Online Appendix for "Common Fund Flows: Flow Hedging and Factor Pricing"

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Contents

1 Proofs for the Model in Dou, Kogan and Wu (2022)

1.1 Proof for Proposition 3.1

Plugging in the budget constraint, the optimization problem can be rewritten as

$$\max_{\phi_{d,t},C_{d,t}} (1-\beta)\ln(C_{d,t}) + \beta\ln(W_{d,t} - C_{d,t} - \overline{\alpha}Q_t) + \beta(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{\left[R_f + \phi_{d,t}^T(R_{t+1} - R_f)\right]^{1-\gamma}\right\}.$$

Thus, the unit EIS allows for the separation of optimal consumption and optimal portfolio problems. The optimal consumption is straightforward to derive:

$$C_{d,t} = (1-\beta)(W_{d,t} - \overline{\alpha}Q_t). \tag{OA.1}$$

Following Campbell and Viceira (1999, 2001), we approximate the dynamic budget constraint $r_{t+1}(\phi_{d,t}) = \ln\left[R_{t+1}(\phi_{d,t})\right]$ as follows

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

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

$$\max_{\phi_{d,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\left[r_f+\phi_{d,t}^T(r_{t+1}-r_f\mathbf{1})+\frac{1}{2}\phi_{d,t}^T\left(v_t-\Sigma_t\phi_{d,t}\right)\right]}\right\} \tag{OA.3}$$

Using the moment generating function of multivariate normal variables, it follows that

$$\mathbb{E}_t\left\{e^{(1-\gamma)\left[r_f+\phi_{d,t}^T(r_{t+1}-r_f\mathbf{1})+\frac{1}{2}\phi_{d,t}^T\left(v_t-\Sigma_t\phi_{d,t}\right)\right]}\right\} = e^{(1-\gamma)\left[r_f+\phi_{d,t}^T(\mu_t-r_f\mathbf{1})+\frac{1}{2}\phi_{d,t}^T\left(v_t-\Sigma_t\phi_{d,t}\right)\right]+(1-\gamma)^2\frac{1}{2}\phi_{d,t}^T\Sigma_t\phi_{d,t}}$$

Thus, the optimal portfolio problem can be further rewritten as

$$\max_{\phi_{d,t}}\phi_{d,t}^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t) - \frac{\gamma}{2}\phi_{d,t}^T\Sigma_t\phi_{d,t}. \tag{OA.4}$$

The first-order condition leads to

$$\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t). \tag{OA.5}$$

1.2 Proof for Proposition 3.2

Denote $\phi_{c,t} \equiv \frac{Q_t}{W_{c,t} - C_{c,t}}$. Plugging in the budget constraint, the optimization problem can be rewritten as

$$\begin{aligned}\max_{\phi_{c,t},C_{c,t}} &(1-\beta)\ln(C_{c,t}) + \beta\ln(W_{c,t} - C_{c,t}) \qquad \text{(OA.6)} \\ &+ \beta(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right]^{1-\gamma}\right\},\end{aligned}$$

Thus, the unit EIS coefficient allows for the separation of optimal consumption and optimal portfolio problems. The optimal consumption is straightforward to derive:

$$\begin{aligned}C_{c,t} &= (1-\beta)W_{c,t} \qquad \text{(OA.7)} \\ &= (1-\beta)\lambda W_t. \qquad \text{(OA.8)}\end{aligned}$$

Following Campbell and Viceira (1999, 2001), we approximate the dynamic budget constraint $r_{\alpha,t+1}(\phi_{d,t}) = \ln\left[R_{t+1}(\phi_{d,t}) + \alpha_t + \omega\right]$ as follows

$$\begin{aligned}r_{\alpha,t+1}(\phi_{d,t}) &\approx \ln\left[R_{t+1}(\phi_{d,t}) + \alpha_t + \omega\right] \qquad \text{(OA.9)} \\ &\approx \alpha_t + \omega + r_f + \phi_{d,t}^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi_{d,t}^T\left(v_t - \Sigma_t\phi_{d,t}\right), \qquad \text{(OA.10)}\end{aligned}$$

where $v_t \equiv \text{diag}(\Sigma_t)$ is the vector that contains the diagonal elements of Σ_t. Again, appealing to Campbell and Viceira's approximation method, the following log-linearization approximation holds:

$$\ln\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right] \\ \approx r_f + \phi_{c,t}\left[r_{\alpha,t+1}(\phi_{d,t}) - r_f\right] + \frac{1}{2}\phi_{c,t}(1-\phi_{c,t})\phi_{d,t}^T\Sigma_t\phi_{d,t}. \tag{OA.11}$$

The optimal portfolio problem can be approximately rewritten as

$$\max_{\phi_{c,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\left[\phi_{c,t}(\alpha_t+\omega)+\phi_{c,t}\phi_{d,t}^T(r_{t+1}-r_f\mathbf{1})+\frac{1}{2}\phi_{c,t}(1-\phi_{c,t})\phi_{d,t}^T\Sigma_t\phi_{d,t}+\frac{1}{2}\phi_{c,t}\phi_{d,t}^T\left(v_t-\Sigma_t\phi_{d,t}\right)\right]}\right\}.$$

After calculating the moment generating function and rearranging terms, searching for the optimal $\phi_{c,t}$ is equivalent to solving the following maximization problem:

$$\max_{\phi_{c,t}}\phi_{c,t}(\alpha_t+\omega) + \phi_{c,t}\phi_{d,t}^T\left(\mu_t - r_f + \frac{1}{2}v_t\right) - \frac{1}{2}\gamma\phi_{c,t}^2\phi_{d,t}^T\Sigma_t\phi_{d,t}. \tag{OA.12}$$

The first-order condition is

$$0 = \alpha_t + \omega + \phi_{d,t}^T\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right) - \gamma\phi_{c,t}\phi_{d,t}^T\Sigma_t\phi_{d,t}. \tag{OA.13}$$

Thus, according to Proposition 2.2, the optimal delegation $\phi_{c,t}$ is

$$\phi_{c,t} = \frac{1}{\gamma}\frac{1}{\phi_{d,t}^T\Sigma_t\phi_{d,t}}\left(\alpha_t + \omega + \gamma\phi_{d,t}^T\Sigma_t\phi_{d,t}\right) = 1 + \frac{\omega+\alpha_t}{\gamma_t}, \tag{OA.14}$$

where the effective risk aversion is

$$\gamma_t \equiv S_t/\gamma, \quad \text{with } S_t \equiv \left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right)^T\Sigma_t^{-1}\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right). \tag{OA.15}$$

We conjecture that

$$\mu_t - r_f\mathbf{1} = \overline{\zeta}h_t, \tag{OA.16}$$

where $\overline{\zeta}$ depends on the model parameters and such dependence is determined in the equilibrium.

Therefore, by plugging (OA.16) into (OA.14), it follows that

$$\phi_{c,t} = 1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}, \tag{OA.17}$$

where $\overline{\gamma} = \left(\overline{\zeta} + \frac{1}{2}\nu\right)^T \Sigma^{-1} \left(\overline{\zeta} + \frac{1}{2}\nu\right) / \gamma$ and $\nu = \text{diag}(\Sigma)$.

