{2.9}$$

Below, we derive the expression for the conditional expected log excess return, which is approximately proportional to the stochastic variance h_t (see Online Appendix 1.2 for proof).

Proposition 2.2 (Expected log excess return.)**.** *The equilibrium expected log excess return is*

$$\mu_t - r_f \mathbf{1} \approx (\rho L - I_n)\zeta_h h_t, \tag{2.10}$$

where $\mu_t = \mathbb{E}_t [r_{t+1}]$ is expected log return defined in (2.6), and ρ, L, and ζ_h are defined in (2.2), (2.3), and (2.4), respectively.

2.2 Funds

To focus on the common component of fund flow shocks, we assume that the funds are homogenous.[10] The funds are typically active mutual funds and pension management, while fund clients are typically individual investors and pension sponsors. Funds can trade all assets freely, and they charge an advisory fee from fund clients. The advisory fee is a constant $f > 0$ fraction of AUM.[11]

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 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.[12] More precisely, the value that a mutual fund extracts from capital markets is essentially a transfer of wealth from passive to active funds at least in the following three

[10] Heterogenous funds have been considered in studies on cross-fund flows (e.g., Berk and Green, 2004; Barber, Huang and Odean, 2016; Berk and van Binsbergen, 2015; Roussanov, Ruan and Wei, 2020*a*).

[11] 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).

[12] 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. Further, some researchers have argued that active fund managers can create value to investors, even without compromising the passive funds, by improving the efficiency of the capital market as a whole (i.e., it is not a zero-sum game).

ways. 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).

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

$$\Psi(q) \equiv \theta^{-1}q^{1+\xi}, \text{ with } \xi > 0. \tag{2.11}$$

Our specification implies decreasing return to scale for the active funds.[13]

The expected excess total payout by the active funds to their clients is

$$TP_t = \overbrace{\overline{\alpha}Q_t - \Psi(q_t)W_t}^{\text{net gain of funds}} - fQ_t, \tag{2.12}$$

[13] The literature has advanced two hypotheses regarding the nature of the convex operating cost. The first one is fund-level decreasing returns to scale: as the size of an active fund increases, the fund's ability to outperform its benchmark declines (e.g., Perold and Salomon, 1991; Berk and Green, 2004). The second hypothesis is industry-level decreasing returns to scale: as the size of the active mutual fund industry increases, the ability of any given fund to outperform declines (Pástor and Stambaugh, 2012; Pástor, Stambaugh and Taylor, 2015). Both hypotheses are motivated by the price impact of trading and they are not mutually exclusive. At the fund level, a larger fund's trades have a larger impact on asset prices, eroding the fund's performance. At the industry level, as more money chases opportunities to outperform, prices move, making such opportunities more elusive. Consistent with such price impact of trading, there is mounting evidence showing that trading by mutual funds can exert meaningful price pressure in equity markets. Edelen and Warner (2001) and Ben-Rephael, Kandel and Wohl (2011) find that aggregate flow into equity mutual funds has an impact on aggregate market returns. Coval and Stafford (2007), Edmans, Goldstein and Jiang (2012), Khan, Kogan and Serafeim (2012), and Lou (2012) also find significant firm-level price impact associated with mutual fund trading. Edelen, Evans and Kadlec (2007) argue that trading costs are a major source of diseconomies of scale for mutual funds.

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 in period t.

We define the net alpha as $\alpha_t \equiv \frac{TP_t}{Q_t}$, which is the expected return received by the fund clients in period t in excess of the benchmark return:

$$\alpha_t = \overline{\alpha} - \psi(q_t) - f, \tag{2.13}$$

where $\psi(q_t) \equiv \Psi(q_t)/q_t = \theta^{-1}q_t^{\xi}$. We assume that $\xi = 1$ for the rest of this paper, and thus, the relation (2.13) can be rewritten as a linear relation between the amount of asset management service supplied by funds and the net alpha:

$$q_t = \theta(\overline{\alpha} - \alpha_t) - \theta f. \tag{2.14}$$

2.3 Agents

Different Types of 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. Fund clients, labeled by c, can choose to delegate their investment to professional fund managers. 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 direct investor or fund client 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). Each fund manager consumes all her compensation within the period.

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. The newly-born fund managers have a unit measure of population but zero endowment.

We adopt an overlapping-generation framework to avoid tracking the wealth shares as endogenous state variables when characterizing the equilibrium.[14] Moreover, we assume that agents in our model do not internalize their descendants' utility.[15] As a result, agents are myopic. To simplify the consumption policy, we set agents' EIS to 1. At the same time, we do not restrict the relative risk aversion, γ.

Direct Investors. The direct investor's wealth is $W_{d,t} = (1-\lambda)W_t$. Direct investors solve a standard optimal portfolio problem. Denoting by $\phi_{d,t}$ the optimal portfolio weights of time t investable wealth $W_{d,t} - C_{d,t}$, we have

$$U_d(W_{d,t}) = \max_{\phi_{d,t}, C_{d,t}} (1-\beta)\ln(C_{d,t}) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left[W_{d,t+1}^{1-\gamma} \right], \tag{2.15}$$

subject to the dynamic budget constraint:

$$W_{d,t+1} = (W_{d,t} - C_{d,t} - \overline{\alpha} Q_t) \left[R_f + \phi_{d,t}^T (R_{t+1} - R_f) \right]. \tag{2.16}$$

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

Proposition 2.3 (Direct investors)**.** *The optimal consumption of direct investors is*

$$C_{d,t} = (1-\beta)(1-\lambda-\overline{\alpha} q_t) W_t, \tag{2.17}$$

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

$$\phi_{d,t} = \frac{1}{\gamma} \Sigma_t^{-1} \left(\mu_t - r_f \mathbf{1} + \frac{1}{2} \nu_t \right), \tag{2.18}$$

where μ_t and Σ_t are defined in Proposition 2.1, and ν_t contains the diagonal elements of Σ_t.

See Online Appendix 1.3 for the proof in detail.

[14] Such a simplification assumption is innocuous in the sense that Kaniel and Kondor (2013) show that the constant wealth share of fund clients can endogenously arise as an equilibrium outcome.

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

Fund Clients. Fund clients decide the amount of wealth to delegate to the funds, 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 behave myopically and do not hold rational expectations about funds' strategies. In particular, fund clients in our model do not properly anticipate that portfolios of fund managers depend on the delegation choice of the next generation of fund clients. Instead, we assume that fund clients care about the net alpha of the active managers relative to investing in the passive benchmark.[16] The fund clients are also free to become direct investors and manage their own portfolios.

We assume that the fund clients solve the following problem:

$$U_c(W_{c,t}) = \max_{C_{c,t},Q_t} (1-\beta)\ln(C_{c,t}) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left[(W_{c,t+1} + \omega Q_t)^{1-\gamma} \right], \tag{2.19}$$

subject to the budget constraint:

$$W_{c,t+1} = (W_{c,t} - C_{c,t})R_f + Q_t[R_{t+1}(\phi_{d,t}) + \alpha_t - R_f], \tag{2.20}$$

and the participation constraint:

$$U_c(W_{c,t}) \geq U_d(W_{c,t}). \tag{2.21}$$

The utility function in (2.19) contains the non-pecuniary benefit ωQ_t echoing the important insight that the net alpha in the eyes of a fund client depends on the client's specific utility of delegation (e.g., Ferson and Lin, 2014). And more specifically, the non-pecuniary benefit ωQ_t can be interpreted as the trust in active managers perceived by fund clients (Gennaioli, Shleifer and Vishny, 2015). The wealth evolution according to budget constraint (2.20) is intuitive. The fund client consumes $C_{c,t}$ out of wealth $W_{c,t}$, invests $W_{c,t} - C_{c,t} - Q_t$ to the risk-free bond, and delegates Q_t to the fund manager with perceived return $R_{t+1}(\phi_{d,t}) + \alpha_t$ and additional non-pecuniary benefit ωQ_t. The participation constraint (2.21) recognizes that

[16] 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.

fund clients are free to switch to direct investors, and it needs to hold to ensure that fund clients would decide to trust the active funds and delegate their investment management. When the term, ωQ_t, is sufficiently large, fund clients would choose to delegate their investment management even when the net alpha α_t is negative.

The following proposition characterizes the optimal consumption and delegation decision of fund clients.

Proposition 2.4 (Fund clients)**.** *If the perceived benefit from active management is sufficiently large relative to the cost of delegation, i.e., $\overline{\alpha} + \omega > \theta^{-1}\beta\lambda + f$, fund clients choose to delegate their portfolios to the active funds. In this case, the optimal consumption of fund clients is*

$$C_{c,t} = (1-\beta)\lambda W_t, \tag{2.22}$$

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

$$q_t = \beta\lambda\left(1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}\right), \tag{2.23}$$

where ω is the non-pecuniary benefit as in (2.19), and the term $\overline{\gamma}h_t$ captures the effective risk aversion with $\overline{\gamma} \equiv \left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]^T \Sigma^{-1}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]$, and $\nu \equiv \mathrm{diag}(\Sigma)$. Here ρ, L, and ζ_h are defined in (2.2), (2.3), and (2.4), respectively.

In our theory, delegation to active funds is endogenously caused by (i) the net alpha of the active asset management α_t, (ii) the non-pecuniary benefit of the fund client, ω, and (iii) the degree to which the excess return incentivizes the investors to delegate their wealth to active asset management, captured by economic uncertainty h_t. The proof of Proposition 2.4 is in Online Appendix 1.4.

Fund Managers. Quantity Q_t is a fund manager's AUM at the beginning of period t. For each t, the fund manager of cohort $t-1$ and that of cohort t collect compensation $C_{m,t} = \frac{1}{2} f Q_t$ in period t. Thus, the total compensation for two generations of fund managers is fQ_t in period t. Similar compensation specification has been adopted in the literature.[17] Following the literature, we take the compensation specification between the fund complex and the fund manager as exogenously given in the spirit of Shleifer and Vishny (1997), instead of deriving the incentive contracts from first principles. Importantly, motivated by the empirical

[17] 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).

findings of Ibert et al. (2018), we consider the compensation contract specification, which mainly depends on the AUM Q_t.[18]

Moreover, we assume that the manager must consume her compensation each period. This assumption has been adopted in the literature (e.g., Berk and Green, 2004; Cuoco and Kaniel, 2011; Kaniel and Kondor, 2013) for technical simplicity, which allows us to avoid keeping track of the fund manager's private wealth, and modeling her private investment decisions. Under this assumption, the fund manager invests delegated funds Q_t in a portfolio with weights $\phi_{m,t}$ on the n risky assets and $1 - \phi_{m,t}^T \mathbf{1}$ in the risk-free bond.

The optimal consumption and portfolio choice solve the following two-period optimization problem:

$$\max_{\phi_{m,t}} (1-\beta)\ln(C_{m,t}) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left[C_{m,t+1}^{1-\gamma} \right], \tag{2.24}$$

with $C_{m,t} = \frac{1}{2} f Q_t$, $C_{m,t+1} = \frac{1}{2} f Q_{t+1}$, and subject to the dynamic budget constraint of the fund's AUM:

$$Q_{t+1} = \underbrace{Q_t \left[R_{t+1}(\phi_{m,t}) + \alpha_t \right]}_{\text{fund returns}} + \underbrace{Q_t flow_{t+1}}_{\text{fund flows}}, \tag{2.25}$$

where Q_t is the delegation characterized in (2.23) 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.

