Delegated Portfolio Choice: Asset Pricing with Fund Flows

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Abstract

We consider an economy populated by myopic investors, in which some investors delegate investment decisions to professional fund managers. Managers care about the size of the fund, which fluctuates due to fund returns and fund flows. They have hedging motives against fund flow fluctuations, thereby tilting their portfolios towards stocks with low flow betas. The resulting demand boosts the valuation of low-flow-beta stocks. In equilibrium, fund flows respond to aggregate economic shocks, and thus risk premium analogous to the hedging term in the ICAPM emerges even in a myopic environment. In the data, we find that fund-level flows obey a strong factor structure and that shocks to the common fund flows factor are priced. We also document that fund portfolios are tilted for flow hedging at the expense of losing Sharpe ratio. Particularly, we examine the portfolio choice of mutual funds after the breakout of the US-China trade war which leads to an exogenous increase in the flow beta of China-related stocks. In such a quasi experiment, we find that active mutual funds rebalance their portfolio holdings of the China-unrelated stocks towards low-flow-beta stocks, consistent with their hedging motives.

Keywords: Fund flow, Financial intermediary, Tilted portfolio, Uncertainty, Trade war.
(JEL: G11, G12, G23)

1 Introduction

Over the past few decades, delegated asset management such as mutual funds and pension funds have become the dominant player in the U.S. financial markets (e.g., French, 2008). For example, the combination of mutual funds and pension funds held more than 44% of the U.S. equity market in 2016.

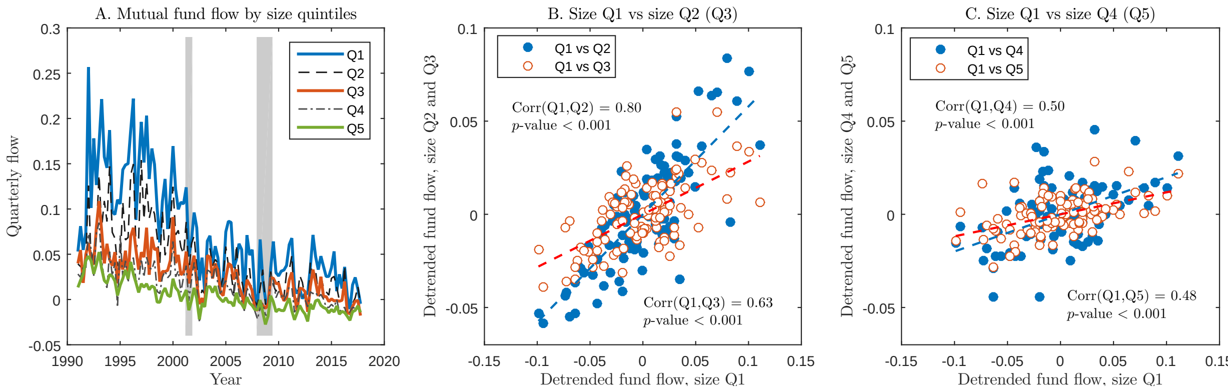
Because mutual funds and pension funds charge asset management fees based on the asset under management (AUM), fund managers' incentives are closely related to fund size, which fluctuates due to fund returns and fund flows.[1] If fund flows exhibit a systematic aggregate pattern, fund managers will have incentive to hedge against the common flow fluctuations. This hedging motive creates additional demand for low-flow-beta stocks, which should affect stock prices in the equilibrium.

As a motivating fact, we show that fund-level flows indeed share a striking degree of common time variation. Panel A of Figure 1 plots value-weighted fund-level flows within fund size quintiles. Panel B and C of Figure 1 plot the detrended fund flows of Quintile 1 size group against the detrended flows of other size groups. We find that funds of all sizes demonstrate very similar time series flow patterns. The correlation between mutual fund flows within size quintiles one and five is 48% (p value < 0.001). The minimum correlation among fund flows of the five size groups is 47% (p value < 0.001), which corresponds to the Quintile 2 size group versus the Quintile 5 size group.[2]

How does delegated asset management's incentive to hedge against fund flow fluctua-

[1] Recent studies show that the compensation structure of fund mangers exhibits large amount of heterogeneity (e.g., Ibert et al., 2018; Ma, Tang and Gómez, 2019). Nonetheless, the empirical evidence is consistent with the notion that fund managers care about fund size.

[2] Besides fund size, fund flows sorted on other characteristics also exhibit a high degree of common time variation. Figure A.1 in the appendix plots the fund flows sorted on expense ratios (Panel A of Figure A.1), industry concentration as defined in Kacperczyk, Sialm and Zheng (2005) (Panel B of Figure A.1), and portfolio liquidity as defined in Pastor, Stambaugh and Taylor (2017) (Panel C of Figure A.1). Similar to fund size, we find that fund flows sorted on these characteristics also share common time variation.



Note: Panel A shows the mutual fund flows sorted by fund size quintiles. The lines represent the value-weighted fund flows of each fund size quintiles. Panel B and C of Figure 1 plot the detrended fund flows of Quintile 1 size group against the detrended flows of other size groups. We define fund-level flows as follows:

$$f_{i,t} = \frac{(TNA_{i,t} - TNA_{i,t-1} \times Ret_{i,t})}{TNA_{i,t-1}}, \tag{1.1}$$

where $TNA_{i,t}$ is the total net asset for fund i at month t, and $Ret_{i,t}$ is the net total return of the fund i at month t. TNA and return data come from CRSP and Morningstar. Following Elton, Gruber and Blake (2001), we require lagged total net assets ($TNA_{i,t-1}$) to be larger than \$15 million.

Figure 1: Mutual fund flows by fund size quintiles.

tions affect stock prices? In this paper, we build a simple model to illustrate the effect of fund manager's hedging motives on equilibrium asset prices. Specifically, we introduce fund managers into an overlapping-generation (OLG) exchange economy with myopic agents and multiple risky assets. We show that common fund flows respond to aggregate economic shocks in equilibrium, and thus risk premia analogous to the hedging term in the ICAPM emerges even in a myopic environment. As a result, common fund flows are priced in the cross section.

We provide three lines of empirical evidence to support our model by employing detailed data on the returns, asset size, and holdings of mutual funds. First, we find that stocks with higher flow betas are associated with higher excess returns and higher CAPM alphas. This finding remains robust after we double sort on stock size and market liquidity. The magnitudes of the flow-beta spreads are both statistically and economically significant.

Second, we show that active mutual funds hedge against fund flows. Their holdings are tilted away from high-flow-beta stocks. Undoing the tilt can improve the annualized Sharpe ratio by 0.09, suggesting that mutual funds hedge at the expense of performance. Furthermore, we use a quasi-experiment setting to study the hedging behavior of mutual funds. Specifically, we study how mutual funds rebalance their portfolio holdings on the China-related stocks following the onset of the US-China trade war. The flow betas of the China-related stocks increase substantially after the trade war during which the trade policy uncertainty skyrocketed. Mutual funds do not reduce their holdings of China-related stocks and therefore have incentive to hedge against the increased exposure to fund flows. We find that mutual funds tilt their holdings of China-unrelated stocks towards the low-flow-beta stocks after the trade war. This rebalancing pattern is more pronounced for funds that hold a higher weight of the China-related stocks prior to the trade war.

Finally, we study the relation between fund flows and aggregate macroeconomic shocks. We find that mutual fund flows are negatively correlated with market volatility and consumption dispersion shocks, suggesting that mutual fund flows response to aggregate economic shocks.