And hence, it holds that

$$q_t = \phi_{c,t} \frac{W_{c,t} - C_{c,t}}{W_t} \tag{OA.18}$$

$$= \beta\lambda \left(1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}\right). \tag{OA.19}$$

1.3 Proof for Proposition 3.3

The equilibrium net alpha α_t and asset management services (i.e., delegation) q_t are determined by solving the intersection point of the following equations:

$$q_t = \theta(\overline{\alpha} - f) - \theta\alpha_t \quad (q_t \text{ supplied by funds}), \tag{OA.20}$$

$$q_t = \beta\lambda \left[1 + (\omega + \alpha_t)/(\overline{\gamma} h_t)\right] \quad (q_t \text{ demanded by fund clients}). \tag{OA.21}$$

Plugging (OA.21) into (OA.20) leads to the result that $q_t = q(h_t)$ with $q'(\cdot) < 0$.

By definition, the aggregate fund flow is

$$\begin{aligned} flow_{t+1} &= \frac{Q_{t+1}}{Q_t} - R_{t+1}(\phi_{m,t}) - \alpha_t \\ &= \frac{q_{t+1}}{q_t} \frac{W_{t+1}}{W_t} - R_{t+1}(\phi_{m,t}) - \alpha_t \\ &= \frac{q_{t+1}}{q_t} \frac{W_{d,t} - C_{d,t} + (1 - \overline{\alpha}) Q_t}{W_t} R_{t+1}(\phi_t^{mkt}) - R_{t+1}(\phi_{m,t}) - \alpha_t. \end{aligned}$$

Thus, the aggregate fund flow can be rewritten as

$$flow_{t+1} = \frac{q_{t+1}}{q_t}\left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right] R_{t+1}(\phi_t^{mkt}) - R_{t+1}(\phi_{m,t}) - \alpha_t \tag{OA.22}$$

$$= e^{\Delta \ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] + r_{t+1}(\phi_t^{mkt})} - e^{r_{t+1}(\phi_{m,t})} - \alpha_t. \tag{OA.23}$$

Log-linear approximation leads to

$$\begin{aligned} flow_{t+1} \approx\ & \Delta \ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] \\ & + r_{t+1}(\phi_t^{mkt}) - r_{t+1}(\phi_{m,t}) - \alpha_t + \text{Jensen's term at } t. \end{aligned} \tag{OA.24}$$

Thus, it holds that

$$\begin{aligned} flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T K u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T \varepsilon_{t+1}\right] \\ &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T K u_{t+1}\right], \end{aligned} \tag{OA.25}$$

where the approximation in (OA.25) is based on $(\phi_t^{mkt} - \phi_{m,t})^T \varepsilon_{t+1} \approx 0$ as n approaches infinity.

Given the market clearing condition on assets, we have the (approximated) relation in Theorem 1, which leads to

$$\begin{aligned} \phi_t^{mkt} &= \eta_t \phi_{m,t} + (1-\eta_t)\phi_{d,t} \\ &\approx \eta(\bar{h})\phi_{m,t} + [1-\eta(\bar{h})]\phi_{d,t}, \end{aligned}$$

where $\eta_t \equiv q_t / \left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right]$.

Thus, it holds that

$$
\begin{aligned}
flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] &\approx \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\left(\phi_{d,t} - \phi_{m,t}\right)^T K u_{t+1}\right\} \\
&= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\left(\Sigma_t^{-1}\mathcal{B}_t\right)^T K u_{t+1}\right\} \\
&= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\mathcal{B}^T\Sigma^{-1} K u_{t+1}\right\} \\
&= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\mathcal{B}^T\left(I_n + KK^T\right)^{-1} K u_{t+1}\right\}.
\end{aligned}
$$

According to Theorem 1, we can further obtain that

$$
flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]AK^T\left(I_n + KK^T\right)^{-1} K u_{t+1}\right\}. \tag{OA.26}
$$

Therefore, the exposure coefficient is

$$
A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma + [1-\eta(\bar{h})]AK^T\left(I_n + KK^T\right)^{-1} K. \tag{OA.27}
$$

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

$$
A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma\left\{I_k - \left[1-\eta(\bar{h})\right]K^T\left(I_n + KK^T\right)^{-1} K\right\}^{-1}, \tag{OA.28}
$$

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 1. If we define ς as follows:

$$
\varsigma \equiv \sigma\left\{I_k - \left[1-\eta(\bar{h})\right]K^T\left(I_n + KK^T\right)^{-1} K\right\}^{-1}, \tag{OA.29}
$$

then the exposure of common fund flows to the aggregate primitive shocks can be rewritten as

$$
A = \frac{q'(\bar{h})}{q(\bar{h})}\varsigma. \tag{OA.30}
$$

Moreover, in the data, $K^T \left(I_n + KK^T\right)^{-1} K$ is small, and thus, it holds that

$$\varsigma \approx \sigma. \tag{OA.31}$$

Thus, fund flows are conditionally negatively correlated with uncertainty shocks:

$$Cov_t[flow_{t+1}, h_{t+1} - h_t] = \sqrt{h_t} A\sigma^T = \frac{q'(\bar{h})}{q(\bar{h})}\varsigma\sigma^T < 0. \tag{OA.32}$$

1.4 Proof for Proposition 3.4

To compute the flow betas $\mathcal{B}^{flow}$, we first compute $\text{Cov}_t\left[r_{t+1}, flow_{t+1}\right]$ and $\text{var}_t\left[flow_{t+1}\right]$ as follows:

$$\text{Cov}_t\left[r_{t+1}, flow_{t+1}\right] = h_t K A^T \text{ and } \text{var}_t\left[flow_{t+1}\right] = h_t A A^T. \tag{OA.33}$$

Thus, $\mathcal{B}^{flow} = KA^T(AA^T)^{-1}$. Further, because $A \approx \frac{q'(\bar{h})}{q(\bar{h})}\sigma$, it follows that

$$\mathcal{B}^{flow} \approx \left[\frac{q'(\bar{h})}{q(\bar{h})}\right]^{-1} K\sigma^T(\sigma\sigma^T)^{-1}. \tag{OA.34}$$

1.5 Proof for Theorem 1

The portfolio choice is based on the competitive prices and aggregate fund flows in the equilibrium, including r_f, P_t, α_t, and $flow_{t+1}$. We can rewrite $R_{t+1}(\phi_{m,t}) + \alpha_t + flow_{t+1}$ as follows:

$$R_{t+1}(\phi_{m,t}) + \alpha_t + \pi_{t+1} = \tilde{R}_{t+1}(\tilde{\phi}_{m,t}) \tag{OA.35}$$

$$\equiv R_f + \tilde{\phi}_m^T(\tilde{R}_{t+1} - R_f\mathbf{1}), \tag{OA.36}$$

where

$$\tilde{\phi}_m \equiv \begin{bmatrix} 1 \\ \phi_m \end{bmatrix} \text{ and } \tilde{R}_{t+1} = \begin{bmatrix} R_f + \alpha_t + flow_{t+1} \\ R_{t+1} \end{bmatrix}. \tag{OA.37}$$

Similar to Campbell and Viceira (1999, 2001), we can derive the approximation based on Proposition 2.5 as follows:

$$\ln(R_f + \alpha_t + flow_{t+1}) \approx \ln(1 + r_f + \alpha_t + flow_{t+1}) \tag{OA.38}$$

$$\approx r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t, \tag{OA.39}$$

where $-\frac{1}{2}AA^T h_t$ is the Jensen's term. Therefore, the log returns are

$$\tilde{r}_{t+1} = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + flow_{t+1} \\ r_{t+1} \end{bmatrix}, \tag{OA.40}$$

and the log returns are distributed as

$$\tilde{r}_{t+1} = \tilde{\mu}_t + \tilde{\Sigma}_t u_{t+1}, \tag{OA.41}$$

where

$$\tilde{\mu}_t = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + \mathbb{E}_t\left[flow_{t+1}\right] \\ \mu_t \end{bmatrix} \text{ and } \tilde{\Sigma}_t = \begin{bmatrix} AA^T & AK^T \\ KA^T & \Sigma \end{bmatrix} h_t. \tag{OA.42}$$