Equation (2.25) essentially gives the definition of the fund flow, denoted by $flow_{t+1}$:

$$flow_{t+1} \equiv \frac{Q_{t+1} - Q_t \left[R_{t+1}(\phi_{m,t}) + \alpha_t \right]}{Q_t}. \tag{2.26}$$

The dynamic budget constraint in equation (2.25) 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

[18]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.

focus stemming from their career concerns (e.g., Prat, 2005; Hermalin and Weisbach, 2012).

2.4 Equilibrium

Fund flow $flow_{t+1}$ and net alpha α_t after fees are endogenous, driven by aggregate shocks in a predictable way in equilibrium. Below, we describe how fund flows depend on fund managers' portfolio $\phi_{m,t}$ and aggregate shocks u_t.

Equilibrium Delegation and Endogenous Flows. Market clearing in the market for delegated funds is described by the two relations between the total amount of delegated capital and the net alpha – the first describing the alpha production technology of mutual funds, and the second describing the delegation decision of fund clients:

$$q_t = \theta(\overline{\alpha} - f) - \theta\alpha_t \quad \text{(funds' supply for asset management service)},$$
$$q_t = \beta\lambda\left(1 + \frac{\omega + \alpha_t}{\overline{\gamma}h_t}\right) \quad \text{(clients' demand for asset management service)}.$$

Proposition 2.5 below summarizes the solution.

Proposition 2.5 (Equilibrium delegation and alpha)**.** *The equilibrium amount of delegation q_t and the net alpha α_t are given by*

$$\alpha_t = -\omega + \frac{\theta(\overline{\alpha} + \omega - f) - \beta\lambda}{\theta + \beta\lambda/(\overline{\gamma}h_t)} \quad \textit{and} \quad q_t = \beta\lambda\left[1 + \frac{\theta(\overline{\alpha} + \omega - f) - \beta\lambda}{\theta\overline{\gamma}h_t + \beta\lambda}\right], \tag{2.27}$$

where ω is the non-pecuniary benefit term in (2.19), $\overline{\gamma}$ is defined in (2.23), and gross alpha $\overline{\alpha}$, cost coefficient θ, and advisory fee f are defined in Section 2.2.

Corollary 2.1 (Countercyclical net alpha and pro-cyclical delegation)**.** *When the benefits from active management are large relative to the cost of delegation, i.e., $\overline{\alpha} + \omega > \theta^{-1}\beta\lambda + f$, the equilibrium net alpha of funds is countercyclical and the equilibrium delegation is pro-cyclical. That is, α_t rises and q_t declines as uncertainty h_t increases:*

$$\frac{\partial\alpha_t}{\partial h_t} > 0 \quad \textit{and} \quad \frac{\partial q_t}{\partial h_t} < 0. \tag{2.28}$$

With the characterization of equilibrium delegation q_t, we are now ready to characterize the endogenous fund flows in equilibrium. We first conjecture the equilibrium aggregate fund flow

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t}Au_{t+1}, \tag{2.29}$$

where $\mathbb{E}_t\left[flow_{t+1}\right] \in \mathbb{R}$ and $A \in \mathbb{R}^{1\times k}$ are to be determined in the equilibrium. According to (2.25), the process of fund flows can be approximated as shown in Proposition 2.6, whose proof is in Online Appendix 1.6.

Proposition 2.6 (Equilibrium aggregate fund flows)**.** *The exposure of common fund flows to the aggregate primitive shocks satisfies*

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma + \left[1-\eta(\bar{h})\right] AK^T \left(I_n + KK^T\right)^{-1} K, \tag{2.30}$$

and thus, the exposure of common fund flows to the aggregate primitive shocks is

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma \left\{ I_k - \left[1-\eta(\bar{h})\right] K^T \left(I_n + KK^T\right)^{-1} K \right\}^{-1}, \tag{2.31}$$

where $\eta(\bar{h}) \equiv q(\bar{h}) / \left[(1-\lambda)\beta + (1-\overline{\alpha})q(\bar{h})\right]$ *and* $\eta(h_t)$ *captures the endogenous delegation intensity, which is derived in Theorem 2 below.*

According to Corollary 2.1, each element of $\frac{q'(\bar{h})}{q(\bar{h})}\sigma$ is negative, which captures the negative relation between primitive shocks and changes in equilibrium delegation q_t, as well as the mechanical relation between fund flows and fund size, q_t. Because the $k \times k$ matrix $\left[1-\eta(\bar{h})\right] K^T \left(I_n + KK^T\right)^{-1} K$ is positive definite, Proposition 2.6 shows that the flow-hedging portfolio held by the active fund managers has a dampening effect on the sensitivity of fund flows to primitive shocks in equilibrium (i.e., the magnitude of A decreases in $\eta(\bar{h})$). Meanwhile, the eigenvalues of $\left[1-\eta(\bar{h})\right] K^T \left(I_n + KK^T\right)^{-1} K$ are all between 0 and 1, and thus, exposure of fund flows to aggregate primitive shocks exists and is (approximately) equal to the quantity in (2.31). We emphasize the endogenous nature of fund flows, which is manifested by the fact that the endogenous steady-state delegation intensity is determined by the market clearing condition of competitive equilibrium illustrated in Theorem 2 below.

Theorem 1 shows that the optimal portfolio of the fund manager has two components — a myopic and a flow-hedging component. See Online Appendix 1.7 for proof.

Theorem 1 (Equilibrium fund portfolio)**.** *Fund managers hold a tilted portfolio to hedge against fluctuations in fund flows at the cost of a reduced Sharpe ratio:*

$$\phi_{m,t} = \phi_{d,t} - \phi_{\tau,t}, \tag{2.32}$$

where the optimal portfolio of the fund manager, $\phi_{m,t}$*, is different from that of the direct investors,* $\phi_{d,t}$

(i.e., the mean-variance efficiency portfolio), and the portfolio tilt of active fund $\phi_{\tau,t}$ is the hedging demand for the common fund flow:

$$\phi_{\tau,t} = \Sigma_t^{-1}\mathcal{B}_t. \tag{2.33}$$

Here, $\mathcal{B}_t \equiv Cov_t\left[r_{t+1}, flow_{t+1}\right]$ is the vector of fund flow betas, and in equilibrium, $\mathcal{B}_t = \mathcal{B}h_t$ with $\mathcal{B} \approx KA^T \in \mathbb{R}^{n\times 1}$. Subscript τ in $\phi_{\tau,t}$ stands for tilting.

The main theoretical result of this paper is that the portfolio tilt of the active fund relative to the benchmark is, on average, greater when the common fund flow beta is higher. We formalize this insight in Corollary 2.2, whose proof can be found in Online Appendix 1.8.

Corollary 2.2 (Portfolio tilt and common flow beta)**.** *The cross-sectional covariance between the two n-dimensional vectors $\mathcal{B}_t$ and $\phi_{\tau,t}$ is always positive:*

$$Cov\left[\mathcal{B}_t, \phi_{\tau,t}\right] > 0, \quad \text{for each } t. \tag{2.34}$$

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 2.1 (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 $C_{c,t}$ and $C_{d,t}$ of investors, and portfolio processes $\phi_{d,t}$, $\phi_{m,t}$, and q_t of investors 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 (2.15) subject to (2.16);

(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 (2.19) subject to (2.20);

(i.c) each fund manager's portfolio strategy $\phi_{m,t}$ is optimal in terms of maximizing the utility in (2.24) subject to (2.25);

(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: $\sum_{i=1}^{n} D_{i,t} = C_{d,t} + C_{c,t} + fQ_t + \Psi(q_t)W_t$;

(ii.b) *delegation market:* $\psi^{-1}(\overline{\alpha} - \alpha_t - f) = q_t$;

(ii.c) *assets market:* $Q_t\phi_{m,t} + [W_{d,t} - C_{d,t} - \overline{\alpha}Q_t]\,\phi_{d,t} = [W_{d,t} - C_{d,t} + (1-\overline{\alpha})Q_t]\,\phi_{M,t}$.

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., $C_{d,t} + C_{c,t} + fQ_t$) 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 (2.14), and the supply curve of delegation (2.23) 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 2.

The great contribution of the CAPM theory is to connect systematic risk to return covariance with the market portfolio returns, which can be approximated in the data. Considering the deviation of active equity mutual funds' holdings $\phi_{m,t}$ from the market portfolio, $\phi_{M,t}$, we can construct useful empirical tests for our fund flow hedging results. Specifically, the testable implication can be summarized in Theorem 2. See Online Appendix 1.9 for proof.

Theorem 2 (Portfolio tilt from the market portfolio and common flow beta)**.** *The fund managers hold a tilted portfolio to hedge against fluctuations in fund flows, relative to the market portfolio:*

$$\phi_{m,t} = \phi_{M,t} - (1-\eta_t)\phi_{\tau,t}, \tag{2.35}$$

where $\eta_t = \eta(h_t) \equiv q_t / [(1-\lambda)\beta + (1-\overline{\alpha})q_t] \in [0,1]$*, and portfolio tilt of an active fund* $(1-\eta_t)\phi_{\tau,t}$ *is the additional hedging demand for the common fund flow relative to the market portfolio, with* $\phi_{\tau,t}$ *defined in (2.33). Thus, the cross-sectional covariance between the deviation of fund holdings from the market portfolio and the common flow beta is always negative:*

$$Cov\left[\mathcal{B}_t, \phi_{m,t} - \phi_{M,t}\right] < 0, \quad \textit{for each } t. \tag{2.36}$$

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 3 is based on Theorem 1 and the market clearing condition of risky assets, and its proof is in Online Appendix 1.10.

Theorem 3 (Conditional two-beta asset pricing model)**.** *For any portfolio* $r_{t+1}(\phi) = \phi^T r_{t+1}$ *with* $\mathbf{1}^T\phi = 1$*, the risk premium is explained by the covariance with the market return, denoted by*

$r_{t+1}(\phi_{M,t})$*, and the covariance with the common fund flow, denoted by* $flow_{t+1}$*:*

$$\mathbb{E}_t\left[r_{t+1}(\phi)\right] - r_f + \frac{1}{2}\phi^T \nu_t \approx \underbrace{\gamma Cov_t\left[r_{t+1}(\phi),\ r_{t+1}(\phi_{M,t})\right]}_{\textit{explained by market beta}} + \underbrace{\eta_t \gamma Cov_t\left[r_{t+1}(\phi),\ flow_{t+1}\right]}_{\textit{explained by flow beta}},$$

where $\frac{1}{2}\phi^T \nu_t$ *is the Jensen's term and* η_t *is defined in Theorem 2.*

If $\mathrm{Cov}_t\left[r_{t+1}(\phi),\ flow_{t+1}\right] < 0$, portfolio ϕ provides a natural hedging against fluctuations in the common fund flow.