Our paper contributes to the emerging literature on the role of delegated portfolio management in asset pricing (e.g., Brennan, 1993; Goldman and Slezak, 2003; Cornell and Roll, 2005; Basak, Pavlova and Shapiro, 2007; Hugonnier and Kaniel, 2010; Cuoco and Kaniel, 2011; He and Krishnamurthy, 2011; Vayanos and Woolley, 2011; Basak and Pavlova, 2013; He and Krishnamurthy, 2013; Kaniel and Kondor, 2013; Vayanos and Woolley, 2013; Koijen, 2014). We add to this literature by showing that mutual funds tilt their portfolios towards stocks with low flow betas, which boosts the valuation of these stocks.

Our paper is also related to the large literature on mutual fund flows (e.g., Warther, 1995; Edelen and Warner, 2001; Berk and Green, 2004; Coval and Stafford, 2007; Frazzini and Lamont, 2008; Ben-Rephael, Kandel and Wohl, 2011; Khan, Kogan and Serafeim, 2012; Lou, 2012; Christoffersen, Musto and Wermers, 2014; Goldstein, Jiang and Ng, 2017; Kaniel, Tompaidis and Zhou, 2018; Ben-Rephael, Choi and Goldstein, 2019). We show that mutual fund flows obey a strong factor structure and that shocks to the common fund flows factor are priced. We also show that mutual fund flows respond to aggregate economic shocks such as shocks to market volatility and consumption dispersion.

2 Model

In this section, we introduce fund managers into an overlapping-generation (OLG) exchange economy with myopic agents and multiple risky assets. The goal is to set up a simplest model. Our main focus is the effect of delegated investment and fund manager's hedging motives against fund flow fluctuations on equilibrium asset prices. We show that common fund flows respond to aggregate economic shocks in equilibrium, and thus risk premia analogous to the hedging term in the ICAPM emerges even in a myopic environment. As a result, common fund flows are priced in the cross section. In what follows, we introduce our framework, define our equilibrium concept, and the properties of the equilibrium.

2.1 Economic setup

We consider a discrete-time, infinite-horizon, overlapping-generation (OLG) exchange economy with multiple risky assets, one riskfree asset, and a single perishable consumption good. The dividend processes of n risky assets $D_t = [D_{1,t}, \cdots, D_{n,t}]^T$ are characterized by

$$d_{t+1} = d_t + y_{t+1}, \tag{2.1}$$

where the log dividend is $d_t = \ln(D_t)$ and the log growth process $y_t = [y_{1,t}, \cdots, y_{n,t}]^T$ follows the linear factor structure:

$$y_t = \mu + B^T u_t + \varepsilon_t, \tag{2.2}$$

with k factors $u_t = [u_{1,t}, \cdots, u_{k,t}]^T$ to be i.i.d. $u_t \sim N(0, I)$ and residuals $\varepsilon_t = [\varepsilon_{1,t}, \cdots, \varepsilon_{n,t}]^T$ to be i.i.d. $\varepsilon_t \sim N(0, V_t)$ with $V_t = e^{h_t}\overline{V}$. Here, the $n \times k$ matrix B are the loadings of growth y_t on the factors x_t. The stochastic variances are driven by the aggregate shocks x_t as follows:

$$h_{t+1} = \rho h_t + \tau^T u_{t+1}, \quad \text{with } \rho \in (0, 1). \tag{2.3}$$

There is one riskfree bond and n risky stocks. The riskfree bond is in zero net supply, while the stock $j \in \{1, \cdots, n\}$ is a claim to the dividend stream $D_{j,t}$ and is in unit net supply. We denote the riskfree rate by $R_{f,t}$ and the return of risky asset j by $R_{j,t+1} \equiv (P_{j,t+1} + D_{j,t+1})/P_{j,t}$ where $P_{j,t}$ is the price of risky asset j at time t for $j = 1, \cdots, n$. The log returns are $r_{f,t} = \ln(R_{f,t})$ and $r_{t+1} = \ln(R_{t+1})$ with return vector $R_{t+1} = [R_{1,t+1}, \cdots, R_{n,t+1}]^T$. According to Campbell-Shiller approximation, the return vector R_{t+1} can be expressed as

$$\begin{aligned} r_{t+1} &\approx K^T p_{t+1} - p_t + \ell + (I - K)^T d_{t+1} && (2.4) \\ &= K^T z_{t+1} - z_t + \ell + (I - K)^T y_{t+1}, && (2.5) \end{aligned}$$

where $p_t = \ln(P_t)$ is the log price and $z_t = \ln(P_t/D_t)$ is the log price-dividend ratio, K is the diagonal matrix with elements $\kappa_j = e^{\overline{z}_j}/(1 + e^{\overline{z}_j})$ and $\overline{z}_j$ to be the long-run average of log price-dividend ratio for asset j, and $\ell_j = -\ln(\kappa_j) + (1-\kappa_j)\ln(1/\kappa_j - 1)$. The coefficients will be determined in equilibrium.

We conjecture the log price-dividend ratio to be

$$z_t \approx a_0 + a_1 h_t \tag{2.6}$$

where a_0 and $a_0 \in \mathbb{R}^n$ will be determined in equilibrium by market clearing conditions. The equilibrium log returns are

$$r_{t+1} \sim N(\mu_t, \Sigma_t) \tag{2.7}$$

where

$$\mu_t = \left[\ell - (I-K)^T(\mu + a_0)\right] - (K^T a_1 \rho - a_1) h_t \tag{2.8}$$

$$\Sigma_t = e^{h_t}\left[K^T a_1 \tau^T + (I-K)^T B^T\right] \overline{V} \left[K^T a_1 \tau^T + (I-K)^T B^T\right]^T \tag{2.9}$$

The return on a portfolio with portfolio weights of w in the risky assets and $1 - w^T\mathbf{1}$ in the riskfree bond is denoted by

$$\widetilde{R}_{t+1}(w) \equiv R_{f,t} + w^T(R_{t+1} - R_{f,t}). \tag{2.10}$$

Following Campbell and Viceira (1999, 2001), we approximate the log return $\widetilde{r}_{t+1}(w) = \ln\left(\widetilde{R}_{t+1}(w)\right)$ as follows

$$\widetilde{r}_{t+1}(w) = r_{f,t} + w^T \mu_t + \frac{1}{2} w^T \left(\sigma_t^2 - \Sigma_t w\right) \tag{2.11}$$

where $\sigma_t^2 = \text{diag}(\Sigma_t)$ is the diagonal of Σ_t.

The economy is populated by investors and fund managers. The cohort t of agents are born at the beginning of period t and die at the beginning of period $t+1$. All agents have the same log utility, and each agent i cares about her consumption $C_{i,t}$ in period t and the bequest $W_{i,t+1}$ to her descendant. The utility is

$$\ln(C_{i,t}) + \beta \mathbb{E}_t \left[\ln(W_{i,t}) \right] \tag{2.12}$$

where β is the subjective discount rate.

Investors own the stocks, but some of them, referred to as *fund investors*, need to delegate their investment to professional fund managers. The rest of the investors, referred to as *direct traders*, can trade risky assets directly on their own accounts. At the beginning of each period, λ fraction of investors are born to be fund investors and $1-\lambda$ fraction of investors are born to be direct traders. Zero mass of fund managers are born each period.