Now, we can apply the approximation of Campbell and Viceira (1999, 2001) again to obtain the following relation:

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) = \ln\left[\tilde{R}_{t+1}(\tilde{\phi}_{m,t})\right] \tag{OA.43}$$

$$\approx r_f + \tilde{\phi}_{m,t}^T(\tilde{r}_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\tilde{\phi}_{m,t}^T(\tilde{v}_t - \tilde{\Sigma}_t\tilde{\phi}_{m,t}), \tag{OA.44}$$

where $\tilde{v}_t$ is the diagonal vector of $\tilde{\Sigma}_t$:

$$\tilde{v}_t = \begin{bmatrix} AA^T h_t \\ v_t \end{bmatrix}. \tag{OA.45}$$

As a result, the augmented log returns are

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) \approx r_f + (r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t - r_f) + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\tilde{\phi}_{m,t}^T\tilde{v}_t - \frac{1}{2}\tilde{\phi}_{m,t}^T\tilde{\Sigma}_t\tilde{\phi}_{m,t}$$
$$= r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1} + \frac{1}{2}v_t) - \frac{1}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} - AK^T h_t\phi_{m,t}.$$

Define $\mathcal{B}_t \equiv (AA^T)\mathcal{B}^{flow}h_t$ with $\mathcal{B} = KA^T$. This, $\mathcal{B}_t$ is actually the covariance of the stock log returns and the aggregate flow:

$$\mathcal{B}_t = \mathrm{Cov}_t\left[r_{t+1}, flow_{t+1}\right]. \tag{OA.46}$$

Then, the augmented log returns are

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) = r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1} + \frac{1}{2}v_t) - \frac{1}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} - \mathcal{B}_t^T\phi_{m,t}.$$

The optimal portfolio problem for fund managers can be simplified as

$$\max_{\phi_{m,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\tilde{r}_{t+1}(\tilde{\phi}_{m,t})}\right\}. \tag{OA.47}$$

After calculating the moment-generating function, the optimal portfolio problem can be further rewritten as

$$\max_{\phi_{m,t}}\phi_{m,t}^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t - \mathcal{B}_t) - \frac{\gamma}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} + (1-\gamma)\phi_{m,t}^T\mathcal{B}_t. \tag{OA.48}$$

The standard quadratic optimization problem leads to the optimal portfolio of fund managers:

$$\phi_{m,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f + \frac{1}{2}\nu_t\right) - \Sigma_t^{-1}\mathcal{B}_t \tag{OA.49}$$
$$= \phi_{d,t} - \Sigma_t^{-1}\mathcal{B}_t. \tag{OA.50}$$

Because $\mathcal{B}_t = h_t\mathcal{B}^{flow}(AA^T)$ and $\Sigma_t = h_t\Sigma$, it holds that

$$\phi_{m,t} = \phi_{d,t} - \phi_{\tau,t}, \quad \text{with} \;\; \phi_{\tau,t} \equiv \Sigma^{-1}\mathcal{B}^{flow}(AA^T). \tag{OA.51}$$

The cross-sectional covariance between $\mathcal{B}_t$ and $\phi_{\tau,t}$ for each t is equal to

$$\text{Cov}\left[\mathcal{B}_t, \phi_{\tau,t}\right] = n^{-1}\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t - n^{-2}\left(\mathbf{1}^T\mathcal{B}_t\right)\left(\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t\right). \tag{OA.52}$$

Because Σ_t is a positive definite symmetric matrix, according to the Cauchy-Schwarz inequality, it holds that

$$n^{-1}\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t = n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1/2})(\Sigma_t^{-1/2}\mathcal{B}_t) \tag{OA.53}$$

$$\leq n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathbf{1}\mathbf{1}^T\mathcal{B}_t)^{1/2}(\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t)^{1/2}. \tag{OA.54}$$

Thus, to show $\text{Cov}\left[\mathcal{B}_t, \phi_{\tau,t}\right] \geq 0$, it is sufficient to show that

$$n^{-1}\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathbf{1}\mathbf{1}^T\mathcal{B}_t \leq n^{-1}\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t. \tag{OA.55}$$

We denote $x \equiv n^{-1/2}\Sigma_t^{-1/2}\mathcal{B}_t$ and $y \equiv n^{-1/2}\Sigma_t^{-1/2}\mathbf{1}$, and thus, the inequality above can be rewritten as

$$x^T H_y x \leq x^T x, \tag{OA.56}$$

where H_y is the orthogonal projection matrix, $H_y \equiv y(y^Ty)^{-1}y^T$. Inequality (OA.166) is obviously true once we realize that H_y is an orthogonal projection matrix.

1.6 Proof for Theorem 2

Based on the fund manager's optimal portfolio derived in the proof of Theorem 1, it holds that

$$\mu_t - r_f + \frac{1}{2}\nu_t = \gamma\Sigma_t\phi_{m,t} + \gamma\mathcal{B}_t. \tag{OA.57}$$

According to the market-clearing condition of assets

$$\phi_{m,t} = \eta_t^{-1}\phi_t^{mkt} - (\eta_t^{-1} - 1)\phi_{d,t} \tag{OA.58}$$
$$= \eta_t^{-1}\phi_t^{mkt} - (\eta_t^{-1} - 1)\frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f + \frac{1}{2}v_t). \tag{OA.59}$$

Plugging (OA.59) into (OA.57) and rearranging terms leads to

$$\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t = \gamma\Sigma_t\phi_t^{mkt} + \eta_t\gamma\mathcal{B}_t. \tag{OA.60}$$

Therefore, 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 market return, denoted by r_{t+1}^{mkt}, and the covariance with common fund flow, denoted by $flow_{t+1}$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_t^{mkt})\right] + \eta_t\gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), flow_{t+1}\right]. \tag{OA.61}$$

1.7 Proof of Corollary 3.1

According to Proposition 2.4 and Theorem 1, when $\lambda = 0$, $q_t = 0$ and thus $\eta_t = 0$. Therefore, Theorem 2 implies the conditional CAPM when $\lambda = 0$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_t^{mkt})\right] \tag{OA.62}$$
$$= \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi_t^{mkt})\right] \tag{OA.63}$$

with $\hat{r}_{t+1}(\phi_t^{mkt}) \equiv r_{t+1}(\phi_t^{mkt}) - \mathbb{E}_t r_{t+1}(\phi_t^{mkt})$.

When $\lambda = 0$, the market portfolio is the mean-variance efficient portfolio:

$$\phi_t^{mkt} = \phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t) \tag{OA.64}$$
$$= \frac{1}{\gamma}\Sigma^{-1}\left(\bar{\zeta} + \frac{1}{2}\nu\right), \tag{OA.65}$$

where $\mu_t - r_f\mathbf{1} = \overline{\zeta}h_t$ with $\overline{\zeta}$ to be determined in the equilibrium. Thus, ϕ_t^{mkt} has constant portfolio weights, denoted by ϕ^{mkt}.

Further, according to (OA.63), it holds that

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]\frac{\text{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi^{mkt})\right]}{Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]} \tag{OA.66}$$

$$= \gamma Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}}. \tag{OA.67}$$

Taking unconditional expectations on both sides leads to

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \Lambda\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}} \tag{OA.68}$$

where $\Lambda \equiv \gamma\bar{h}\left(\overline{\zeta} + \frac{1}{2}\nu\right)^T\Sigma^{-1}\left(\overline{\zeta} + \frac{1}{2}\nu\right)$.