Corollary 2.3 (CAPM holds when there is no delegation)**.** *When there is no delegation in the economy, i.e.,* $\lambda = 0$*, Theorem 3 implies the conditional CAPM:*

$$\mathbb{E}_t\left[r_{t+1}(\phi)\right] - r_f + \frac{1}{2}\phi^T \nu_t \approx \gamma Cov_t\left[r_{t+1}(\phi),\ r_{t+1}(\phi_{M,t})\right]. \tag{2.37}$$

It further implies that the CAPM holds:

$$\mathbb{E}\left[r_{t+1}(\phi) - r_f + \frac{1}{2}\phi^T \nu_t\right] \approx \beta_M(\phi)\Lambda. \tag{2.38}$$

where $\beta_M(\phi) \equiv Cov\left[r_{t+1}(\phi),\ \hat{r}_{t+1}(\phi_{M,t})\right] / Var\left[\hat{r}_{t+1}(\phi_{M,t})\right]$ *is the market beta with* $\hat{r}_{t+1}(\phi_{M,t}) \equiv r_{t+1}(\phi_{M,t}) - \mathbb{E}_t\left[r_{t+1}(\phi_{M,t})\right]$*, and* $\Lambda \equiv \gamma\bar{h}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]^T \Sigma^{-1}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]$ *is the market price of risk.*

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 2.5, 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 proof of Corollary 2.3 is in Online Appendix 1.11.

Corollary 2.4 (Multifactor asset pricing)**.** *The primitive aggregate shocks are correlated with the common component of fund flows, so they are priced in the cross section just as in the ICAPM framework:*

$$\mathbb{E}_t\left[r_{t+1}(\phi)\right] - r_f + \frac{1}{2}\phi^T \nu_t \approx \gamma Cov_t\left[r_{t+1}(\phi),\ r_{t+1}(\phi_{M,t})\right] + \sum_{j=1}^{k} \eta_t \gamma A_j \sqrt{h_t} Cov_t\left[r_{t+1}(\phi),\ u_{j,t+1}\right],$$

where $\frac{1}{2}\phi^T \nu_t$ *is the Jensen's term,* A_j *is the j-th element of A, and* η_t *is defined in 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.[19] We further identify and exclude index funds based on their names and the index fund identifiers in the CRSP data.[20] 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.[21] Around 63% of fund share-month observations in the CRSP panel data are matched with the Morningstar data.

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

[19] 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.

[20] 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), we also define a fund as an index fund if its name contains any of the following text strings: Index, Ind, Idx, Indx, Mkt, Market, Composite, S&P, SP, Russell, Nasdaq, DJ, Dow, Jones, Wilshire, NYSE, iShares, SPDR, HOLDRs, ETF, Exchange-Traded Fund, PowerShares, StreetTRACKS, 100, 400, 500, 600, 1000, 1500, 2000, 3000, 5000.

[21] 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).

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 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).

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 common 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. A mutual fund often offers multiple share classes with different fee structures and minimum investment requirements. These share classes cater to investors with different investment horizons and wealth levels. We perform our main analysis of fund flow shocks at the level of fund share classes, following previous studies (e.g., Chen, Goldstein and Jiang, 2010; Goldstein, Jiang and Ng, 2017). This is because we want to extract the common component of fund flow shocks across different investors. Specifically, we define flows at the level of fund share class 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 share class 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.

Because fund flows respond to past fund performance,[22] we control for the flow-performance sensitivity to construct the unpredictable component in fund flows. 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:[23]

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

where $ExRet_{i,t}$ is the fund share excess return relative to the market return, R_t^M, over month t, 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 share class level as follows:

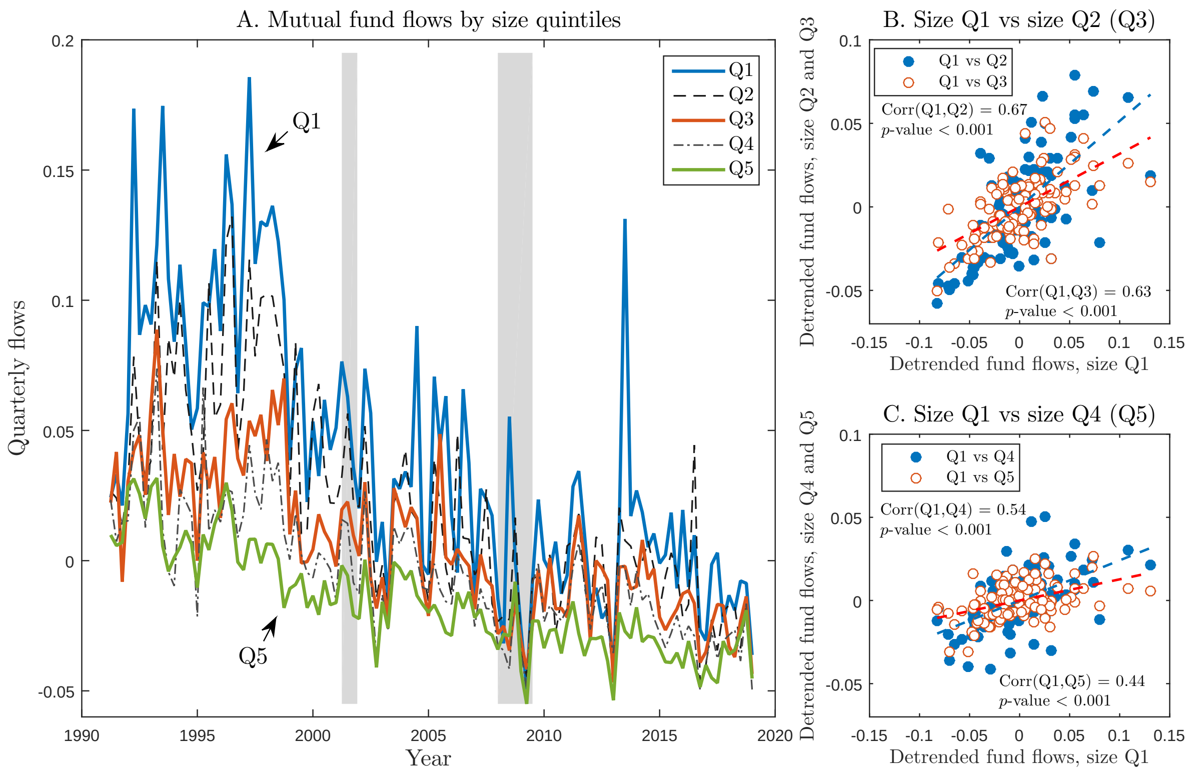
$$flow_{i,t} = \theta_t + \varepsilon_{i,t}. \tag{4.3}$$

In Online Appendix 2, we conduct robustness analysis by aggregating flows of all fund share classes that belong to the same fund and addressing the concern on the incubation bias suggested by previous research (see Evans, 2010). Our results are robust when considering fund-level flows and dealing with the incubation bias.

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

[22] 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*b*).

[23] 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.



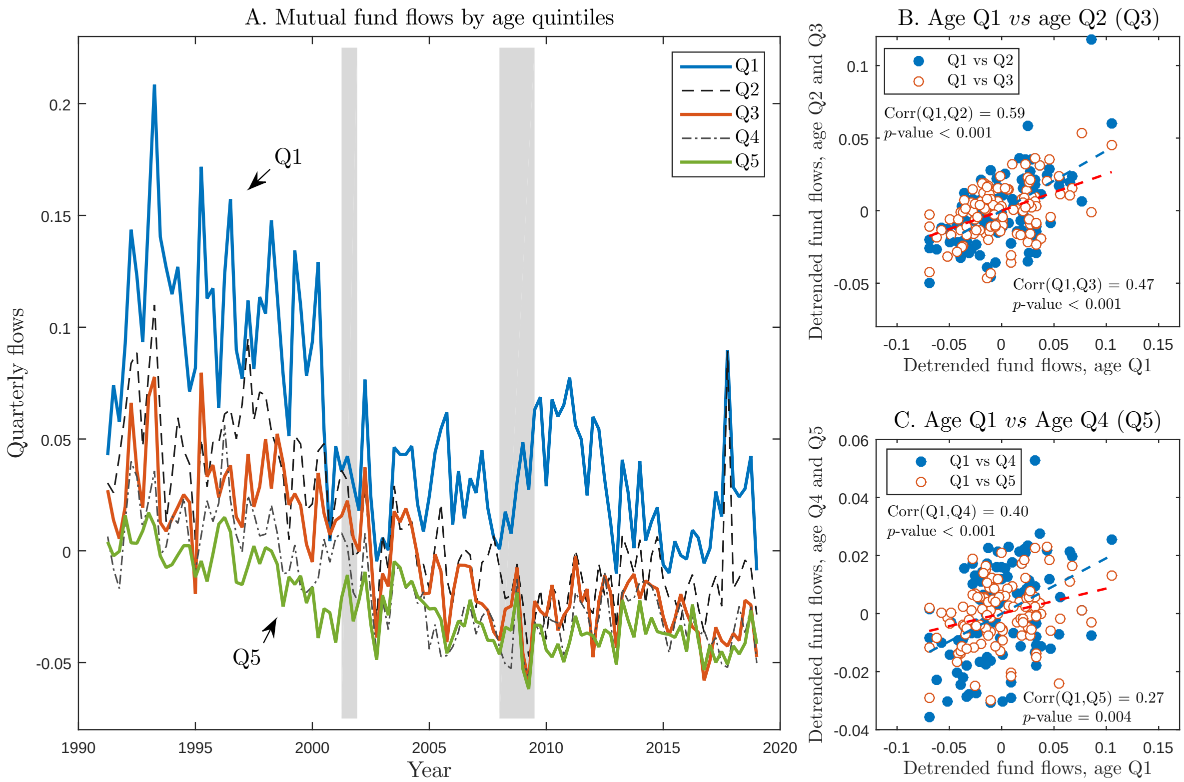
Note: Panel A plots active mutual fund flows by quintiles sorted on asset size of fund shares after removing relative performance. We control for the flow-performance sensitivity at the fund share class level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the National Bureau of Economic Research (NBER) recession periods. Panels B and C plot the detrended flows of the fund shares with smallest asset (Q1) 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 fund shares 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 fund shares 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.[24]

[24]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 by Pástor, Stambaugh and Taylor (2019). Similar to asset size and age, we find that fund flow shocks



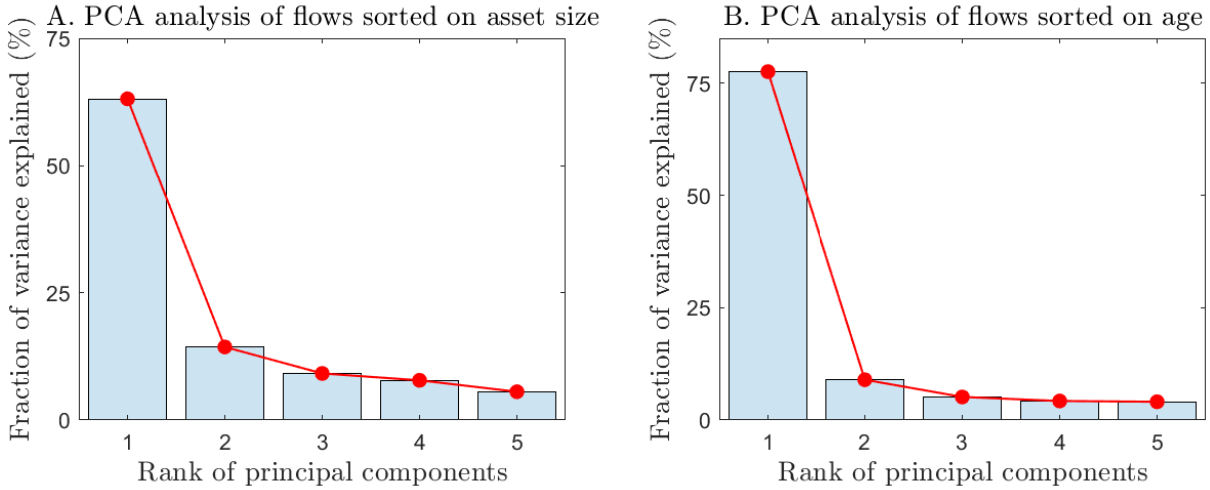
Note: Panel A plots active mutual fund flows by quintiles sorted on the age of fund shares after removing relative performance. We measure the age of fund shares by the number of years since the inception dates. We control for the flow-performance sensitivity at the fund share class level. The lines 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 youngest fund shares (Q1) 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 fund shares sorted on asset size. It is clear that fund flow shocks comove across different fund share classes with different asset sizes. Panels B and C of Figure 1 plot the detrended fund flows of quintile 1 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 1 and 2 is 0.67 with p-value < 0.001, and that of size quintiles 1 and 5 is 0.44 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 fund shares sorted on age. The same high-frequency comovement across different groups of fund flow shocks with different ages robustly shows

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 share age presented in panel A.