Fund investors can only choose how much to invest in the riskfree bond and the delegated portfolio managed by professional fund managers with an advisory fee, while direct traders and fund managers can trade all assets freely except that fund managers charge an advisory fee from fund investors. In what follows, we first describe the optimal portfolio problem of each of the three groups of agents in detail and then characterize the equilibrium.

Household investors. Given the household investor's wealth $W_{h,t} = \lambda W_t$ and the fund manager's portfolio choice $w_{f,t}$ and the expense ratio α_t, the household investors optimally choose the share of their wealth delegated to the professional fund managers, denoted by

ϕ_t. The optimization problem of household investors can be characterized by

$$\max_{\phi_t, C_{h,t}} \left\{ \ln\left(C_{h,t}\right) + \beta \mathbb{E}_t \left[\ln\left(W_{h,t+1}\right) \right] \right\}. \tag{2.13}$$

subject to

$$W_{h,t+1} = (\lambda W_t - C_{h,t} - \alpha_t A_t) \left(R_{f,t} + \phi_t (\widetilde{R}_{t+1}(w_{f,t}) - R_{f,t}) \right) \tag{2.14}$$

$$A_t = \phi_t (W_{h,t} - C_{h,t}). \tag{2.15}$$

In equilibrium, it must hold that

$$C_{h,t} = (1-\beta)\lambda W_t. \tag{2.16}$$

The myopic portfolio is

$$\phi_t = \phi(h_t) \equiv \frac{w_{f,t}^T(\mu_t - r_{f,t}\mathbf{1}) + \frac{1}{2} w_{f,t}^T \Sigma_t w_{f,t}}{w_{f,t}^T \Sigma_t w_{f,t}}. \tag{2.17}$$

Therefore, the asset under management at the beginning of period t is

$$A_t = \phi_t \beta \lambda W_t, \tag{2.18}$$

and the fund flows can be approximated by

$$\Pi_{t+1} = \frac{A_{t+1} - A_t(1-\alpha_t)\widetilde{R}_{t+1}(w_{f,t})}{A_t} \tag{2.19}$$

$$\approx \frac{\phi_{t+1} - \phi_t}{\phi_t} + \alpha_t \widetilde{R}_{t+1}(w_{m,t}) \tag{2.20}$$

Further, the log-linearization leads to

$$\pi_{t+1} = \ln(\Pi_{t+1}) \approx \ln(\alpha_t) + \frac{\phi'(h_t)}{\phi(h_t)}\left[(\rho-1)h_t + \tau^T u_{t+1}\right] + \widetilde{r}_{t+1}(w_{m,t}). \tag{2.21}$$

The risky assets have heterogeneous betas with respect to the endogenous fund flows:

$$\Psi_t = \mathrm{Cov}_t\left[r_{t+1}, \pi_{t+1}\right] \approx \frac{\phi'(h_t)}{\phi(h_t)}\tau^T B + \Sigma_t w_{m,t}. \tag{2.22}$$

Fund managers. In period t, each manager with assets under management (AUM) A_t choose the expense ratio α_t for the advisory fee. We assume the manager must consume her fee $\alpha_t A_t$ in period t. She then invests the remaining $(1-\alpha_t)A_t$ in a portfolio with portfolio weights $w_{f,t}$ on risky assets and $1 - w_{f,t}^T\mathbf{1}$ in the bond. The optimization problem of fund managers is

$$\max_{\alpha_t, w_{f,t}} \ln\left(\alpha_t A_t\right) + \beta\mathbb{E}_t\left[\ln\left(A_{t+1}\right)\right] \tag{2.23}$$

subject to

$$A_t = \phi_t(W_{h,t} - C_{h,t}) \tag{2.24}$$

$$A_{t+1} \approx A_t(1-\alpha_t)\widetilde{R}_{t+1}(w_{f,t}) + A_t\Pi_{t+1}. \tag{2.25}$$

Direct traders. Direct traders solve a standard optimal portfolio problem. Denoting by $w_{d,t}$ the optimal portfolio weights of time t wealth $W_{d,t}$, we have

$$\max_{w_{d,t}} \ln\left(C_{d,t}\right) + \beta\mathbb{E}_t\left[\ln\left(W_{d,t+1}\right)\right] \tag{2.26}$$

subject to

$$W_{d,t+1} = (W_{d,t} - C_{d,t})\widetilde{R}_{t+1}(w_{d,t}). \tag{2.27}$$

2.2 Equilibrium

In equilibrium, the optimal consumption is $C_{h,t} = (1-\beta)W_{h,t}$ and $C_{d,t} = (1-\beta)W_{d,t}$. The optimal expense ratio is $\alpha_t = 1-\beta$. The direct traders hold the standard tangent portfolio

$$w_{d,t}^* = \Sigma_t^{-1}(\mu_t - r_{f,t}\mathbf{1}). \tag{2.28}$$

The fund managers hold a tilted portfolio to hedge against fluctuations in fund flows at the cost of losing Sharpe ratio:

$$w_{f,t}^* = \Sigma_t^{-1}(\mu_t - r_{f,t}\mathbf{1}) - \Sigma_t^{-1}\Psi_t/2. \tag{2.29}$$

Therefore, the market portfolio $w_{m,t}$ deviates from the mean-variance tangent portfolio which has the largest Sharpe ratio. It becomes

$$\begin{aligned} w_{m,t} &= \lambda w_{f,t}^* + (1-\lambda)w_{d,t}^* && (2.30)\\ &= \Sigma_t^{-1}(\mu_t - r_{f,t}\mathbf{1}) - \lambda\Sigma_t^{-1}\Psi_t/2. && (2.31)\end{aligned}$$

The market portfolio is the mean-variance tangent portfolio if and only if the economy does not need delegated investment (i.e., $\lambda = 0$). Given other things fixed, the equilibrium interest rate $r_{f,t}$ clears the riskfree bond market by setting $\mathbf{1}^T w_{m,t} = 1$.

In equilibrium, fund flows respond to aggregate economic shocks, and thus risk premia analogous to the hedging term in the ICAPM emerges even in a myopic environment, which is summarized in the following theorem.

Theorem 1. *For any portfolio $\widetilde{r}_{t+1}(w_{h,t}) = w_{h,t}^T\widetilde{r}_{t+1}$ with $\mathbf{1}^T w_{h,t} = 1$, it holds that*

$$\mathbb{E}_t\left[\widetilde{r}_{t+1}(w_{h,t})\right] - r_{f,t} = Cov_t\left[\widetilde{r}_{t+1}(w_{h,t}),\ \widetilde{r}_{t+1}(w_{m,t})\right] + \frac{\lambda}{2}Cov_t\left[\widetilde{r}_{t+1}(w_{h,t}),\ \pi_{t+1}\right]$$

If $\text{Cov}_t\left[\widetilde{r}_{t+1}(w_{h,t}),\ \pi_{t+1}\right] < 0$, it means that the portfolio $w_{h,t}$ provides a natural hedging against the fluctuations in fund flows. As a result, with a high level of delegated investment (i.e., high level of λ), such a portfolio faces high demand from the fund managers, which boosts its valuation, and thus a lower equilibrium excess return is required by investors.

3 Empirical analysis

In this section, we systematically test the main predictions of our model. Section 3.1 describes the data. Section 3.2 shows that fund flow betas are priced in the cross section. Section 3.3 studies the hedging behavior of active mutual funds. Section 3.4 examines the relation between fund flows and aggregate macroeconomic shocks.