Lastly, $\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}}$ is actually the unconditional CAPM beta:

$$\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}} = \beta^{mkt}(\phi) \equiv \frac{\text{Cov}\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi^{mkt})\right]}{Var\left[\hat{r}_{t+1}(\phi^{mkt})\right]}. \tag{OA.69}$$

Therefore, the unconditional CAPM holds as follows:

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \beta^{mkt}(\phi)\Lambda. \tag{OA.70}$$

2 Extended Model

Although the contribution of this paper comes mainly from the empirical results, we use the illustrative model to establish the simplest conceptual framework for clearly explaining the basic economics and setting up the hypotheses.

Despite the simplicity of the illutrative model, we need to consider a general-equilibrium framework to illustrate endogenous aggregate fund flows and their equilibrium asset pricing implications. Specifically, 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, 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).

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

$$\Delta d_{t+1} = \mu + \sqrt{h_t}\,(Bu_{t+1} + \varepsilon_{t+1})\,, \tag{OA.71}$$

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

By postulating distributional structure (OA.71) 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.

We assume that the number of assets in this economy, n, is large, and various cross-sectional averages of idiosyncratic shocks, e.g., $(1/n)\sum_{i=1}^{n} \varepsilon_i$, are approximately equal to 0, which is essentially the assumption of the Arbitrage Pricing Theory (e.g., Ross, 1976). In particular, the number of assets is much larger than the number of primitive factors, i.e., $1 \leq k \ll n$.

The time-varying uncertainty is characterized by univariate state variable h_t, which is driven by k aggregate shocks u_t as follows:[1]

$$h_{t+1} = \bar{h} + \rho(h_t - \bar{h}) + \sqrt{h_t}\sigma u_{t+1}, \quad \text{with } \rho \in (0,1) \text{ and } \sigma \in \mathbb{R}^{1\times k}. \tag{OA.72}$$

Without loss of generality, we assume that the $1 \times k$ vector $\sigma = [\sigma_1, \cdots, \sigma_k]$ has positive elements, i.e., $\sigma_j > 0$ for $j = 1, \cdots, k$.

Stock i is a claim to dividend stream $D_{i,t}$ for $i = 1, \cdots, n$, and is in unit net supply. Similar to Kozak, Nagel and Santosh (2018), we assume that the supply of the risk-free bond is perfectly elastic, with a constant risk-free rate of $R_f > 1$.[2] Let $r_f = \ln(R_f)$ denote the log risk-free interest rate. The return of risky asset i is given by $R_{i,t+1} \equiv (P_{i,t+1} + D_{i,t+1})/P_{i,t}$ where $P_{i,t}$ is the price of risky asset i at time t for $i = 1, \cdots, n$. The vector that stacks the risky asset returns is denoted by $R_{t+1} = [R_{1,t+1}, \cdots, R_{n,t+1}]^T$.

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, $r_{t+1} \equiv \ln(R_{t+1})$, can be expressed as

$$r_{t+1} \approx Lz_{t+1} - z_t + \Delta d_{t+1} + \ell, \tag{OA.73}$$

where $z_t = \ln(P_t/D_t)$ is the $n \times 1$ vector of log price-dividend ratios with elements $z_{i,t} = \ln(P_{i,t}/D_{i,t})$. The matrix L in (OA.73) is a $n \times n$ 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 vector ℓ in (OA.73) is a $n \times 1$ vector with the ith element equal to $\ell_i = -\ln(L_i) + (1 - L_i)\ln(1/L_i - 1)$.

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

[1] We impose a zero lower bound on h_t similar to Bansal and Yaron (2004), Chen, Dou and Kogan (2021), and Cheng, Dou and Liao (2022).

[2] 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).

variable h_t:

$$z_t \approx \zeta + \zeta_h (h_t - \bar{h}), \tag{OA.74}$$

where $\zeta, \zeta_h \in \mathbb{R}^{n\times 1}$ are constant vectors to be determined in equilibrium.

Based on the representation of log returns in (OA.73) and the equilibrium log price-dividend ratio in (OA.74), equilibrium log returns r_{t+1} can thus be characterized as follows. The proof is in Online Appendix 3.1.

Proposition 2.1 (Excess log returns of risky assets)**.** *The equilibrium excess log returns of risky assets are*

$$r_{t+1} - r_f \mathbf{1} \approx \mu_t + \sqrt{h_t} \left(K u_{t+1} + \varepsilon_{t+1} \right), \tag{OA.75}$$

where $\mathbf{1} \in \mathbb{R}^{n\times 1}$ is a vector of ones, $\mu_t \in \mathbb{R}^{n\times 1}$ is the conditional expected excess log return given the information set up to time t, and $K \in \mathbb{R}^{n\times k}$ captures stock returns' systematic risk exposure:

$$\mu_t = (\rho L - I_n)\zeta_h h_t \;\; \text{and} \;\; K = L\zeta_h \sigma + B, \tag{OA.76}$$

where B is defined in (OA.71), ρ and σ are defined in (OA.72), L is defined in (OA.73), and ζ_h is defined in (OA.74). The variance-covariance matrix of the log returns is

$$\Sigma_t = \Sigma h_t, \;\; \text{with} \;\; \Sigma = I_n + KK^T. \tag{OA.77}$$

In principle, factor models can arise in the equilibrium whether expected returns reflect systematic risk or mispricing. The macro factors u_{t+1} can capture systematic risks for which investors require compensation, or they can capture common sources of mispricing, such as market-wide investor sentiment (e.g., Hirshleifer and Jiang, 2010; Stambaugh and Yuan, 2016; Kozak, Nagel and Santosh, 2018).[3] Particularly, if the kth column of the loading matrix B in (OA.71) is zero and the kth element of σ in (OA.72) is strictly positive, the macro factor u_k tends to

[3]Moreover, as emphasized, for example, by Long et al. (1990), there need not be a clear-cut distinction between mispricing and risk compensation as alternative justifications for multi-factor models of expected return. Specifically, Long et al. (1990) show that fluctuations in market-wide sentiment of noise traders give rise to a source of systematic risk for which rational traders require compensation.

be a non-fundamental one (e.g., a sentiment factor or "mispricing factor").

Next, we approximate the portfolio's log return. Let $r_{t+1}(\phi) = \ln[R_{t+1}(\phi)]$ 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

$$r_{t+1}(\phi) \approx r_f + \phi^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi^T(v_t - \Sigma_t\phi), \tag{OA.78}$$

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

2.2 Funds

To focus on the common component of fund flow shocks, we assume that the funds are homogenous.[4] 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.[5]

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.[6] 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 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.

[4]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, 2021).

[5]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).

[6]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.

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

$$\Psi(q) \equiv \theta^{-1} q^{1+\xi}, \text{ with } \xi > 0. \tag{OA.79}$$

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

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.

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

$$TP_t = \overbrace{\overline{\alpha} Q_t - \Psi(q_t) W_t}^{\text{net gain of funds}} - f Q_t, \tag{OA.80}$$

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 $f Q_t$ 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:

$$\alpha_t = \overline{\alpha} - \psi(q_t) - f, \tag{OA.81}$$

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 (OA.81) can be rewritten as a linear relation between the amount of asset management service supplied by funds and the net alpha:

$$q_t = \theta(\overline{\alpha} - \alpha_t) - \theta f. \tag{OA.82}$$

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, 2021). 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.[7] Moreover, we assume that agents in our model do not internalize their descendants' utility.[8] 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

$$U_d(W_{d,t}) = \max_{\phi_{d,t}, C_{d,t}} (1-\beta)\ln(C_{d,t}) + \beta(1-\gamma)^{-1}\ln \mathbb{E}_t\left[W_{d,t+1}^{1-\gamma}\right], \tag{OA.83}$$

[7] 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.