Figure 3: Eigen-decomposition of flow covariance.

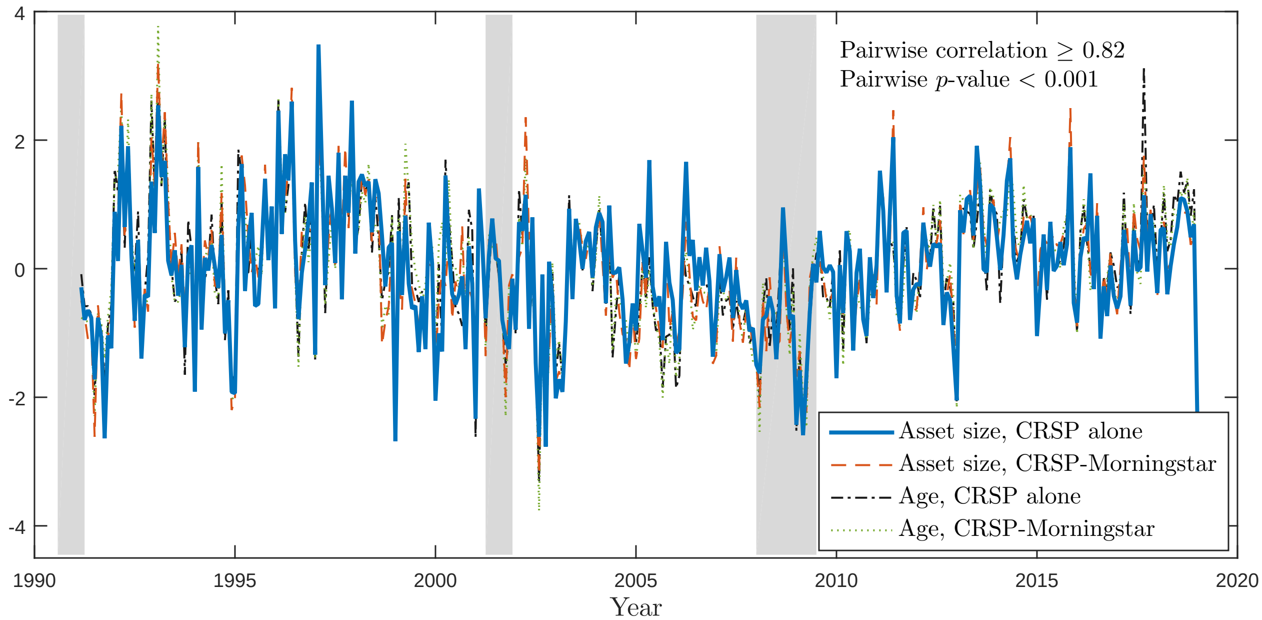
up. Further, panels B and C of Figure 2 plot the detrended flows of quintile 1 age group against the detrended flows of other age groups presented in panel A. The correlation between mutual fund flow shocks of age quintiles 1 and 2 is 0.59 with p-value < 0.001, and that of age quintiles 1 and 5 is 0.27 with p-value $= 0.004$.

To obtain the common fund flow, we extract the first principal component of the fund flows across fund share quintiles.[25] 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 common factor that drives much of the covariances of fund flow shocks — the first principal component (PC1).[26] 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 fund shares is analogous 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 fund share

[25]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.

[26]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.



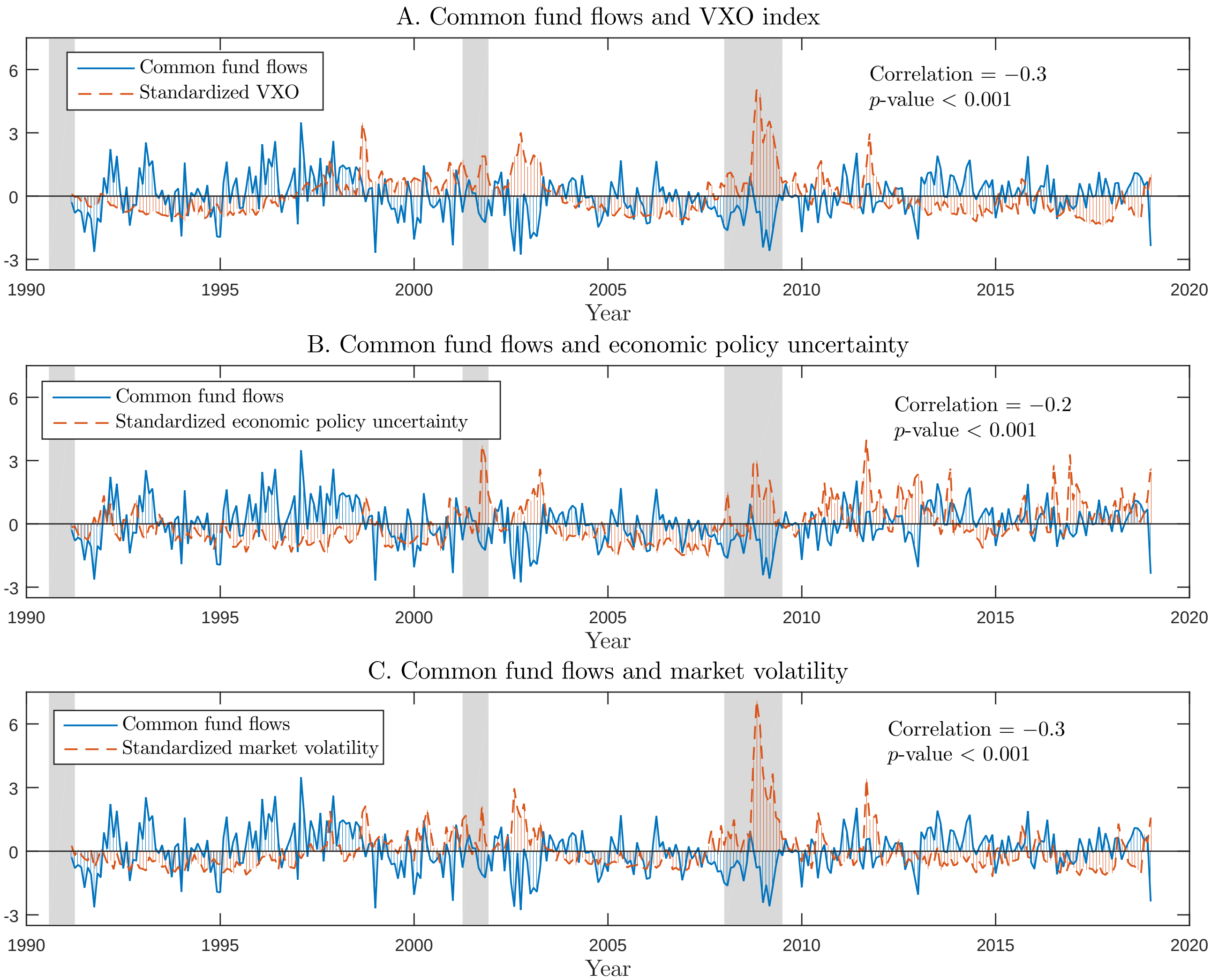
Note: This figure plots the monthly common fund flows constructed based on asset size and age of fund shares using the CRSP mutual fund data and CRSP-Morningstar intersection mutual fund data. The four common flows are standardized to have means of 0 and standard deviations of 1. The pairwise correlation coefficients among these four common flows range from 0.82 to 0.92, 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 asset size and age of fund shares.

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 0.82 to 0.92. 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.[27]

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 2.6). We are

[27]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 verity 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 $[0.3913, 0.4491, 0.4668, 0.4799, 0.4439]$, those over 1991 – 2004 are $[0.4017, 0.4519, 0.4734, 0.4647, 0.4408]$, and those over 2005 – 2018 are $[0.3701, 0.4454, 0.4557, 0.5057, 0.4487]$ when using the CRSP mutual data. We find similar results when using the CRSP-Morningstar intersection data.



Note: Panel A shows the common fund flow and the VXO index, which is the CBOE S&P 100 volatility index. Panel B shows the common fund flow and the economic policy uncertainty index, which is the news based policy uncertainty index (Baker, Bloom and Davis, 2016). Panel C shows the common fund flow and the market volatility, which is 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 common fund flow is constructed from the CRSP mutual fund data. Gray areas represent the NBER recession periods.

Figure 5: Common fund flows and economic uncertainty.

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. Our findings are also related to those of Ben-Rephael, Choi and Goldstein (2019), who show that mutual fund flows are correlated with fluctuations in credit and business cycles. Furthermore, Hoopes et al. (2016)

Table 1: Common fund flows comove negatively with uncertainty and market volatility.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. CRSP mutual funds alone			Panel B. CRSP-Morningstar intersection		
	$Common\_flows_t$			$Common\_flows_t$		
VXO_t	-0.418^{***}			-0.533^{***}		
	[−3.982]			[−6.081]		
VXO_{t-1}	0.221^{**}			0.339^{***}		
	[2.257]			[3.867]		
EPU_t		-0.163^{***}			-0.192^{***}	
		[−2.788]			[−2.831]	
EPU_{t-1}		0.069			0.167^{**}	
		[1.131]			[2.491]	
$MktVol_t$			-0.184^{**}			-0.328^{***}
			[−2.581]			[−4.246]
$MktVol_{t-1}$			−0.013			0.138^{**}
			[−0.190]			[2.050]
$Common\_flows_{t-1}$	0.268^{***}	0.270^{***}	0.249^{***}	0.414^{***}	0.429^{***}	0.390^{***}
	[4.836]	[4.788]	[4.431]	[7.965]	[8.782]	[7.639]
Dec_t	-1.144^{***}	-1.100^{***}	-1.136^{***}	-0.938^{***}	-0.892^{***}	-0.939^{***}
	[−6.233]	[−5.594]	[−6.120]	[−6.889]	[−5.953]	[−6.807]
Observations	334	334	334	334	334	334
R-squared	0.248	0.199	0.219	0.347	0.278	0.315

Note: This table shows the relation between uncertainty and common fund flows ($Common\_flows_t$). VXO_t is the CBOE S&P 100 volatility index at month t. EPU_t is the news based policy uncertainty index at month t (Baker, Bloom and Davis, 2016). $MktVol_t$ is the standard deviation of the daily returns of the S&P 500 index in month t. Dec_t is an indicator variable that equals 1 for Decembers. All variables except Dec_t 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. Sample period spans from 1991 to 2018.