3.1 Data description

We obtain fund names, monthly returns, total net assets (TNA), investment objectives, and other fund characteristics from 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 U.S. equity mutual funds based on their objective codes and their disclosed asset compositions.[3] We identify and exclude index funds based on their names and the index fund identifiers in the CRSP data.[4]

[3]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 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 are available and the fund has a CS policy or holds more than 80% of its value in common shares, then the fund will be included.

[4]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

Following Berk and Van Binsbergen (2015) and Pástor, Stambaugh and Taylor (2015), we also use Morningstar data to cross-check the accuracy of the fund returns and asset size in the CRSP data.[5] We compute monthly fund flows based on monthly returns and fund asset size as explained in Figure 1. Because CRSP and Morningstar provide extensive coverage on the monthly TNAs after 1991, the fund flow data in our analysis span the period from 1991 to 2018.

We obtain the portfolio holdings of mutual funds from the Thomson Reuters Mutual Fund Holding Data (S12). Because Thomson data suffer from data quality problems such as missing funds after 2008 (Zhu, 2019), we follow Shive and Yun (2013) and Zhu (2019) by using CRSP Mutual fund holding data starting for the third quarter of 2008. Our resulting mutual holding data span the period from 1980 to 2018.

3.2 Common fund flow betas are priced

Our findings suggest that fund-level flows obey a strong factor structure. We extract the PCA of the fund flows of the size quintiles and define it as the common fund flow.[6] We next test whether stocks' exposure to common fund flows is priced in the cross section using the portfolio sorting approach.

Monthly TNA is extensively covered by CRSP and Morningstar only after 1991. This

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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.

[5] Following Pástor, Stambaugh and Taylor (2015), we define a share class as well matched if and only if 1) 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 2) the 60th percentile of the absolute value of the difference between the CRSP and Morningstar monthly total net assets is less than $100,000. Around 60% of fund shares in the CRSP data are matched with the Morningstar data.

[6] Results of our paper are robust to the common fund flow defined as the PCA of fund flows across all cross sections (i.e., the pool of size quintiles, expense ratio quintiles, industry concentration quintiles, and portfolio liquidity quintiles).

relatively short time period could be a concern for asset pricing tests. To address this problem, we use the mimicking portfolio approach to extend our sample period. We construct a mimicking portfolio for the common fund flows by projecting them onto the space of excess returns. Specifically, we run the following regression:

$$CommonFlow_t = a + b'[BL, BM, BH, SL, SM, SH]_t + \varepsilon_t. \tag{3.1}$$

Here, $CommonFlow_t$ is the common fund flow. BL, BM, BH, SL, SM and SH are the excess returns of the six Fama-French benchmark portfolios on size (*S*mall and *B*ig) and book-to-market (*L*ow, *M*edium, and *H*igh) in excess of the risk-free rate.

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

	Excess returns	CAPM alphas	Excess returns	CAPM alphas
Quintiles of flow betas	Data: CRSP mutual funds alone		Data: CRSP/Morningstar intersection	
Q1	5.35**	−1.72*	5.19*	−2.54**
	[2.17]	[−1.91]	[1.84]	[−2.02]
Q2	7.17***	1.09*	6.97***	0.65
	[3.47]	[1.80]	[3.24]	[1.03]
Q3	7.74***	1.72**	7.56***	1.59**
	[3.61]	[2.19]	[3.66]	[2.22]
Q4	10.28***	3.30***	10.12***	3.49***
	[4.07]	[3.34]	[4.18]	[3.50]
Q5	10.24**	2.07	10.47***	2.99*
	[3.13]	[1.24]	[3.46]	[1.82]
Q5 − Q1	4.89**	3.79*	5.28**	5.53**
	[2.32]	[1.81]	[2.32]	[2.31]

Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on fund flow betas. The fund flow betas are computed based on returns of the fund-flow-mimicking portfolio. In June of year t, we sort firms into five quintiles based on this firm's fund flow betas. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We exclude financial firms and utility firms from the analysis. We only include stocks with share code 10 and 11, and stocks that are listed on the NYSE, NASDAQ, and Amex. Sample period spans from July 1963 to June 2018. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

We then estimate the fund flow betas for all the stocks in the CRSP-Compustat universe based on the mimicking portfolio returns. For each stock i, we estimate its fund flow beta in month t by regressing its excess stock returns on the common-flow-mimicking returns

Table 2: Excess returns and CAPM alphas of portfolios sorted on common flow betas, double sorted on stock market cap and the Amihud illiquidity measure.

	Excess returns	CAPM alphas	Excess returns	CAPM alphas
Quintiles of flow betas	Data: CRSP mutual funds alone		Data: CRSP/Morningstar intersection	
Panel A: double sort on stock market cap				
Q1	4.62*	−2.69***	4.83*	−2.96**
	[1.79]	[−2.71]	[1.70]	[−2.33]
Q2	7.43***	1.38**	6.59***	0.33
	[3.60]	[2.29]	[3.07]	[0.51]
Q3	6.90***	0.89	7.52***	1.57**
	[3.31]	[1.36]	[3.67]	[2.37]
Q4	7.85***	1.81**	7.24***	1.39*
	[3.64]	[2.14]	[3.44]	[1.69]
Q5	10.06***	2.79***	10.32***	3.42***
	[3.80]	[2.72]	[4.11]	[3.33]
Q5 − Q1	5.44***	5.48***	5.48**	6.38***
	[3.37]	[3.31]	[2.97]	[3.31]
Panel B: double sort on the Amihud illiquidity measure				
Q1	4.89*	−2.44**	5.00*	−2.87**
	[1.88]	[−2.34]	[1.72]	[−2.15]
Q2	7.09***	0.97**	6.62***	0.25
	[3.39]	[1.64]	[3.05]	[0.39]
Q3	7.49***	1.46**	7.53***	1.66***
	[3.60]	[2.26]	[3.72]	[2.61]
Q4	7.08***	1.06	7.26***	1.31
	[3.31]	[1.29]	[3.46]	[1.62]
Q5	9.99***	2.65**	10.08***	3.09***
	[3.73]	[2.47]	[3.93]	[2.84]
Q5 − Q1	5.10***	5.09***	5.08**	5.96***
	[3.02]	[2.94]	[2.63]	[2.94]

Note: We first sort stocks into five groups based on stock market cap (Panel A) or the Amihud illiquidity measure (Panel B). We then sort stocks within each group into five quintiles based on the stocks' fund flow betas. Sample period spans from July 1963 to June 2018. We include t-statistics in parentheses. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

using a three-year rolling window (month $t-36$ to $t-1$). We control for market returns in the regressions to partial out the impact of market exposure. In June of year t, we sort firms into five quintiles based on this firm's fund flow betas (lagged yearly average flow betas).

Table 1 tabulates the excess returns and CAPM alphas of the long-short portfolios sorted on the fund flow betas. We find that the fund flow betas constructed based on the active US equity funds are positively priced. Stocks with higher fund flow betas are associate with higher excess returns and higher CAPM alphas. This finding remain robust if we compute fund flows using only the mutual funds that have matched returns and asset size across the CRSP and Morningstar datasets.

One potential explanation for the results in Table 1 is that fund beta betas may capture some stock characteristics that are priced. In particular, it is possible that stocks with higher flow betas have smaller size or are less liquid, and hence the return spreads of fund flow betas may simply capture size premium or illiquidity premium. To rule out this possibility, we perform double sort analyses. Table 2 tabulates the results. We find that the return spreads of fund flow betas are robust to the double sort of stock market cap and the Amihud illiquidity measure (Amihud, 2002).