[8] 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.

subject to the dynamic budget constraint:

$$W_{d,t+1} = (W_{d,t} - C_{d,t} - \overline{\alpha} Q_t) \left[R_f + \phi_{d,t}^T (R_{t+1} - R_f) \right]. \tag{OA.84}$$

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

Proposition 2.2 (Direct investors)**.** *The optimal consumption of direct investors is*

$$C_{d,t} = (1-\beta)(1-\lambda-\overline{\alpha} q_t) W_t, \tag{OA.85}$$

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

$$\phi_{d,t} = \frac{1}{\gamma} \Sigma_t^{-1} \left(\mu_t - r_f \mathbf{1} + \frac{1}{2} \nu_t \right), \tag{OA.86}$$

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 1.1 for the proof in detail.

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.[9] The fund clients are also free to become direct investors and manage

[9]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.

their own portfolios.

We assume that the fund clients solve the following problem:

$$U_c(W_{c,t}) = \max_{C_{c,t}, Q_t} (1-\beta)\ln(C_{c,t}) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left[(W_{c,t+1} + \omega Q_t)^{1-\gamma} \right], \quad \text{(OA.87)}$$

subject to the budget constraint:

$$W_{c,t+1} = (W_{c,t} - C_{c,t})R_f + Q_t[R_{t+1}(\phi_{d,t}) + \alpha_t - R_f], \quad \text{(OA.88)}$$

and the participation constraint:

$$U_c(W_{c,t}) \geq U_d(W_{c,t}). \quad \text{(OA.89)}$$

The utility function in (OA.87) 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 (OA.88) 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 (OA.89) recognizes that 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 2.3 (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*

$$C_{c,t} = (1-\beta)\lambda W_t, \tag{OA.90}$$

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

$$q_t = \beta\lambda \left(1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}\right), \tag{OA.91}$$

where ω is the non-pecuniary benefit as in (OA.87), 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 (OA.72), (OA.73), and (OA.74), 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 2.3 is in Online Appendix 3.3.

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 $f Q_t$ in period t. Similar compensation specification has been adopted in the literature.[10] 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 findings of Ibert et al. (2018), we consider the compensation contract specification, which mainly depends on the AUM Q_t.[11]

[10] 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).

[11] 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.

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:

$$\max_{\phi_{m,t}} (1-\beta) \ln(C_{m,t}) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left[C_{m,t+1}^{1-\gamma} \right], \tag{OA.92}$$

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:

$$Q_{t+1} = \underbrace{Q_t \left[R_{t+1}(\phi_{m,t}) + \alpha_t \right]}_{\text{fund returns}} + \underbrace{Q_t flow_{t+1}}_{\text{fund flows}}, \tag{OA.93}$$

where Q_t is the delegation characterized in (OA.91) 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 (OA.93) essentially gives the definition of the fund flow, denoted by $flow_{t+1}$:

$$flow_{t+1} \equiv \frac{Q_{t+1} - Q_t \left[R_{t+1}(\phi_{m,t}) + \alpha_t \right]}{Q_t}. \tag{OA.94}$$

The dynamic budget constraint in equation (OA.93) 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 $\bar{\alpha} Q_t$ for the funds. The AUM at the beginning of period $t+1$ is the sum of the fund return and fund flow: $Q_{t+1} = Q_t \left[R_{t+1}(\phi_{m,t}) + \alpha_t + flow_{t+1} \right]$.

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

2.4 Equilibrium

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:

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

Proposition 2.4 below summarizes the solution.

Proposition 2.4 (Equilibrium delegation and alpha)**.** *The equilibrium amount of delegation q_t and the net alpha α_t are given by*

$$
\alpha_t = -\omega + \frac{\theta(\overline{\alpha} + \omega - f) - \beta\lambda}{\theta + \beta\lambda/(\overline{\gamma} h_t)} \quad \textit{and} \quad q_t = \beta\lambda \left[1 + \frac{\theta(\overline{\alpha} + \omega - f) - \beta\lambda}{\theta\overline{\gamma} h_t + \beta\lambda}\right], \tag{OA.95}
$$

where ω is the non-pecuniary benefit term in (OA.87), $\overline{\gamma}$ is defined in (OA.91), 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:*

$$
\frac{\partial \alpha_t}{\partial h_t} > 0 \quad \textit{and} \quad \frac{\partial q_t}{\partial h_t} < 0. \tag{OA.96}
$$

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

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t} A u_{t+1}, \tag{OA.97}$$

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 (OA.93), the process of fund flows can be approximated as shown in Proposition 2.5, whose proof is in Online Appendix 3.5.

Proposition 2.5 (Equilibrium aggregate fund flows). *The exposure of common fund flows to the aggregate primitive shocks satisfies*

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma + \left[1 - \eta(\bar{h})\right] A K^T \left(I_n + KK^T\right)^{-1} K, \tag{OA.98}$$

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

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma \left\{ I_k - \left[1 - \eta(\bar{h})\right] K^T \left(I_n + KK^T\right)^{-1} K \right\}^{-1}, \tag{OA.99}$$

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 1 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 2.5 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 (OA.99). 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 1 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 3.6 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:*

$$\phi_{m,t} = \phi_{d,t} - \phi_{\tau,t}, \tag{OA.100}$$

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:

$$\phi_{\tau,t} = \Sigma_t^{-1}\mathcal{B}_t. \tag{OA.101}$$

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 3.7.

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:*

$$Cov\left[\mathcal{B}_t, \phi_{\tau,t}\right] > 0, \quad \text{for each } t. \tag{OA.102}$$

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 (OA.83) subject to (OA.84);

(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 (OA.87) subject to (OA.88);

(i.c) each fund manager's portfolio strategy $\phi_{m,t}$ is optimal in terms of maximizing the utility in (OA.92) subject to (OA.93);

(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: $Q_t\phi_{m,t} + [W_{d,t} - C_{d,t} - \overline{\alpha}Q_t]\,\phi_{d,t} = [W_{d,t} - C_{d,t} + (1-\overline{\alpha})Q_t]\,\phi_t^{mkt}$.

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 (OA.82), and the supply curve of delegation (OA.91) 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, ϕ_t^{mkt}, 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 3.8 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:*

$$\phi_{m,t} = \phi_t^{mkt} - (1-\eta_t)\phi_{\tau,t}, \tag{OA.103}$$

where $\eta_t = \eta(h_t) \equiv q_t / \left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right] \in [0,1]$, 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 (OA.101). Thus, the cross-sectional covariance between the deviation of fund holdings from the market portfolio and the common flow beta is always negative:

$$Cov\left[\mathcal{B}_t, \phi_{m,t} - \phi_t^{mkt}\right] < 0, \quad \textit{for each } t. \tag{OA.104}$$

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

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

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

If $\text{Cov}_t\left[r_{t+1}(\phi),\ flow_{t+1}\right] < 0$, 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:*

$$\mathbb{E}_t\left[r_{t+1}(\phi)\right] - r_f + \frac{1}{2}\phi^T \nu_t \approx \gamma Cov_t\left[r_{t+1}(\phi),\ r_{t+1}(\phi_t^{mkt})\right]. \tag{OA.105}$$

It further implies that the CAPM holds:

$$\mathbb{E}\left[r_{t+1}(\phi) - r_f + \frac{1}{2}\phi^T \nu_t\right] \approx \beta^{mkt}(\phi)\Lambda. \tag{OA.106}$$

where $\beta^{mkt}(\phi) \equiv Cov\left[r_{t+1}(\phi),\ \hat{r}_{t+1}(\phi_t^{mkt})\right] / Var\left[\hat{r}_{t+1}(\phi_t^{mkt})\right]$ *is the market beta with* $\hat{r}_{t+1}(\phi_t^{mkt}) \equiv r_{t+1}(\phi_t^{mkt}) - \mathbb{E}_t\left[r_{t+1}(\phi_t^{mkt})\right]$*, 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 2.4, 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 3.10.