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.

Figure 5 plots the common fund flow against various proxies for economic uncertainty. It is clear that the common flow comoves negatively with both economic policy uncertainty and market volatility. We further perform regression analysis to confirm the findings in Figure 5. Specifically, we regress common fund flows on the contemporaneous and lagged measures of economic uncertainty. We include a December dummy to the list of independent variables to control for seasonality in mutual fund flows (e.g., Ferson and Kim, 2012; Kamstra et al., 2017). As shown in panel A of Table 1, active mutual funds experience outflows when contemporaneous economic uncertainty arises. The negative relation is both statistically and economically significant. A one-standard-deviation increase in the VXO index, the economic policy uncertainty index, and the market volatility is associated with a 0.418-, 0.163-, and 0.184-standard-deviation decline in common fund flows constructed from the CRSP mutual fund data, respectively. In panel B, we find similar results for common fund

Table 2: Consumption dispersion shocks and common fund flows.

	(1) CRSP mutual funds alone $Common\_flows_t$	(2)	(3) CRSP-Morningstar intersection $Common\_flows_t$	(4)
$Consumption\_disp\_shock_{t-1}$	-0.154^{***}	-0.138^{***}	-0.134^{**}	-0.116^{**}
	[−2.844]	[−2.717]	[−2.550]	[−2.403]
$Common\_flows_{t-1}$	0.314^{***}	0.326^{***}	0.456^{***}	0.469^{***}
	[5.711]	[6.276]	[9.349]	[9.706]
Ret_t^M		0.326^{***}		0.369^{***}
		[5.548]		[7.280]
Ret_{t-1}^M		0.013		0.016
		[0.266]		[0.359]
Dec_t	-1.016^{***}	-1.117^{***}	-0.800^{***}	-0.914^{***}
	[−5.281]	[−6.065]	[−5.734]	[−6.934]
Observations	322	322	322	322
R-squared	0.194	0.289	0.268	0.388

Note: This table shows the relation between consumption dispersion shocks and the common fund flows of active mutual funds ($Common\_flows_t$). Consumption dispersion shocks ($Consumption\_disp\_shock_t$) are measured as $(Dispersion_t - Dispersion_{t-1})/Dispersion_{t-1}$, where $Dispersion_t$ is 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. Dec_t is an indicator variable that equals 1 for Decembers. All variables except Dec_t 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. Sample period spans from 1991 to 2017.

flows constructed from the CRSP-Morningstar intersection data.

We next examine the relation between common fund flows and 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 following an increase 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 households and drive their fund flows. 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 partial step toward this goal, we show that common fund flows comove negatively with aggregate discount rates and positively with sentiment in Table OA.3 in Online Appendix 2.

4.2 Common 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 3).

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

β_i^{flow} quintiles	CRSP mutual funds alone: Excess returns	CRSP mutual funds alone: CAPM α	CRSP-Morningstar intersection: Excess returns	CRSP-Morningstar intersection: CAPM α
Q1	5.98	-5.04^{**}	5.82	-3.60^{*}
	[1.58]	[−2.33]	[1.60]	[−1.88]
Q2	7.03^{**}	−1.89	7.53^{**}	0.08
	[1.98]	[−1.34]	[2.36]	[0.09]
Q3	8.16^{**}	0.22	8.82^{***}	0.84
	[2.49]	[0.14]	[3.61]	[0.77]
Q4	9.48^{***}	2.07^{*}	10.78^{***}	1.58
	[4.03]	[1.67]	[3.90]	[1.33]
Q5	10.89^{***}	1.14	12.10^{***}	0.51
	[3.46]	[0.65]	[3.32]	[0.28]
Q5 − Q1	4.90^{**}	6.18^{**}	6.28^{***}	4.11^{*}
	[2.37]	[2.47]	[2.91]	[1.79]

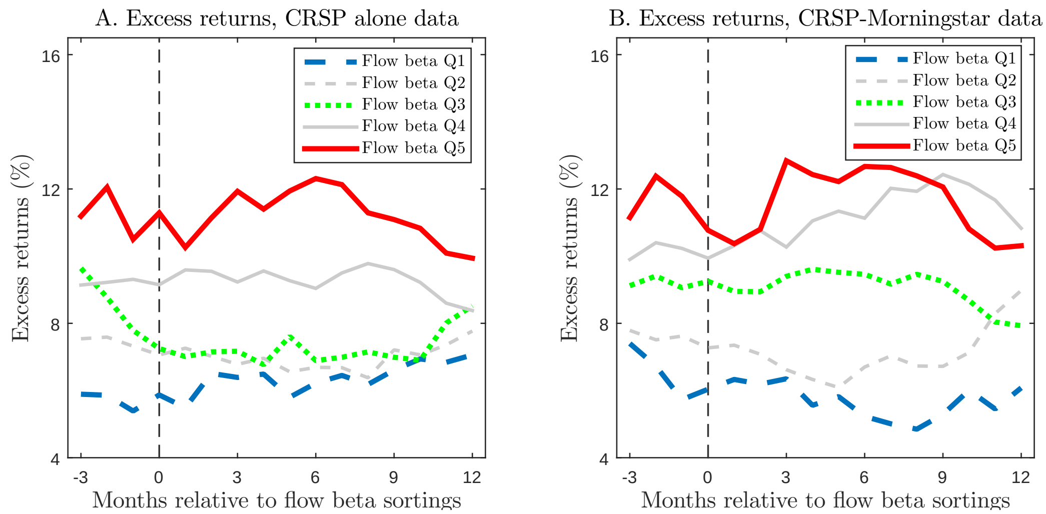
Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on common flow betas. In June of year t, we sort firms into quintiles based on their average common flow betas from January to June of year t. Once the portfolios are formed, their monthly returns 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. Sample period spans from July 1992 to June 2018. Because flow betas are estimated based on historical returns using 3-year rolling windows, we compute standard errors using the Newey-West estimator with 3-year lags allowing for serial correlation in returns. Results are robust to the Newey-West estimator with longer lags and to the automatic lag selected based on the method of Newey and West (1994). We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Portfolio Sorting Analyses. We first perform portfolio sorting analyses. For each stock, we estimate its common 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):

$$ret_{i,t-\tau} = a_{i,t} + \beta_{i,t}^{flow} \times common\_flow_{t-\tau} + \varepsilon_{i,t-\tau}, \quad \text{with } \tau = 0, 1, \cdots, 35, \tag{4.4}$$

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

In June of each year, we sort firms into quintiles based on their common flow betas. Table 3 shows average excess returns and CAPM alphas of the long-short portfolios sorted on the common 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 estimated using the CRSP mutual fund data, 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 4.90%, while the spread in their CAPM alphas is 6.18%. These spreads are comparable to the equity premium and the value premium. We find a similar pattern when estimating common flow betas based on the CRSP-Morningstar



Note: This figure plots the annualized value-weighted monthly excess returns of the portfolios sorted on the common flow betas.

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

intersection sample.[28] Figure 6 plots the annualized value-weighted excess returns of the portfolios sorted on common flow betas. We find that higher flow betas predict higher excess returns cross portfolios in the 12 month window after portfolio formation.

Because estimates of the common flow betas can be noisy, we examine the pattern of the post-formation betas (e.g., Fama and French, 1992; Pástor and Stambaugh, 2003) of portfolios sorted on the stocks' common flow betas. We estimate these by regressing the value-weighted excess returns of stock portfolios on the common fund flow. As shown in Table OA.4 of the Online Appendix, the post-formation betas increase across the quintile portfolios sorted on the common flow betas. The difference in the post-formation betas between the stocks with the highest flow betas (Q5) and those with the lowest flow betas (Q1) is statistically significant, suggesting that the estimated common flow betas indeed capture stocks' future exposure to the common fund flows.

We find that, although stocks with higher flow betas tend to be those with lower market liquidity, flow beta has independent information about expected stock returns. We perform a double sort on flow betas and liquidity measures in Table 4. We find that the return spreads of the common flow betas remain robust after controlling for the historical liquidity beta

[28]Our portfolio sorting analyses focus on fund flows at the fund share level following previous studies (e.g., Chen, Goldstein and Jiang, 2010; Goldstein, Jiang and Ng, 2017). In Online Appendix 2, we conduct a robustness test by aggregating fund-share-level flows to the fund level. In addition, we address the incubation bias following Evans (2010). As shown in Table OA.5 of the Online Appendix, the common flow betas computed based on fund-level flows exhibit similar asset pricing implications to those computed based on flows at the fund share level.

Table 4: Double-sort analysis.

β_i^{flow} quintiles	Panel A: Double sort on historical liquidity betas				Panel B: Double sort on Amihud illiquidity			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α
Q1	6.55*	−4.79***	5.73*	−3.52**	5.54	−5.38***	6.06*	−2.92*
	[1.88]	[−2.66]	[1.86]	[−2.27]	[1.41]	[−2.55]	[1.74]	[−1.71]
Q2	6.91*	−2.16	6.51*	−1.41	7.65**	−0.71	7.59**	0.05
	[1.85]	[−1.22]	[1.72]	[−1.07]	[2.29]	[−0.52]	[2.27]	[0.05]
Q3	7.84**	0.19	9.22***	1.52	7.89**	−0.08	8.01***	0.57
	[2.53]	[0.15]	[4.24]	[1.24]	[2.26]	[−0.06]	[3.02]	[0.65]
Q4	9.66***	2.03	9.53***	1.10	9.29***	2.06	10.36***	1.86*
	[3.71]	[1.65]	[3.51]	[1.17]	[3.96]	[1.52]	[4.02]	[1.94]
Q5	9.93***	1.20	12.90***	1.82	10.53***	2.03*	11.12***	0.73
	[3.30]	[1.09]	[3.49]	[0.91]	[3.59]	[1.87]	[3.49]	[0.49]
Q5 − Q1	3.38**	5.99***	7.17***	5.34**	4.99***	7.41***	5.06***	3.64*
	[2.20]	[3.31]	[3.96]	[2.56]	[2.69]	[3.00]	[3.53]	[1.80]

Note: This table shows the results from the double-sort analysis. In each June, we first sort stocks into five groups based on historical liquidity betas (panel A) and the Amihud illiquidity measure (panel B). Next, we sort stocks within each liquidity group into quintiles based on their average common 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 liquidity groups. Thus, in each June, we effectively sort firms into common flow beta quintiles controlling for the liquidity 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 historical liquidity betas are estimated by regressing stock returns on the shocks of aggregated liquidity following Pástor and Stambaugh (2003). We annualize the average excess returns and CAPM alphas by multiplying them by 12. 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.

(Pástor and Stambaugh, 2003) and the Amihud illiquidity measure (Amihud, 2002).

In Online Appendix 2, we examine the pricing of the betas to common flows of index funds. As we show in Table OA.6 of the Online Appendix, the long-short portfolios sorted on the betas to common flows of index funds have insignificant average (risk-adjusted) returns. This is consistent with our theoretical model, where flow shocks are priced because of the hedging demand by mutual funds. Index funds are less able to hedge against fund flow shocks than active funds.