3.3 Mutual funds hedge against common fund flows

In this subsection, we provide several lines of evidence to show that mutual funds hedge against common fund flows. First, we show that active mutual funds tilt their portfolios away from stocks with high flow betas. Second, we show that by undoing the tilt, mutual funds can improve their Sharpe ratio. Finally, we examine the portfolio choice of mutual funds after the breakout of the US-China trade war which leads to an exogenous increase in the flow betas of China-related stocks. In such a quasi experiment, we find that active mutual funds rebalance their portfolio holdings of the China-unrelated stocks towards low-flow-beta stocks, consistent with their hedging motives.

3.3.1 Evidence from portfolio choices

Our model predicts that active mutual funds tilt their holdings away from stocks with high flow betas. To test this prediction, we run the following regression:

$$w_{i,t}^{MF} - w_{i,t}^{mkt} = a + b\beta_{i,t-1}^{flow} + \varepsilon_{i,t}. \tag{3.2}$$

Here, $\beta_{i,t-1}^{flow}$ is the common fund flow beta for stock i at quarter $t-1$; $w_{i,t}^{MF}$ is the weight of stock i in the aggregate active mutual fund holdings at quarter t; and $w_{i,t}^{mkt}$ is the weight of stock i in the equity market portfolio.[7] The term $(w_{i,t}^{MF} - w_{i,t}^{mkt})$ represents the weight deviation of the aggregate active mutual fund portfolio from the equity market portfolio.

Table 3 tabulates the regression results. In Panel A, we exclude stocks with zero aggregate mutual fund weight. In Panel B, we include stocks with zero aggregate mutual fund weight conditional on these stocks have non-zero aggregate mutual fund weight in the previous two years. In both panels, we find that the estimated coefficient $\hat{b}$ is negative, suggesting that active mutual funds indeed tilt holdings away from high-flow-beta stocks.

3.3.2 Estimate the costs of hedging by undoing the tilt of mutual funds

If active mutual funds hedge fund flows, their aggregate portfolios will deviate from the tangency portfolio. As shown by our model, this deviation means active mutual funds hedge at the expense of Sharpe ratio. To estimate the costs of hedging, we undo the tilt of mutual funds and document the resulting changes of Sharpe ratio.

Specifically, we adjust the weights of mutual fund holdings by increasing the weights of the high-flow-beta stocks and decreasing the weights of low-flow-beta stocks. Denote the weight for stock i in active mutual fund f at quarter t as $weight_{i,f,t}$. We create the adjusted weights as follows:

$$w_{i,f,t}^{adj}(\delta, \gamma) = w_{i,f,t} + \delta(\beta_{i,t}^{flow} + \gamma). \tag{3.3}$$

[7] In this analysis and the analyses in the rest of the paper, we directly use common fund flows instead of the mimicking portfolio returns to estimate fund flow betas in order to get a more precise estimation. Our sample period starts from 1991 as a result.

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

Panel A: excluding stocks with zero mutual fund weight								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$							
	Data: CRSP mutual funds alone				Data: CRSP/Morningstar intersection			
$\beta_{i,t-1}^{flow}$	-0.037^{***}	-0.019^{***}	-0.019^{***}	-0.010^{**}	-0.033^{***}	-0.017^{***}	-0.020^{***}	-0.007
	[−5.134]	[−2.733]	[−3.659]	[−2.092]	[−4.911]	[−2.693]	[−4.505]	[−1.533]
Amihud illiquidity measure$_{i,t-1}$	-0.079^{***}	-0.089^{***}	0.009^{***}	0.007^{***}	-0.078^{***}	-0.090^{***}	0.009^{***}	0.007^{***}
	[−16.417]	[−15.144]	[6.398]	[3.410]	[−16.520]	[−15.184]	[6.629]	[3.392]
Returns$_{i,t-4:t-1}$	0.123^{***}	0.126^{***}	0.107^{***}	0.109^{***}	0.122^{***}	0.125^{***}	0.106^{***}	0.109^{***}
	[7.164]	[7.543]	[9.185]	[9.756]	[7.040]	[7.525]	[9.126]	[9.739]
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	377931	377931	377271	377271	377931	377931	377271	377271
R-squared	0.009	0.016	0.665	0.667	0.009	0.016	0.665	0.667

Panel B: including stocks with zero mutual fund weight								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	$w_{i,t}^{MF} - w_{i,t}^{mkt}$							
	Data: CRSP mutual funds alone				Data: CRSP/Morningstar intersection			
$\beta_{i,t-1}^{flow}$	-0.035^{*}	-0.011^{*}	-0.020^{***}	-0.008^{**}	-0.028^{***}	-0.013^{**}	-0.017^{***}	-0.006
	[−5.174]	[−1.900]	[−4.280]	[−2.027]	[−4.464]	[−2.346]	[−4.421]	[−1.603]
Amihud illiquidity measure$_{i,t-1}$	-0.056^{***}	-0.071^{***}	0.008^{***}	0.005^{***}	-0.056^{***}	-0.071^{***}	0.008^{***}	0.005^{***}
	[−13.454]	[−13.941]	[7.319]	[3.013]	[−13.524]	[−13.957]	[7.404]	[3.007]
Returns$_{i,t-4:t-1}$	0.103^{***}	0.105^{***}	0.076^{***}	0.081^{***}	0.102^{***}	0.105^{***}	0.076^{***}	0.081^{***}
	[7.908]	[8.570]	[9.027]	[9.474]	[7.704]	[8.563]	[8.894]	[9.459]
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	424268	424268	423729	423729	424268	424268	423729	423729
R-squared	0.006	0.012	0.649	0.650	0.006	0.012	0.649	0.650

Note: This table studies the relation between common flow betas and active mutual funds' weight deviation from the market. $w_{i,t}^{MF}$ is the weight for stock i in the aggregate active mutual fund holdings at quarter t; and $w_{i,t}^{mkt}$ is the weight for stock i in the equity market portfolio. $w_{i,t}^{MF} - w_{i,t}^{mkt}$ represents the weight deviation of the aggregate active mutual fund portfolio from the equity market portfolio. In Panel A, we exclude stocks with zero aggregate mutual fund weight. In Panel B, we include stocks with zero aggregate mutual fund weight conditional on these stocks have non-zero aggregate mutual fund weight in the previous two years. The common flow betas, the mutual fund weight deviation from the market, and the Amihud illiquidity measure are all standardized. The analysis is performed at quarterly frequency. Standard errors are double clustered at the stock and quarter level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1991 to 2018.

Here, $\beta_{i,t}^{flow}$ is the common flow beta for stock i at quarter t (winsorized at the 1% level). The minimum, maximum, mean, median, and standard deviation of $\beta_{i,t}^{flow}$ are −2.43, 7.27, 1.15, 0.87, and 1.71, respectively. Since mutual funds rarely engage in short selling, we impose that the weights for all stocks are positive after the weight adjustment. Specifically, we add a positive constant γ that is larger than 2.43 in equation (3.3), which puts the $\beta_{i,t}^{flow}$ to the positive domain.