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:*

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

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 1.*

3 Proofs for the Extended Model

3.1 Proof for Proposition 2.1

According to (OA.73), the log-linearization approximation leads to the following representation:

$$r_{t+1} = Lz_{t+1} - z_t + \Delta d_{t+1} + \ell. \tag{OA.107}$$

Plugging (OA.71) and (OA.74) into the equation above, we can obtain

$$r_{t+1} = L(\zeta + \zeta_h(h_{t+1} - \bar{h})) - (\zeta + \zeta_h(h_t - \bar{h})) + \mu + \sqrt{h_t}Bu_{t+1} + \sqrt{h_t}\varepsilon_{t+1} + \ell. \tag{OA.108}$$

Further, if we plug (OA.72) into the relation above, we can obtain

$$r_{t+1} = L(\zeta + \zeta_h(\rho(h_t - \bar{h}) + \sqrt{h_t}\sigma u_{t+1})) - (\zeta + \zeta_h(h_t - \bar{h})) + \mu + \sqrt{h_t}Bu_{t+1} + \sqrt{h_t}\varepsilon_{t+1} + \ell. \tag{OA.109}$$

Rearranging terms further leads to

$$r_{t+1} = \mathbb{E}_t\left[r_{t+1}\right] + \sqrt{h_t}Ku_{t+1} + \sqrt{h_t}\varepsilon_{t+1}, \tag{OA.110}$$

where

$$\mathbb{E}_t\left[r_{t+1}\right] = \mu + \ell + (L - I_n)\zeta + (\rho L - I_n)\zeta_h(h_t - \bar{h}) \;\; \text{and} \;\; K = L\zeta_h\sigma + B. \tag{OA.111}$$

Moreover, 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 (OA.76), the log risk-free rate must satisfy the following condition in the equilibrium to rule out arbitrage opportunities:

$$r_f\mathbf{1} = [\mu + \ell + (L - I_n)\zeta] - (\rho L - I_n)\zeta_h\bar{h}. \tag{OA.112}$$

We now derive the expression for the conditional expected log excess return, which is approximately proportional to the stochastic variance h_t In fact, based on (OA.76) and (OA.112), it follows that

$$\mathbb{E}_t\left[r_{t+1}\right] - r_f \mathbf{1} \approx (\rho L - I_n)\zeta_h h_t. \tag{OA.113}$$

3.2 Proof for Proposition 2.2

Plugging in the budget constraint, the optimization problem can be rewritten as

$$\max_{\phi_{d,t}, C_{d,t}} (1-\beta)\ln(C_{d,t}) + \beta \ln(W_{d,t} - C_{d,t} - \overline{\alpha} Q_t) + \beta(1-\gamma)^{-1} \ln \mathbb{E}_t \left\{ \left[R_f + \phi_{d,t}^T (R_{t+1} - R_f) \right]^{1-\gamma} \right\}.$$

Thus, the unit EIS allows for the separation of optimal consumption and optimal portfolio problems. The optimal consumption is straightforward to derive:

$$C_{d,t} = (1-\beta)(W_{d,t} - \overline{\alpha} Q_t). \tag{OA.114}$$

Following Campbell and Viceira (1999, 2001), we approximate the dynamic budget constraint $r_{t+1}(\phi_{d,t}) = \ln\left[R_{t+1}(\phi_{d,t})\right]$ as follows

$$r_{t+1}(\phi_{d,t}) \approx r_f + \phi_{d,t}^T (r_{t+1} - r_f \mathbf{1}) + \frac{1}{2}\phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t}\right) \tag{OA.115}$$

where $v_t \equiv \operatorname{diag}(\Sigma_t)$ is the vector that contains the diagonal elements of Σ_t. The optimal portfolio problem becomes

$$\max_{\phi_{d,t}} (1-\gamma)^{-1} \ln \mathbb{E}_t \left\{ e^{(1-\gamma)\left[r_f + \phi_{d,t}^T (r_{t+1} - r_f \mathbf{1}) + \frac{1}{2}\phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t}\right)\right]} \right\} \tag{OA.116}$$

Using the moment generating function of multivariate normal variables, it follows that

$$\mathbb{E}_t \left\{ e^{(1-\gamma)\left[r_f + \phi_{d,t}^T (r_{t+1} - r_f \mathbf{1}) + \frac{1}{2}\phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t}\right)\right]} \right\} = e^{(1-\gamma)\left[r_f + \phi_{d,t}^T (\mu_t - r_f \mathbf{1}) + \frac{1}{2}\phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t}\right)\right] + (1-\gamma)^2 \frac{1}{2}\phi_{d,t}^T \Sigma_t \phi_{d,t}}$$

Thus, the optimal portfolio problem can be further rewritten as

$$\max_{\phi_{d,t}} \phi_{d,t}^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t) - \frac{\gamma}{2}\phi_{d,t}^T\Sigma_t\phi_{d,t}. \tag{OA.117}$$

The first-order condition leads to

$$\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t). \tag{OA.118}$$

3.3 Proof for Proposition 3.2

Denote $\phi_{c,t} \equiv \frac{Q_t}{W_{c,t} - C_{c,t}}$. Plugging in the budget constraint, the optimization problem can be rewritten as

$$\begin{aligned} \max_{\phi_{c,t}, C_{c,t}} & (1-\beta)\ln(C_{c,t}) + \beta\ln(W_{c,t} - C_{c,t}) \quad \text{(OA.119)} \\ & + \beta(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right]^{1-\gamma}\right\}, \end{aligned}$$

Thus, the unit EIS coefficient allows for the separation of optimal consumption and optimal portfolio problems. The optimal consumption is straightforward to derive:

$$\begin{aligned} C_{c,t} &= (1-\beta)W_{c,t} \quad \text{(OA.120)} \\ &= (1-\beta)\lambda W_t. \quad \text{(OA.121)} \end{aligned}$$

Following Campbell and Viceira (1999, 2001), we approximate the dynamic budget constraint $r_{\alpha,t+1}(\phi_{d,t}) = \ln\left[R_{t+1}(\phi_{d,t}) + \alpha_t + \omega\right]$ as follows

$$\begin{aligned} r_{\alpha,t+1}(\phi_{d,t}) &\approx \ln\left[R_{t+1}(\phi_{d,t}) + \alpha_t + \omega\right] \quad \text{(OA.122)} \\ &\approx \alpha_t + \omega + r_f + \phi_{d,t}^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi_{d,t}^T\left(v_t - \Sigma_t\phi_{d,t}\right), \quad \text{(OA.123)} \end{aligned}$$

where $v_t \equiv \text{diag}(\Sigma_t)$ is the vector that contains the diagonal elements of Σ_t. Again, appealing to Campbell and Viceira's approximation method, the following log-linearization approximation holds:

$$\ln\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right] \approx r_f + \phi_{c,t}\left[r_{\alpha,t+1}(\phi_{d,t}) - r_f\right] + \frac{1}{2}\phi_{c,t}(1-\phi_{c,t})\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.124)}$$