Fama-MacBeth Regressions. We perform Fama-MacBeth tests by regressing monthly stock returns on the common flow betas. As Table 5 shows, the slope coefficient for the common flow beta is positive and statistically significant. The slope coefficient is also economically significant. According to column (1) of Table 5, a one-standard-deviation increase in the common flow beta is associated with a 0.198- (2.376-) percentage-point increase in the monthly (annualized) stock returns. This result is robust to data choices in computing common flow betas (i.e., panel A vs. panel B). The relation between flow betas and returns is not subsumed by the stock characteristics in columns (2–5) and (7–10), including market betas, market cap, book-to-market ratio, historical liquidity betas, Amihud illiquidity, betas

Table 5: Fama-MacBeth regressions.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. CRSP mutual funds alone					Panel B. CRSP-Morningstar intersection				
	$Ret_{i,t}$ (%)					$Ret_{i,t}$ (%)				
$\beta^{flow}_{i,t-1}$	0.198***	0.196***	0.156***	0.156***	0.165***	0.137**	0.141***	0.080**	0.081**	0.088**
	[2.728]	[3.710]	[3.047]	[2.824]	[2.911]	[2.306]	[2.984]	[2.280]	[2.202]	[2.208]
$\beta^{M}_{i,t-1}$		0.001	0.054	0.110	0.077		−0.016	0.046	0.105	0.081
		[0.001]	[0.622]	[1.190]	[0.520]		[−0.186]	[0.512]	[1.098]	[0.528]
$Lnsize_{i,t-1}$			−0.307**	−0.156	−0.163			−0.308**	−0.157	−0.163
			[−2.452]	[−1.349]	[−1.460]			[−2.482]	[−1.375]	[−1.475]
$LnBEME_{i,t-1}$			0.036	0.017	0.020			0.040	0.019	0.021
			[0.414]	[0.202]	[0.238]			[0.473]	[0.235]	[0.259]
$Liqbeta_{i,t-1}$				0.003	−0.010				0.017	0.012
				[0.067]	[−0.190]				[0.365]	[0.235]
$AIM_{i,t-1}$				0.898***	0.915***				0.896***	0.916***
				[3.448]	[3.459]				[3.445]	[3.441]
$\beta^{VXO}_{i,t-1}$					−0.105					−0.109
					[−0.865]					[−0.863]
$\beta^{EPU}_{i,t-1}$					0.050					0.050
					[0.745]					[0.730]
$\beta^{MktVol}_{i,t-1}$					0.021					0.042
					[0.315]					[0.597]
Constant	1.348***	1.330***	1.309***	1.430***	1.464***	1.315***	1.315***	1.298***	1.427***	1.468***
	[5.558]	[5.495]	[5.175]	[6.015]	[5.995]	[5.475]	[5.493]	[5.217]	[6.104]	[6.087]
Average obs./month	3022	3022	2903	2834	2834	3022	3022	2903	2834	2834
Average R-squared	0.003	0.013	0.025	0.029	0.033	0.003	0.012	0.024	0.029	0.032

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly stock returns ($ret_{i,t}$) on the common flow betas ($\beta^{flow}_{i,t-1}$) and a set of control variables, which include market betas ($\beta^{M}_{i,t-1}$), natural log of market cap ($lnsize_{i,t-1}$), natural log of book-to-market ratio ($lnBEME_{i,t-1}$), historical liquidity betas ($liqbeta_{i,t-1}$), Amihud illiquidity ($AIM_{i,t-1}$), betas to the monthly changes of the CBOE S&P 100 volatility index ($\beta^{VXO}_{i,t-1}$), betas to the monthly changes of the news based policy uncertainty index $\beta^{EPU}_{i,t-1}$, and betas to the monthly changes of the market volatility ($\beta^{MktVol}_{i,t-1}$). $\beta^{flow}_{i,t-1}$ and the control variables are standardized to have means of 0 and standard deviations of 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. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1992 to 2018.

to the monthly changes of the CBOE S&P 100 volatility index, betas to the monthly changes of the news-based policy uncertainty index (Baker, Bloom and Davis, 2016), and betas to the monthly changes of the market volatility.

Common Flow Betas and Stock Characteristics. We now examine the relation between common flow betas and several stock characteristics. We regress common flow betas on contemporaneous stock characteristics including market cap, book-to-market ratio, historical liquidity betas, and Amihud illiquidity. The t-statistics are computed using the Fama-MacBeth approach. As Table 6 shows, stocks with high flow betas tend to be small, value, illiquid, and high-liquidity-risk stocks.[29] Previous studies have shown that these characteristics are priced

[29]In Table OA.7 of the Online Appendix, we show that the mean values of the stock characteristics across the stock quintile portfolios sorted on the common flow betas. Consistent with Table 6, we find that stocks

Table 6: Relation between common flow betas and stock characteristics.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Panel A. CRSP mutual funds alone					Panel B. CRSP-Morningstar intersection				
	$\beta^{flow}_{i,t}$					$\beta^{flow}_{i,t}$				
$Lnsize_{i,t}$	-0.05^{**}				-0.00	-0.09^{***}				-0.07^{***}
	[-2.59]				[-0.02]	[-5.31]				[-3.32]
$LnBEME_{i,t}$		0.07^{***}			0.06^{***}		0.04^{***}			0.02^{*}
		[4.32]			[3.41]		[2.87]			[1.54]
$Liqbeta_{i,t}$			0.21^{***}		0.21^{***}			0.24^{***}		0.24^{***}
			[4.02]		[3.95]			[4.63]		[4.55]
$AIM_{i,t}$				0.07^{***}	0.06^{***}				0.06^{**}	0.02
				[4.26]	[3.08]				[2.71]	[1.01]
Constant	-0.02	-0.03	-0.02	-0.02	-0.03	-0.04	-0.05	-0.05	-0.03	-0.07
	[-0.25]	[-0.32]	[-0.26]	[-0.16]	[-0.35]	[-0.30]	[-0.39]	[-0.43]	[-0.23]	[-0.61]
Average obs./month	3069	2932	3052	3071	2913	3069	2932	3072	3052	2913
Average R-squared	0.010	0.013	0.057	0.008	0.082	0.016	0.011	0.075	0.008	0.103

Note: This table shows the slope coefficients and test statistics in brackets from Fama-MacBeth regressions that regress common flow betas on stock characteristics. $\beta^{flow}_{i,t}$ is the common flow beta for stock i in month t. $Lnsize_{i,t}$ is natural log of the market cap. $LnBEME_{i,t}$ is natural log of the book-to-market ratio. $Liqbeta_{i,t}$ is the historical liquidity beta estimated by regressing stock returns on the shocks of aggregated liquidity. $AIM_{i,t}$ is the Amihud illiquidity measure. All variables are standardized to have means of 0 and standard deviations of 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1992 to 2018.

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 common flow betas suggests that such characteristics may be partially priced through common flow betas.

Because common flow betas are closely associated with stock characteristics, we use the predicted beta approach to further strengthen our results (e.g., Pástor and Stambaugh, 2003; Kogan and Papanikolaou, 2013). In particular, we use lagged market cap, lagged book-to-market ratio, lagged historical liquidity betas, lagged Amihud illiquidity, and lagged common flow betas to predict common flow betas. The predicted common flow betas are negatively associated with market cap and positively correlated with book-to-market ratio, historical liquidity betas, and Amihud illiquidity (see Table OA.8 of the Online Appendix). Using Fama-MacBeth regressions, we show that the predicted common flow betas are also positively priced in the cross section (see panel A of Table OA.9 in the Online Appendix).

4.3 Common Fund Flows Are Hedged

In this subsection, we provide several lines of evidence showing that mutual funds hedge against common fund flows. Using a panel regression approach, we first show that active

with higher flow betas tend to have lower market cap, higher book-to-market ratio, higher historical betas, and higher Amihud illiquidity.

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 their underlying stocks experience natural disaster shocks. We find that 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, active mutual funds rebalance their holdings of the stocks that are unaffected by natural disasters toward those with lower flow betas. 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 common flow beta of the China-related stocks. We find that active mutual funds 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

Our model (Theorem 2) predicts that active mutual funds tilt their portfolio holdings farther away from the benchmark portfolio on the stocks with higher flow betas. To test this prediction, we run the following regression:

$$w_{i,t}^{MF} - w_{i,t}^{M} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{M} + \varepsilon_{i,t}. \tag{4.5}$$

Here, $\beta_{i,t-1}^{flow}$ is the common flow beta for stock i in quarter $t-1$; $\beta_{i,t-1}^{M}$ is the market beta for stock i in quarter $t-1$; $w_{i,t}^{MF}$ is the weight of stock i in the aggregate active mutual fund portfolio in quarter t; and $w_{i,t}^{M}$ is the weight of stock i in the market portfolio in quarter t. The term, $w_{i,t}^{MF} - w_{i,t}^{M}$, represents the weight deviation of the aggregate active mutual fund portfolio from the equity market portfolio.[30] We standardize both the weight deviation and the common flow betas to ease the interpretation of the regression coefficient.

Panel A of Table 7 shows the regression results. We find that coefficient $\hat{b}$ is significantly negative, suggesting that active mutual funds underweigh the stocks with higher flow betas

[30] For a given quarter t, we exclude from our analysis the stocks with zero aggregate mutual fund holdings in current quarter t and 8 preceding quarters (i.e., quarter $t-8$ to quarter $t-1$). We use the raw stock weights to compute $w_{i,t}^{MF} - w_{i,t}^{M}$ in Table 7. We perform a robustness check in Table OA.10 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. Our results remain robust to the usage of the rescaled portfolio weights.

Table 7: Active mutual funds tilt their holdings away from stocks with high flow betas.