Next, we normalize the adjusted weights for each fund f at quarter t to make sure the sum of the weights across stocks equals to one. The normalized adjusted weights are referred to as the synthetic weights:

$$w_{i,f,t}^{syn}(\delta,\gamma) = \frac{w_{i,f,t}^{adj}(\delta,\gamma)}{\sum_i w_{i,f,t}^{adj}(\delta,\gamma)}. \tag{3.4}$$

Based on $w_{i,f,t}^{syn}(\delta,\gamma)$, we can construct the weight for stock i in the synthetic aggregate active mutual fund portfolio at quarter t:

$$w_{i,t}^{synMF}(\delta,\gamma) = \sum_f \left(w_{i,f,t}^{syn}(\delta,\gamma) \times w_{f,t} \right), \tag{3.5}$$

where $w_{f,t}$ is the weight of fund f in the aggregate active mutual fund portfolio constructed based on the fund portfolio value. We search for the parameter pairs $(\tilde{\delta}, \tilde{\gamma})$ such that the coefficient $\hat{b}$ of the following regression is zero:

$$w_{i,t}^{synMF}(\tilde{\delta},\tilde{\gamma}) - w_{i,t}^{mkt} = a + b\beta_{i,t-1}^{flow} + \varepsilon_{i,t}. \tag{3.6}$$

Finally, within all the pairs of $(\tilde{\delta}, \tilde{\gamma})$, we select a parameter pair $(\hat{\delta}, \hat{\gamma})$ that minimizes the squared difference between the synthetic mutual fund weight and the actual mutual fund weight:

$$\min_{\hat{\delta},\hat{\gamma}} \sum_{i,t} \left(w_{i,t}^{synMF}(\tilde{\delta},\tilde{\gamma}) - w_{i,t}^{MF} \right)^2. \tag{3.7}$$

The parameter pair $(\hat{\delta}, \hat{\gamma})$ captures the reversed tilt we apply to eliminate aggregate mutual fund portfolio's hedge against the common flow betas. After obtaining $(\hat{\delta}, \hat{\gamma})$, we then compute the synthetic next-quarter returns for each active mutual fund:

$$ret^{syn}_{f,t+1}(\hat{\delta}, \hat{\gamma}) = \sum_i \Big(ret_{i,t+1} \times w^{syn}_{i,f,t}(\hat{\delta}, \hat{\gamma}) \Big). \tag{3.8}$$

We can then quantify the difference in Sharpe ratio between the synthetic mutual fund returns and the mutual fund returns computed based on the actual holdings. We find that after undoing the tilt, the annualized Sharpe ratio increases by 0.09.

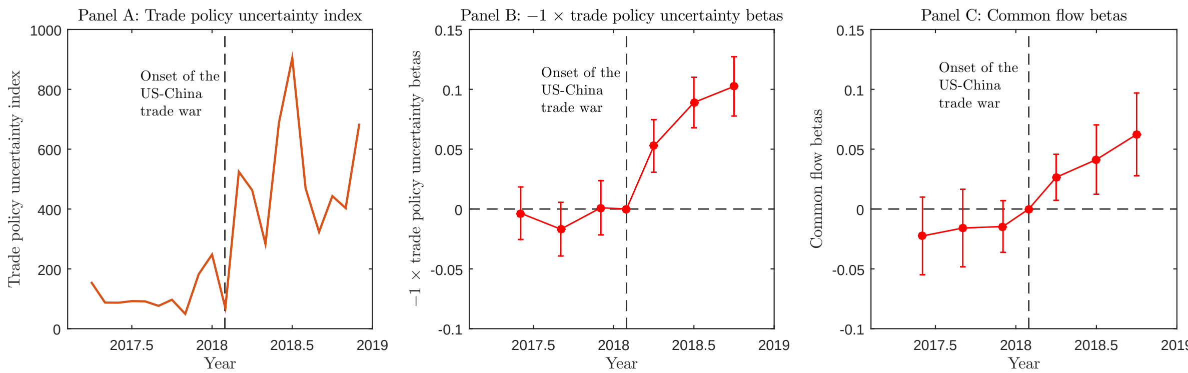
If we do not impose short-selling restriction (i.e., γ = 0), we only need to search $\hat{\delta}$ such that the coefficient $\hat{b}$ in equation (3.6) is zero. In that case, we find that mutual funds give up 0.12 of their annualized Sharpe ratio to hedge fund flows.

3.3.3 Evidence from a quasi-experiment: the US-China trade war

In this subsection, we use a quasi-experiment setting to further study the hedging behavior of active mutual funds. Specifically, we examine how active mutual funds rebalance their holdings of China-unrelated stocks after the US-China trade war, which exogenously increases the flow betas of the China-related stocks.

US-China trade war started in March 2018. On March 22nd, 2018, Trump administration issued the presidential memorandum which proposed 25% tariffs on over $50 billion worth of Chinese imports. After the onset of the trade war, the trade policy uncertainty index (Baker, Bloom and Davis, 2016) skyrocketed (see Panel A of Figure 2). Facing a much more uncertain policy environment, the returns of China-related stocks become more sensitive to uncertainty index (see Panel B) and also to the common fund flows (see Panel C) relative to China-unrelated stocks.

At the same time, active mutual funds as a whole do not appear to decrease their holdings of China-related stocks. Table 5 shows the summary statistics for the weight changes of active mutual funds from the last quarter of 2017 to the last quarter of 2018. We find that active mutual funds largely maintain their positions of the China-related



Note: Panel A plots the trade policy uncertainty index around the onset of the US-China trade war (i.e., March 2018). Data for the trade policy uncertainty index is from the Categorical Economic Policy Uncertainty (EPU) Data (Baker, Bloom and Davis, 2016). Panel B plots the trade policy uncertainty betas around the onset of the US-China trade war for China-related stocks relative to China-unrelated stocks. We multiply the uncertainty beta by -1. China-related stocks are firms that have positive revenue from China in 2016 based on the Factset Revere data. Panel C plots the fund flow betas around the onset of the US-China trade war for China-related stocks relative to China-unrelated stocks.

Figure 2: US-China trade war and fund flow betas.

Table 4: Changes of stocks' flow betas following the trade war.

	(1)	(2)	(3)	(4)
	$\beta^{flow}_{i,t}$		$-1 \times$ trade policy uncertainty betas$_{i,t}$	
China-related dummy$_i$ $\times$ trade war dummy$_{i,t}$	0.054**	0.054**	0.121***	0.121***
	[3.071]	[3.080]	[4.711]	[4.712]
China-related dummy$_i$	−0.120***	−0.120***	−0.192***	−0.192***
	[−4.285]	[−4.281]	[−5.476]	[−5.473]
Trade war dummy$_{i,t}$	0.070***		0.012	
	[4.336]		[0.470]	
Month FE	No	Yes	No	Yes
Observations	141353	141353	141352	141352
R-squared	0.004	0.006	0.005	0.009

Note: This table shows the changes of stocks' common flow betas and trade policy uncertainty betas following the trade war. China-related dummy is constructed based on the Factset Revere data. It equals one if a firm has positive revenue from China in 2016 and zero otherwise. Sample period spans from January 2017 to December 2018. Trade war dummy is one for time period after March 2018. Both the common flow betas and trade policy uncertainty betas are standardized. The analysis is performed at monthly frequency. Standard errors are double clustered at the stock and month level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

stocks. Thus, they have incentive to hedge against the increased exposure to fund flows.

Table 5: Active mutual funds maintain their positions of the China-related stocks.