The optimal portfolio problem can be approximately rewritten as

$$\max_{\phi_{c,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\left[\phi_{c,t}(\alpha_t+\omega)+\phi_{c,t}\phi_{d,t}^T(r_{t+1}-r_f\mathbf{1})+\frac{1}{2}\phi_{c,t}(1-\phi_{c,t})\phi_{d,t}^T\Sigma_t\phi_{d,t}+\frac{1}{2}\phi_{c,t}\phi_{d,t}^T\left(v_t-\Sigma_t\phi_{d,t}\right)\right]}\right\}.$$

After calculating the moment generating function and rearranging terms, searching for the optimal $\phi_{c,t}$ is equivalent to solving the following maximization problem:

$$\max_{\phi_{c,t}}\phi_{c,t}(\alpha_t+\omega) + \phi_{c,t}\phi_{d,t}^T\left(\mu_t - r_f + \frac{1}{2}v_t\right) - \frac{1}{2}\gamma\phi_{c,t}^2\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.125)}$$

The first-order condition is

$$0 = \alpha_t + \omega + \phi_{d,t}^T\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right) - \gamma\phi_{c,t}\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.126)}$$

Thus, according to Proposition 2.2, the optimal delegation $\phi_{c,t}$ is

$$\phi_{c,t} = \frac{1}{\gamma}\frac{1}{\phi_{d,t}^T\Sigma_t\phi_{d,t}}\left(\alpha_t + \omega + \gamma\phi_{d,t}^T\Sigma_t\phi_{d,t}\right) = 1 + \frac{\omega+\alpha_t}{\gamma_t}, \quad \text{(OA.127)}$$

where the effective risk aversion is

$$\gamma_t \equiv S_t/\gamma, \ \ \text{with } S_t \equiv \left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right)^T\Sigma_t^{-1}\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right). \quad \text{(OA.128)}$$

According to Proposition 2.1 and Equation (OA.77), it holds that

$$\mu_t - r_f \mathbf{1} + \frac{1}{2}\nu_t = \left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right] h_t \text{ and } \Sigma_t = \Sigma h_t. \tag{OA.129}$$

Therefore, by plugging (OA.129) into (OA.127), it follows that

$$\phi_{c,t} = 1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}, \tag{OA.130}$$

where $\overline{\gamma} = \left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]^T \Sigma^{-1} \left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right] / \gamma$.

And hence, it holds that

$$q_t = \phi_{c,t} \frac{W_{c,t} - C_{c,t}}{W_t} \tag{OA.131}$$

$$= \beta\lambda \left(1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}\right). \tag{OA.132}$$

Finally, after rearranging terms, it follows that

$$U_c(W_{c,t}) - U_d(W_{c,t}) = \beta\phi_c(\alpha_t + \omega) - \ln\left(1 - \frac{\overline{\alpha}}{\lambda} q_t\right) \tag{OA.133}$$

$$= \beta\phi_c(\omega - \theta^{-1} q_t + \overline{\alpha} - f) - \ln\left(1 - \frac{\overline{\alpha}}{\lambda} q_t\right) \tag{OA.134}$$

$$\geq \beta\phi_c(\omega - \theta^{-1} q_t + \overline{\alpha} - f) \tag{OA.135}$$

$$\geq 0. \tag{OA.136}$$

When $\omega + \overline{\alpha} > f + \theta^{-1}\lambda\beta$ as assumed in the proposition, the last inequality in (OA.136) can be established by plugging in the equilibrium delegation q_t derived in Proposition 2.4.

3.4 Proof for Proposition 2.4

The equilibrium net alpha α_t and asset management services (i.e., delegation) q_t are determined by solving the intersection point of the following equations:

$$q_t = \theta(\overline{\alpha} - f) - \theta\alpha_t \quad (q_t \text{ supplied by funds}), \tag{OA.137}$$

$$q_t = \beta\lambda\left[1 + (\omega + \alpha_t)/(\overline{\gamma}h_t)\right] \quad (q_t \text{ demanded by fund clients}). \tag{OA.138}$$

Plugging (OA.138) into (OA.137) leads to the results.

3.5 Proof for Proposition 2.5

By definition, the aggregate fund flow is

$$\begin{aligned} flow_{t+1} &= \frac{Q_{t+1}}{Q_t} - R_{t+1}(\phi_{m,t}) - \alpha_t \\ &= \frac{q_{t+1}}{q_t}\frac{W_{t+1}}{W_t} - R_{t+1}(\phi_{m,t}) - \alpha_t \\ &= \frac{q_{t+1}}{q_t}\frac{W_{d,t} - C_{d,t} + (1-\overline{\alpha})Q_t}{W_t} R_{t+1}(\phi_t^{mkt}) - R_{t+1}(\phi_{m,t}) - \alpha_t. \end{aligned}$$

Thus, the aggregate fund flow can be rewritten as

$$flow_{t+1} = \frac{q_{t+1}}{q_t}\left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right] R_{t+1}(\phi_t^{mkt}) - R_{t+1}(\phi_{m,t}) - \alpha_t \tag{OA.139}$$

$$= e^{\Delta\ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] + r_{t+1}(\phi_t^{mkt})} - e^{r_{t+1}(\phi_{m,t})} - \alpha_t. \tag{OA.140}$$

Log-linear approximation leads to

$$\begin{aligned} flow_{t+1} \approx\ & \Delta\ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] \\ & + r_{t+1}(\phi_t^{mkt}) - r_{t+1}(\phi_{m,t}) - \alpha_t + \text{Jensen's term at } t. \end{aligned} \tag{OA.141}$$

According to Proposition 2.1, it holds that

$$\begin{aligned} flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T K u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T \varepsilon_{t+1}\right] \\ &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_t^{mkt} - \phi_{m,t})^T K u_{t+1}\right], \end{aligned} \tag{OA.142}$$

where the approximation in (OA.142) is based on $(\phi_t^{mkt} - \phi_{m,t})^T \varepsilon_{t+1} \approx 0$ as n approaches infinity.

Given the market clearing condition on assets, we have the (approximated) relation in Theorem 1, which leads to

$$\begin{aligned} \phi_t^{mkt} &= \eta_t \phi_{m,t} + (1-\eta_t)\phi_{d,t} \\ &\approx \eta(\bar{h})\phi_{m,t} + [1-\eta(\bar{h})]\phi_{d,t}, \end{aligned}$$

where $\eta_t \equiv q_t / \left[(1-\lambda)\beta + (1-\bar{\alpha})q_t\right]$.

Thus, it holds that

$$\begin{aligned} flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] &\approx \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\left(\phi_{d,t} - \phi_{m,t}\right)^T K u_{t+1}\right\} \\ &= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\left(\Sigma_t^{-1}\mathcal{B}_t\right)^T K u_{t+1}\right\} \\ &= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\mathcal{B}^T \Sigma^{-1} K u_{t+1}\right\} \\ &= \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]\mathcal{B}^T \left(I_n + KK^T\right)^{-1} K u_{t+1}\right\}. \end{aligned}$$

According to Theorem 1, we can further obtain that

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]AK^T \left(I_n + KK^T\right)^{-1} K u_{t+1}\right\}. \tag{OA.143}$$

Therefore, the exposure coefficient is

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma + [1-\eta(\bar{h})]AK^T \left(I_n + KK^T\right)^{-1} K. \tag{OA.144}$$