	Panel A: Using the market portfolio as the benchmark portfolio			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$w_{i,t}^{MF} - w_{i,t}^{M}$		$w_{i,t}^{MF} - w_{i,t}^{M}$	
$\beta_{i,t-1}^{flow}$	-0.013^{**}	-0.014^{***}	-0.028^{***}	-0.030^{***}
	[-2.532]	[-2.627]	[-5.218]	[-5.418]
$\beta_{i,t-1}^{M}$	0.051^{***}	0.059^{***}	0.056^{***}	0.065^{***}
	[6.603]	[7.181]	[7.132]	[7.668]
Quarter FE	No	Yes	No	Yes
Observations	413321	413321	413321	413321
R-squared	0.002	0.009	0.003	0.009

	Panel B: Using the self-declared benchmarks as the benchmark portfolio					
	(1)	(2)	(3)	(4)	(5)	(6)
Benchmarks	S&P 500 TR		Russell 1000 Growth TR		Russell 2000 TR	
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
	$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$		$w_{i,t}^{MF} - w_{i,t}^{Benchmark}$	
$\beta_{i,t-1}^{flow}$	-0.101^{***}	-0.060^{**}	-0.070^{***}	-0.059^{***}	-0.027^{***}	-0.034^{***}
	[-3.426]	[-2.438]	[-3.916]	[-3.826]	[-3.024]	[-3.475]
$\beta_{i,t-1}^{M}$	0.113^{***}	0.117^{***}	0.093^{***}	0.104^{***}	-0.021^{*}	-0.016
	[3.033]	[3.050]	[4.622]	[4.908]	[-1.687]	[-1.261]
Observations	26208	26208	30780	30780	88013	88013
R-squared	0.010	0.007	0.010	0.009	0.001	0.001

Note: This table studies the relation between common flow betas ($\beta_{i,t-1}^{flow}$) and active mutual funds' weight deviation from the benchmark portfolios. We control for market betas ($\beta_{i,t-1}^{M}$) in the regressions. In panel A, we use market portfolio as the benchmark portfolio. The variable $w_{i,t}^{MF}$ is the weight for stock i in the aggregate active mutual fund holdings in quarter t; and $w_{i,t}^{M}$ is the weight for stock i in the equity market portfolio. $w_{i,t}^{MF} - w_{i,t}^{M}$ represents the weight deviation of the aggregate active mutual fund portfolio from the equity market portfolio. 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. $\beta_{i,t-1}^{flow}$, $\beta_{i,t-1}^{M}$, and $w_{i,t}^{MF} - w_{i,t}^{M}$ are standardized to have means of zero and standard deviations of one. The analysis is performed at quarterly frequency. Sample period of panel A spans from 1991 to 2018. In panel B, we use the self-declared benchmarks as the benchmark portfolio. We show results for the three most frequently used benchmarks: S&P 500 TR, Russell 1000 Growth TR, and Russell 2000 TR. We aggregate the active mutual fund holdings with the corresponding self-declared benchmarks. The variable $w_{i,t}^{MF}$ is the weight for stock i in quarter t in the aggregate holdings of active mutual funds with a given self-declared benchmark. The variable $w_{i,t}^{Benchmark}$ is the weight for stock i in the self-declared benchmark portfolio. $w_{i,t}^{MF} - w_{i,t}^{Benchmark}$ represents the weight deviation of the aggregate active mutual fund portfolio from the given self-declared benchmark portfolio. The sample in panel B covers the stocks that are included in the benchmark portfolios. $\beta_{i,t-1}^{flow}$, $\beta_{i,t-1}^{M}$, and $w_{i,t}^{MF} - w_{i,t}^{Benchmark}$ are standardized to have means of 0 and standard deviations of 1. The analysis is performed at a quarterly frequency. Sample period of panel B spans from 2004 to 2018. Standard errors 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.

relative to the market portfolio.[31] To evaluate the economic magnitude of the portfolio tilt, we sort stocks into quintiles based on their common flow betas in each quarter and then compute the normalized tilt for each stock quintile, i.e., $(w_{i,p,t}^{MF} - w_{i,t}^{M})/w_{i,t}^{M}$, which expresses portfolio tilt as a fraction of the market weight of each stock. We find that the normalized tilt of the stock portfolio with the highest flow betas (Q5) is 11.2 percentage points more negative than that of the stock portfolio with the lowest flow betas (Q1).

[31] This result is robust with and without quarter fixed effects and across data samples used to compute common flow betas.

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 mutual funds to compute the weight deviation. The top three most frequently self-declared benchmarks for active mutual funds are S&P 500 TR, Russell 1000 Growth TR, and Russell 2000 TR (e.g., Evans and Sun, 2020).[32] We aggregate the active mutual fund holdings with different self-declared benchmarks and run the following regression separately for each benchmark:

$$w_{i,t}^{MF} - w_{i,t}^{Benchmark} = a + b_1 \times \beta_{i,t-1}^{flow} + b_2 \times \beta_{i,t-1}^{M} + \varepsilon_{i,t}. \tag{4.6}$$

Here, variable $w_{i,t}^{MF}$ is the weight for stock i in quarter t in the aggregate holdings of active mutual funds with a given self-declared benchmark. Variable $w_{i,t}^{Benchmark}$ is the weight for stock i in the self-declared benchmark portfolio. The term, $w_{i,t}^{MF} - w_{i,t}^{Benchmark}$, represents the weight deviation of the aggregate active mutual fund portfolio from the given self-declared benchmark portfolio. As we show in panel B of Table 7, coefficient b_1 is significantly negative across all three benchmarks, again suggesting that active mutual funds tilt their holdings farther away from their own benchmarks on the stocks with higher flow betas.

We perform two additional tests for mutual funds' hedging behavior. First, we examine the relation between the weight deviation and the predicted flow betas. Consistent with Table 7, we find that active mutual funds tilt their holdings farther away from the benchmark on the stocks with higher predicted flow betas (see panel B of Table OA.9 of the Online Appendix). Second, we examine the relation between the weight deviation and the theoretical portfolio tilt (i.e, $\Sigma_t^{-1}\beta_t^{flow}$ as illustrated in equation (2.33)). Specifically, we estimate the variance-covariance matrix of stock returns (Σ_t^{-1}) from the data and compute the theoretical portfolio tilt (see Online Appendix 2 for details). We find that the theoretical portfolio tilt is highly correlated with common flow betas. The correlation is 0.70 in the CRSP mutual fund data and 0.71 in the CRSP-Morningstar intersection data. We rerun regression specification (4.5) using the lagged theoretical portfolio tilt as the independent variable. Consistent with Table 7, we find that the weight deviation is significantly negatively correlated with the

[32] 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 panel B of Table 7. Our results remain robust if we use a shorter sample. Our results also hold for other self-declared benchmarks, such as 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.

Table 8: Heterogeneity across funds in hedging fund flow risk.

	Panel A: Heterogeneity across fund size			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone $w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		CRSP-Morningstar intersection $w^{MF}_{i,p,t} - w^{M}_{i,p,t}$	
$Large\_funds_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.042***	0.041***	0.021***	0.021***
	[9.987]	[9.785]	[5.601]	[5.449]
$\beta^{flow}_{i,t-1}$	−0.043***	−0.044***	−0.041***	−0.038***
	[−8.849]	[−8.734]	[−8.050]	[−7.615]
$Large\_funds_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.032***	−0.032***	−0.033***	−0.032***
	[−5.765]	[−5.733]	[−5.873]	[−5.818]
$\beta^{M}_{i,t-1}$	0.057***	0.067***	0.062***	0.071***
	[8.972]	[10.373]	[9.949]	[11.085]
$Large\_funds_{p,t-1}$	−0.111***	−0.114***	−0.111***	−0.114***
	[−11.362]	[−11.686]	[−11.366]	[−11.703]
Quarter FE	No	Yes	No	Yes
Observations	1773870	1773870	1773870	1773870
R-squared	0.006	0.012	0.006	0.012

	Panel B: Heterogeneity across fund age			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone $w^{MF}_{i,p,t} - w^{M}_{i,p,t}$		CRSP-Morningstar intersection $w^{MF}_{i,p,t} - w^{M}_{i,p,t}$	
$Old\_funds_{p,t-1} \times \beta^{flow}_{i,t-1}$	0.026***	0.026***	0.009**	0.010**
	[5.196]	[5.248]	[2.155]	[2.259]
$\beta^{flow}_{i,t-1}$	−0.021***	−0.025***	−0.025***	−0.026***
	[−4.321]	[−4.849]	[−4.458]	[−4.784]
$Old\_funds_{p,t-1} \times \beta^{M}_{i,t-1}$	−0.032***	−0.032***	−0.031***	−0.032***
	[−6.016]	[−6.112]	[−5.713]	[−5.829]
$\beta^{M}_{i,t-1}$	0.045***	0.053***	0.049***	0.057***
	[6.559]	[7.417]	[6.788]	[7.516]
$Old\_funds_{p,t-1}$	−0.075***	−0.074***	−0.075***	−0.074***
	[−8.194]	[−8.058]	[−8.348]	[−8.177]
Quarter FE	No	Yes	No	Yes
Observations	1768854	1768854	1768854	1768854
R-squared	0.003	0.008	0.003	0.008

Note: This table studies the heterogeneity across funds for the flow-hedging behaviors of mutual funds. We sort active mutual funds into quintiles based on lagged asset size (panel A) and fund age (panel B). We compute the active mutual funds' weight deviation for each mutual fund quintile. The variable $w^{MF}_{i,p,t}$ is the weight of stock i in the aggregate holdings of active mutual fund quintile p in quarter t; and $w^{M}_{i,t}$ is the weight of stock i in the equity market portfolio. $w^{MF}_{i,p,t} - w^{M}_{i,t}$ represents the weight deviation of the aggregate portfolio of active mutual fund quintile p from the equity market portfolio. $Large\_funds_{p,t-1}$ is an indicator variable for funds in top asset size quintile in quarter $t-1$, while $old\_funds_{p,t-1}$ is an indicator variable for funds in the top-fund-age quintile in quarter $t-1$. 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 is performed at a quarterly frequency. Standard errors 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. Sample period spans from 1991 to 2018.

theoretical portfolio tilt (see Table OA.11 of the Online Appendix).

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 small market cap (small stocks) or stocks with high book-to-market ratio (value stocks). These patterns are also suggested for a broader set of institutional investors (e.g., Gompers and Metrick, 2001; Bennett, Sias and Starks, 2003; Lewellen, 2011). In a recent paper, Blume and Keim (2017) allow for a more flexible nonlinear relation between the log market cap and the portfolio weight to improve estimation and find that institutional investors overweight large-cap stocks, but have started to underweight mega-cap and overweigh small-cap stocks since a few decades ago. Put together, there is little evidence showing that portfolio overweighting is monotonically decreasing in market cap or increasing in book-to-market ratio.

Our results help make sense of the absence of the systematic and monotonic tilt toward stocks with low book-to-market ratio in active funds' portfolios. As we show above, the book-to-market ratio and the beta on common fund flows are positively correlated in the cross-section of stocks (see Table 6). This suggests that a simple tilt based solely on the book-to-market ratio would expose funds to elevated flow risk. Yet, the common flow beta and book-to-market ratio are imperfectly correlated with each other, and thus funds have an incentive to tilt their portfolios toward value stocks after controlling for common flow betas. We confirm this prediction empirically in panel B of Table OA.12 in the Online Appendix.[33] We also show that the cross-sectional correlation between the book-to-market ratio and common flow betas has fundamental underpinnings. More precisely, we show that value stocks tend to have higher exposure to fluctuations in economic uncertainty (see Table OA.14 of the Online Appendix), which is a major primitive driver behind the common fund flows (see Table 1 and Figure 5). This provides a rationale for why value stocks tend to have higher flow betas.

Next, we examine heterogeneity in mutual funds' hedging behavior by exploring fund-level variation in fund size and fund age. As we show in Figure OA.2 of the Online Appendix, the systematic component of the fund flow shocks of both larger and older funds is much less volatile compared to smaller and younger funds, respectively. Therefore, according to our theory, fund managers of both large and old funds have weaker incentives to hedge against common fund flows than small and young funds, respectively. This is what we find in the data. As shown in Table 8, active mutual funds with the largest fund size (top size quintile) and highest fund age (top age quintile) hedge significantly less against common

[33] Panel B of Table OA.12 also shows that this result is robust after controlling for stocks' market liquidity. Table OA.13 of the Online Appendix further verifies that the relation between the portfolio tilt and market liquidity can be largely subsumed by the common flow beta, but not the other way around.

fund flows compared to other funds.[34]

4.3.2 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.[35] 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 in the US. 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 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.[36] More

[34]Table 8 also shows that both large funds and old funds deviate significantly less from the market than small funds and young funds, respectively.

[35]In Online Appendix 2, 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.

[36]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).

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.[37] 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 $Outflow\_Risk_{f,t}$.[38] 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.[39] 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.