	Mean	SE	t-stat	N
$\Delta w_{i,f}$ of China-unrelated stocks (%)	0.014*	0.007	1.944	226126
$\Delta w_{i,f}$ of China-related stocks (%)	0.005	0.007	0.801	209482

Note: This table shows the changes of the portfolio weights around the US-China trade war. $\Delta w_{i,f}$ is the weight changes of stock i of fund f from December 2017 to December 2018. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Stock rebalancing around the trade war.

	(1)	(2)	(3)	(4)
	$\Delta w_{i,f}(\%)$			
Stock samples:	China-unrelated		China-related	
β_i^{flow}	-0.035^{***}	-0.090^{***}	0.017	0.001
	[-2.965]	[-3.334]	[0.844]	[0.049]
β_i^{flow} × China exposure$_f$		-0.166^{***}		-0.215^{***}
		[-2.651]		[-2.668]
Fund FE	Yes	Yes	Yes	Yes
Observations	178165	140441	186404	152473
R-squared	0.094	0.053	0.064	0.053

Note: This table shows how active mutual funds rebalance their portfolios around the trade war. $\Delta w_{i,f}$ is the weight changes of stock i of fund f from December 2017 to December 2018. β_i^{flow} is the common flow beta for stock i in December 2016. China exposure$_f$ is the weight of China-related stocks of fund f in the last quarter of 2016. Both the common flow betas and the China exposure measure are standardized. Standard errors are clustered at the fund level. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6 examines how active mutual funds rebalance their holdings after the US-China trade war. We find that, for China-unrelated stocks, active mutual funds reduce their holdings of high-flow-beta stocks more relative to low-flow-beta stocks (see column 1 of Table 6). This result is more pronounced for mutual funds that hold more China-related stocks prior to the trade war (see column 2 of Table 6).[8] Taken together, our findings suggest that active mutual funds adjust their holdings to hedge against the increased fund flow betas after the US-China trade war, which is consistent with the predictions of our model.

3.4 Active fund flows and macroeconomic shocks

In this subsection, we examine the relation between mutual fund flows and macroeconomic shocks. We show that mutual fund flows are negatively related to both market volatility and shocks to consumption risks (measured by the dispersion of consumption growth rates). These findings suggest that mutual fund flows are related to macroeco-

[8] In columns 3 and 4 of Table 6, we also examine how mutual funds rebalance their holdings of the China-related stocks. However, we shall point out that the weight changes of China-related stocks can also be driven by cash flow news associated with the trade war.

nomic shocks, which provides corroborative evidence showing why exposure to fund flows are priced. Our findings are consistent with Ben-Rephael, Choi and Goldstein (2019), who show that mutual fund flows are closely correlated with fluctuations in credit and business cycles.

Table 7 shows the relation between market volatility and fund flows. We find that active mutual funds experience outflows when market volatility arises. This result is both statistically and economically significant. One standard deviation increase in the market volatility leads to more than 1/10 of standard deviation decrease in next month's mutual fund flows (columns 1 and 2 of Table 7). The results are more pronounced if we focus on large volatility spikes (columns 3 and 4 of Table 7).

Table 7: Market volatility leads to fund outflows.

	(1)	(2)	(3)	(4)
	Common mutual fund flow$_t$			
Market volatility$_{t-1}$	-0.155^{***}	-0.101^{**}		
	$[-3.927]$	$[-2.109]$		
Market volatility spike dummy$_{t-1}$			-0.478^{***}	-0.217
			$[-3.241]$	$[-1.327]$
Market volatility$_{t-7:t-2}$		-0.085^{*}		-0.122^{**}
		[-1.673]		$[-2.576]$
December dummy$_t$	-0.550^{***}	-0.549^{***}	-0.562^{***}	-0.554^{***}
	$[-2.932]$	$[-2.933]$	$[-2.997]$	$[-2.975]$
Observations	336	336	336	336
R-squared	0.056	0.062	0.042	0.057

Note: This table show the relation between market volatility and active fund flows. Market volatility is computed based on volatility of daily returns. Market volatility spike dummy equals one if the market volatility is ranked at the top 5% across all periods. Both the market volatility and fund flows are standardized. The analysis is performed at monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1991 to 2018.

Next, we examine the relation between fund flows and consumption risks. We compute monthly consumption dispersion shocks from the CEX data following previous studies (e.g., Brav, Constantinides and Geczy, 2002; Vissing-Jørgensen, 2002; Jacobs and Wang, 2004). Table 8 shows that mutual funds experience outflows following an increase in consumption dispersion, suggesting that mutual fund flows react to consumption growth

Table 8: Consumption dispersion shocks and active fund flows.

	(1)	(2)	(3)	(4)
	Common mutual fund flow$_t$		Common hedge fund flow$_t$	
Consumption dispersion shocks$_{t-1}$	-0.116***	-0.104***	0.128***	0.131***
	[-3.235]	[-3.218]	[6.265]	[6.162]
Common mutual fund flow$_{t-1}$	0.758***	0.779***		
	[19.885]	[21.303]		
Common hedge fund flow$_{t-1}$			0.054	0.054
			[0.235]	[0.235]
Market returns$_t$		0.278***		0.030
		[8.284]		[0.903]
Market returns$_{t-1}$		-0.05		0.053
		[-1.361]		[1.550]
December dummy$_t$	-0.458***	-0.529***	-0.172**	-0.191**
	[-4.327]	[-6.056]	[-2.041]	[-2.190]
Observations	324	324	324	324
R-squared	0.593	0.670	0.061	0.072

Note: This table shows the relation between consumption dispersion shocks and active fund flows. Hedge fund flows are computed based on hedge fund returns and AUM from the Thomson Reuters Lipper Hedge Fund Database (TASS). Consumption dispersion shocks$_t$ are measures as $(\text{Dispersion}_t - \text{Dispersion}_{t-1})/\text{Dispersion}_{t-1}$, where Dispersion$_t$ is the cross-sectional dispersion of the growth rate of household consumption in the CEX data. All variables except for the December dummy are standardized. The analysis is performed at the monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1991 to 2017.

shocks.

As a comparison, we also examine the reaction of hedge funds and retail investors to the consumption dispersion shocks. We compute hedge fund flows based on the Thomson Reuters Lipper Hedge Fund Database (TASS). We compute retail investor flows based on Barber and Odean's retail investor holding data (e.g., Barber and Odean, 2000, 2007; Barber, Odean and Zhu, 2008; Barber and Odean, 2013), which contain 66,465 households with accounts at a large discount broker during 1991 to 1996. As shown in columns 3 and 4 of Table 8, hedge funds experience inflows following an increase in consumption dispersion. We also find suggestive evidence showing that sophisticated retail investors (i.e., retail investors with high net worth, rich investment experience and financial knowledge) invest more on common stocks following an increase in consumption dispersion.[9] These results suggest that hedge funds and sophisticated retail investors are

[9]The results are not statistically significant, which is likely due to the short sample period of the retail

likely the counter-party of mutual funds when mutual funds sell their assets following an increase in consumption dispersion.