Panel A of Table 9 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:

$$Abflow_{f,t+k} = a + b \times ND_{f,t} + \varepsilon_{f,t+k}, \quad \text{with } k = 0, 1, 2, 3. \tag{4.7}$$

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 9, we find that the abnormal flows for funds with higher natural disaster

[37] In Table OA.15 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.

[38] 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).

[39] See Table OA.16 of the Online Appendix for the regression results.

Table 9: 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. Sample period spans from 1994 to 2018.

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

Table 10: 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			
	$\Delta(w_{i,f,t} - w_{i,t}^M)$ $(\times 10^3)$				$\Delta(w_{i,f,t} - w_{i,t}^M)$ $(\times 10^3)$			
$\beta_{i,t-1}^{flow} \times ND_{f,t}$	-0.027^{***}	-0.030^{***}	-0.033^{***}	-0.038^{***}	-0.020^{**}	-0.025^{**}	-0.027^{**}	-0.032^{***}
	[−2.959]	[−3.101]	[−3.349]	[−3.616]	[−1.983]	[−2.293]	[−2.517]	[−2.738]
$\beta_{i,t-1}^{flow}$	0.036^{***}	0.054^{***}	0.058^{***}	0.085^{***}	0.017^{**}	0.036^{***}	0.038^{***}	0.056^{***}
	[5.046]	[6.434]	[6.483]	[7.475]	[2.419]	[4.102]	[4.300]	[4.793]
$\beta_{i,t-1}^{M} \times ND_{f,t}$	0.018^{*}	0.029^{***}	0.023^{**}	0.033^{***}	0.021^{**}	0.033^{***}	0.026^{**}	0.037^{***}
	[1.886]	[3.014]	[2.189]	[3.098]	[2.062]	[3.166]	[2.383]	[3.226]
$\beta_{i,t-1}^{M}$	0.011^{*}	−0.005	0.060^{***}	0.034^{***}	0.010^{*}	−0.009	0.058^{***}	0.030^{***}
	[1.866]	[−0.811]	[6.148]	[3.226]	[1.699]	[−1.551]	[6.094]	[2.926]
$ND_{f,t}$	-0.053^{***}	-0.259^{***}	-0.093^{***}	-0.258^{***}	-0.055^{***}	-0.260^{***}	-0.095^{***}	-0.260^{***}
	[−5.372]	[−15.153]	[−8.400]	[−15.459]	[−5.565]	[−15.251]	[−8.652]	[−15.595]
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	0.007	0.007	0.011	0.012	0.007	0.007	0.011	0.011

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. $\Delta(w_{i,f,t} - w_{i,t}^M) = (w_{i,f,t} - w_{i,f,t-1}) - (w_{i,t}^M - w_{i,t-1}^M)$, where $w_{i,f,t}$ represents the weight of stock i in fund f in quarter t and $w_{i,t}^M$ represents the weight of stock i in the market portfolio in quarter t. β_i^{flow} is the flow beta for stock i, β_i^M 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_i^{flow}, β_i^M, 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. Sample period spans from 1994 to 2018.

outflow risk of the fund:

$$\Delta(w_{i,f,t} - w_{i,t}^M) = b_1 \times \beta_{i,t-1}^{flow} \times ND_{f,t} + b_2 \times \beta_{i,t-1}^{flow} + b_3 \times \beta_{i,t-1}^{M} \times ND_{f,t} + b_4 \times \beta_{i,t-1}^{M} + b_5 \times ND_{f,t} + a_i + a_f + a_t + \varepsilon_{i,f,t}, \tag{4.8}$$

where $\Delta(w_{i,f,t} - w_{i,t}^M)$ 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, $\beta_{i,t-1}^{flow}$ is the common 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 $w_{i,t}^M$ 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 10, 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 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).[40] 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 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 $\beta_{i,t}^{flow}$ and portfolio weight changes $\Delta(w_{i,f,t} - w_{i,t}^{M})$, 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.17 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.18 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 $t-1$.[41] 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.20 of the Online Appendix).[42] This loss in performance is larger for funds with higher exposure

[40] In Table OA.19 of the Online Appendix we address the possibility that natural disasters may be somewhat predictable by portfolio characteristics correlated with future portfolio changes.

[41] 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.

[42] 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

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.20 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 common flow betas of a specific subgroup of stocks. The main empirical challenge is that the changes in common 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 common flow betas 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 common flow betas of China-related stocks compared to China-unrelated 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

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 11: Changes in uncertainty betas and common 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 common 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	
	$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$	
$China\_related_i \times \mathbf{1}_{\{t>March\_2018\}}$	0.033**	0.032**	0.038**	0.038**	0.038**	0.037**	0.036**	0.035**
	[2.307]	[2.241]	[2.320]	[2.281]	[2.463]	[2.363]	[2.236]	[2.141]
$China\_related_i$	−0.106***	−0.106***	−0.024	−0.025	−0.148***	−0.148***	−0.103***	−0.103***
	[−4.754]	[−4.751]	[−0.904]	[−0.911]	[−6.155]	[−6.149]	[−3.567]	[−3.575]
$\mathbf{1}_{\{t>March\_2018\}}$	−0.126***		−0.134***		−0.124***		−0.131***	
	[−4.330]		[−4.375]		[−4.381]		[−3.969]	
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	141353	141353	141353	141353	141353	141353	141353	141353
R-squared	0.008	0.013	0.004	0.010	0.010	0.015	0.006	0.011

Note: This table shows the changes in stocks' trade policy uncertainty betas ($\beta_{i,t}^{uncertainty}$ in panel A) and common flow betas ($\beta_{i,t}^{flow}$ in panel B) following the unexpected announcement of the possible US-China trade war in March 2018. 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.

(see panel A of Figure 7). To justify the use of the trade-war announcement as a shifter of the common flow betas 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:

$$
\begin{aligned}
-1 \times \beta_{i,t}^{uncertainty} = {} & b_1 \times China\_related_i \times \mathbf{1}_{\{t>March\_2018\}} \\
& + b_2 \times China\_related_i + b_3 \times \mathbf{1}_{\{t>March\_2018\}} + a_t + \varepsilon_{i,t}. \qquad (4.9)
\end{aligned}
$$

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,[43] we multiply the trade policy uncertainty betas with -1 so that higher values of the left-hand side variable in specification (4.9) 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).[44] 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.

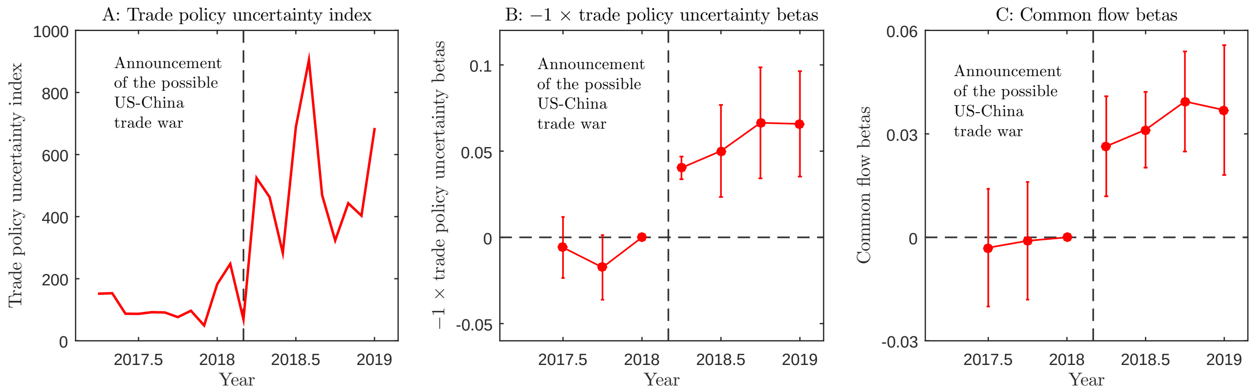
As we show in panel A of Table 11, coefficient b_1 is positive and statistically significant, suggesting that China-related stocks become more sensitive to economic uncertainty relative to China-unrelated stocks following the unexpected trade war announcement. Moreover, we also examine the dynamic impact of the announcement of a possible trade war. We consider the quarterly regression specification as follows:

$$\begin{aligned} -1 \times \beta_{i,t}^{uncertainty} = a + \sum_{\tau=-3}^{3} b_{1,\tau} \times China\_related_i \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} \\ + b_2 \times China\_related_i + \sum_{\tau=-3}^{3} b_{3,\tau} \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} + \varepsilon_{i,t}, \end{aligned} \tag{4.10}$$

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

[43]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).

[44]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 common flow betas 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 7: Uncertainty betas and common flow betas of China-related stocks around the unexpected announcement of a possible US-China trade war.

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 7.

We find that the treatment effect emerges only after the announcement of a possible US-China trade war (see panel B of Figure 7). 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.[45]

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., common

[45] 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).

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 common flow betas of China-related stocks relative. As shown in panel B of Table 11, the common flow betas 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 common flow betas of China-related stocks is also persistent (see panel C of Figure 7).

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.[46] 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, $\beta_{i,Dec2016}^{flow}$. Specifically, we run the following quarterly regression:

$$\Delta(w_{i,f} - w_i^M) = b_1 \times \beta_{i,Dec2016}^{flow} + b_2 \times \beta_{i,Dec2016}^{M} + \alpha_{ind} + \alpha_f + \alpha_t + \varepsilon_{i,f}, \tag{4.11}$$

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 12, the coefficient of the common 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

[46]See Table OA.21 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 12: 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	
	$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)	
$\beta_{i,Dec2016}^{flow}$	-0.020^{**}	-0.028^{**}	-0.026^{**}	-0.040^{**}	-0.041^{***}	-0.033^{**}	-0.035^{**}	-0.044^{**}
	[−2.209]	[−2.317]	[−2.385]	[−2.026]	[−2.775]	[−2.201]	[−2.085]	[−2.124]
$\beta_{i,Dec2016}^{M}$	-0.051^{**}	-0.071^{***}	-0.054^{**}	-0.073^{***}	-0.052^{***}	-0.044^{***}	-0.058^{***}	-0.048^{***}
	[−2.004]	[−3.424]	[−2.160]	[−3.661]	[−2.897]	[−2.395]	[−3.555]	[−2.726]
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	0.036	0.039	0.036	0.039	0.022	0.026	0.022	0.026

	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	
	$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)	
$\beta_{i,Dec2016}^{flow}$	-0.021^{**}	-0.033^{**}	-0.025^{**}	-0.054^{**}	-0.025^{**}	-0.020^{**}	-0.033^{*}	-0.040^{**}
	[−2.104]	[−2.446]	[−2.258]	[−2.567]	[−2.287]	[−2.359]	[−1.888]	[−2.418]
$\beta_{i,Dec2016}^{M}$	−0.002	-0.039^{*}	−0.003	-0.042^{**}	−0.013	-0.041^{**}	−0.017	-0.044^{**}
	[−0.068]	[−1.869]	[−0.123]	[−2.063]	[−0.746]	[−2.176]	[−1.073]	[−2.377]
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	0.048	0.051	0.049	0.052	0.037	0.040	0.037	0.040

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 common 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 common flow betas in 2016 so that the cross-sectional variation in the common 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.

US-China trade war (using industry fixed effects).[47]

We focus on the set of China-unrelated stocks to mitigate the concern that portfolio

[47]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 12).

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.22 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 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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