Table 9: Consumption dispersion shocks and retail investment flows.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Retail investment flow$_t$						
Retail investor sample:	All	High net worth	Low net worth	High experience	Low experience	High knowledge	Low knowledge
Consumption dispersion shocks$_{t-1}$	0.045	0.047	−0.081	0.057	−0.001	0.049	−0.001
	[0.690]	[0.695]	[−0.776]	[0.744]	[−0.026]	[0.615]	[−0.018]
Retail investment flow$_{t-1}$	0.402***	0.329***	0.036	0.121	0.245***	0.119	0.240***
	[5.123]	[3.304]	[0.352]	[1.029]	[3.255]	[1.092]	[3.135]
Market returns$_t$	−0.311**	−0.362**	−0.396**	−0.219	−0.245***	−0.202	−0.417***
	[−2.256]	[−2.531]	[−2.091]	[−1.304]	[−2.829]	[−1.047]	[−2.785]
Market returns$_{t-1}$	−0.120	−0.152	−0.149	−0.104	−0.038	−0.162	−0.088
	[−0.738]	[−0.887]	[−0.857]	[−0.455]	[−0.416]	[−0.634]	[−0.558]
December dummy$_t$	0.046	0.409	1.004**	0.959	0.098	1.005	0.135
	[0.086]	[0.611]	[2.419]	[0.721]	[0.424]	[0.669]	[0.340]
Observations	69	69	69	69	69	69	69
R-squared	0.258	0.196	0.124	0.091	0.168	0.08	0.164

Note: This table shows the relation between the consumption dispersion shocks and retail investment flow. Retail investor flows are computed based on Barber and Odean's retail investor holding data. All variables except for the December dummy are standardized. The analysis is performed at the monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1991 to 1996.

4 Conclusions

In this paper, we build a model to illustrate the effect of fund manager's hedging motives on equilibrium asset prices. Because delegated asset management is compensated based on AUM, fund managers care about the size of the fund. Since fund size fluctuates due to fund returns and fund flows, managers have hedging motives against fund flow fluctuations. In equilibrium, funds tilt their holdings towards low-flow-beta stocks, resulting higher excess returns of these stocks. Fund flows respond to aggregate economic shocks, and thus risk premium analogous to the hedging term in the ICAPM emerges even in a myopic environment. We find strong empirical support for our model. Fund-

investor data.

level flows obey a strong factor structure and shocks to the common fund flows factor are priced. We also show that fund portfolios are tilted towards low-flow-beta stocks at the expense of losing Sharpe ratio.

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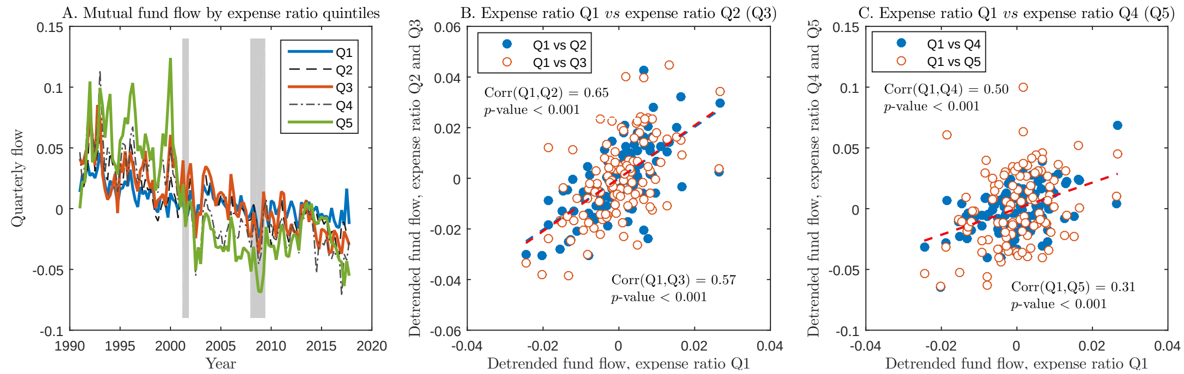
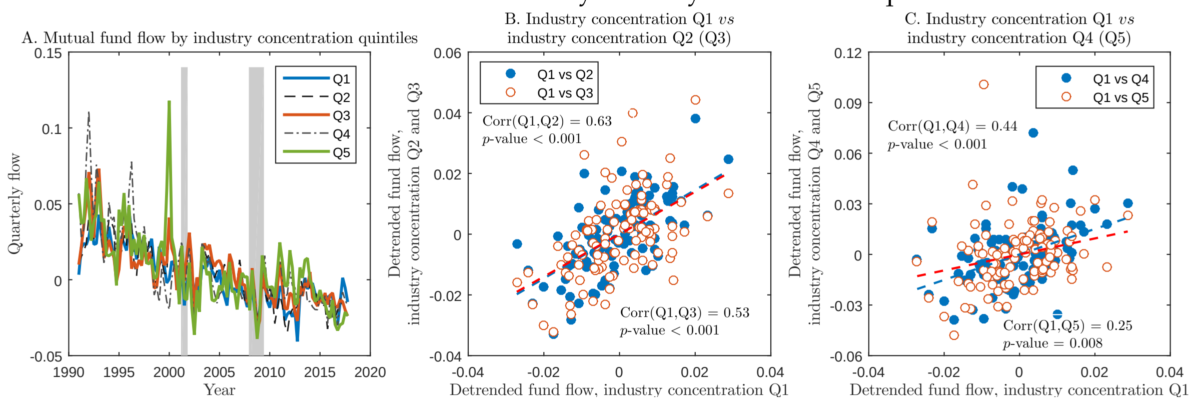
Appendix

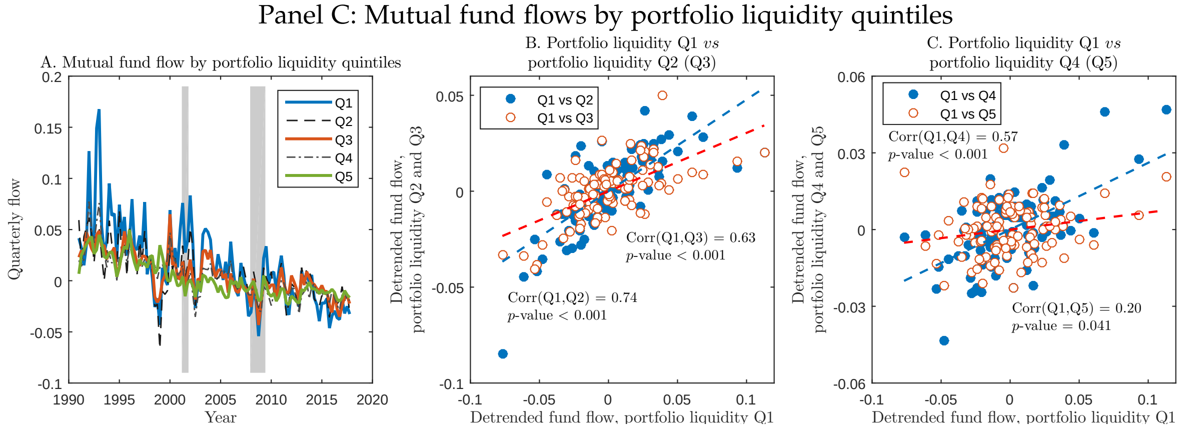
Panel A: Mutual fund flows by expense ratio quintiles



Panel B: Mutual fund flows by industry concentration quintiles



Panel C: Mutual fund flows by portfolio liquidity quintiles



Note: Panel A plots active mutual fund flows by quintiles sorted on expense ratios. Panel B plots active mutual fund flows by quintiles sorted on industry concentration Kacperczyk, Sialm and Zheng (2005). Panel C plots active mutual fund flows by quintiles sorted on portfolio liquidity Pastor, Stambaugh and Taylor (2017).

Figure A.1: Fund flows by expense ratio, industry concentration, and portfolio liquidity.