3.6 Proof for Theorem 1

The portfolio choice is based on the competitive prices and aggregate fund flows in the equilibrium, including r_f, P_t, α_t, and $flow_{t+1}$. We can rewrite $R_{t+1}(\phi_{m,t}) + \alpha_t + flow_{t+1}$ as follows:

$$R_{t+1}(\phi_{m,t}) + \alpha_t + \pi_{t+1} = \tilde{R}_{t+1}(\tilde{\phi}_{m,t}) \tag{OA.145}$$

$$\equiv R_f + \tilde{\phi}_m^T(\tilde{R}_{t+1} - R_f\mathbf{1}), \tag{OA.146}$$

where

$$\tilde{\phi}_m \equiv \begin{bmatrix} 1 \\ \phi_m \end{bmatrix} \text{ and } \tilde{R}_{t+1} = \begin{bmatrix} R_f + \alpha_t + flow_{t+1} \\ R_{t+1} \end{bmatrix}. \tag{OA.147}$$

Similar to Campbell and Viceira (1999, 2001), we can derive the approximation based on Proposition 2.5 as follows:

$$\ln(R_f + \alpha_t + flow_{t+1}) \approx \ln(1 + r_f + \alpha_t + flow_{t+1}) \tag{OA.148}$$

$$\approx r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t, \tag{OA.149}$$

where $-\frac{1}{2}AA^T h_t$ is the Jensen's term. Therefore, the log returns are

$$\tilde{r}_{t+1} = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + flow_{t+1} \\ r_{t+1} \end{bmatrix}, \tag{OA.150}$$

and the log returns are distributed as

$$\tilde{r}_{t+1} = \tilde{\mu}_t + \tilde{\Sigma}_t u_{t+1}, \tag{OA.151}$$

where

$$\tilde{\mu}_t = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + \mathbb{E}_t\left[flow_{t+1}\right] \\ \mu_t \end{bmatrix} \text{ and } \tilde{\Sigma}_t = \begin{bmatrix} AA^T & AK^T \\ KA^T & \Sigma \end{bmatrix} h_t. \tag{OA.152}$$

Now, we can apply the approximation of Campbell and Viceira (1999, 2001) again to obtain the following relation:

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) = \ln\left[\tilde{R}_{t+1}(\tilde{\phi}_{m,t})\right] \tag{OA.153}$$

$$\approx r_f + \tilde{\phi}_{m,t}^T(\tilde{r}_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\tilde{\phi}_{m,t}^T(\tilde{v}_t - \tilde{\Sigma}_t\tilde{\phi}_{m,t}), \tag{OA.154}$$

where $\tilde{v}_t$ is the diagonal vector of $\tilde{\Sigma}_t$:

$$\tilde{v}_t = \begin{bmatrix} AA^T h_t \\ v_t \end{bmatrix}. \tag{OA.155}$$

As a result, the augmented log returns are

$$\begin{aligned}\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) &\approx r_f + (r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t - r_f) + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\tilde{\phi}_{m,t}^T\tilde{v}_t - \frac{1}{2}\tilde{\phi}_{m,t}^T\tilde{\Sigma}_t\tilde{\phi}_{m,t} \\ &= r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1} + \frac{1}{2}v_t) - \frac{1}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} - AK^T h_t\phi_{m,t}.\end{aligned}$$

Define $\mathcal{B}_t \equiv \mathcal{B}h_t$ with $\mathcal{B} = KA^T$. And thus, $\mathcal{B}_t$ is the covariance of the stock log returns and the aggregate flow:

$$\mathcal{B}_t = \mathrm{Cov}_t\left[r_{t+1}, flow_{t+1}\right]. \tag{OA.156}$$

Then, the augmented log returns are

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) = r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t + \phi_{m,t}^T(r_{t+1} - r_f\mathbf{1} + \frac{1}{2}v_t) - \frac{1}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} - \mathcal{B}_t^T\phi_{m,t}.$$

The optimal portfolio problem for fund managers can be simplified as

$$\max_{\phi_{m,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\tilde{r}_{t+1}(\tilde{\phi}_{m,t})}\right\}. \tag{OA.157}$$

After calculating the moment-generating function, the optimal portfolio problem can be further rewritten as

$$\max_{\phi_{m,t}} \phi_{m,t}^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t - \mathcal{B}_t) - \frac{\gamma}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} + (1-\gamma)\phi_{m,t}^T\mathcal{B}_t. \tag{OA.158}$$

The standard quadratic optimization problem leads to the optimal portfolio of fund managers:

$$\phi_{m,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f + \frac{1}{2}v_t\right) - \Sigma_t^{-1}\mathcal{B}_t \tag{OA.159}$$

$$= \phi_{d,t} - \Sigma_t^{-1}\mathcal{B}_t. \tag{OA.160}$$

Because $\mathcal{B}_t = h_t\mathcal{B}$ and $\Sigma_t = h_t\Sigma$, it holds that

$$\phi_{m,t} = \phi_{d,t} - \Sigma^{-1}\mathcal{B}. \tag{OA.161}$$

3.7 Proof for Corollary 2.2

The cross-sectional covariance between $\mathcal{B}_t$ and $\phi_{\tau,t}$ for each t is equal to

$$\text{Cov}\left[\mathcal{B}_t, \phi_{\tau,t}\right] = n^{-1}\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t - n^{-2}\left(\mathbf{1}^T\mathcal{B}_t\right)\left(\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t\right). \tag{OA.162}$$

Because Σ_t is a positive definite symmetric matrix, according to the Cauchy-Schwarz inequality, it holds that

$$n^{-1}\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t = n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1/2})(\Sigma_t^{-1/2}\mathcal{B}_t) \tag{OA.163}$$

$$\leq n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathbf{1}\mathbf{1}^T\mathcal{B}_t)^{1/2}(\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t)^{1/2}. \tag{OA.164}$$

Thus, to show $\text{Cov}\left[\mathcal{B}_t, \phi_{\tau,t}\right] \geq 0$, it is sufficient to show that

$$n^{-1}\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathbf{1}\mathbf{1}^T\mathcal{B}_t \leq n^{-1}\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t. \tag{OA.165}$$

We denote $x \equiv n^{-1/2}\Sigma_t^{-1/2}\mathcal{B}_t$ and $y \equiv n^{-1/2}\Sigma_t^{-1/2}\mathbf{1}$, and thus, the inequality above can be rewritten as

$$x^T H_y x \leq x^T x, \tag{OA.166}$$

where H_y is the orthogonal projection matrix, $H_y \equiv y(y^T y)^{-1} y^T$. Inequality (OA.166) is obviously true once we realize that H_y is an orthogonal projection matrix.

3.8 Proof of Theorem 1

The market-clearing condition of assets (ii.b) can be rewritten as

$$q_t \phi_{m,t} + \left[(1-\lambda)\beta - \overline{\alpha} q_t\right] \phi_{d,t} = \left[(1-\lambda)\beta + (1-\overline{\alpha}) q_t\right] \phi_t^{mkt}. \tag{OA.167}$$

Plugging $\phi_{d,t} = \phi_{m,t} + \phi_{\tau,t}$ into the equation above, we obtain that

$$\phi_{m,t} = \phi_t^{mkt} - (1-\eta_t)\phi_{\tau,t}, \tag{OA.168}$$

where $\eta_t \equiv q_t / \left[(1-\lambda)\beta + (1-\overline{\alpha}) q_t\right]$.

Therefore, the portfolio of direct investors is

$$\phi_{d,t} = \phi_t^{mkt} + \eta_t \phi_{\tau,t}. \tag{OA.169}$$

3.9 Proof for Theorem 2

Based on the fund manager's optimal portfolio derived in Theorem 1, it holds that

$$\mu_t - r_f + \frac{1}{2}\nu_t = \gamma \Sigma_t \phi_{m,t} + \gamma \mathcal{B}_t. \tag{OA.170}$$

According to the market-clearing condition of assets

$$\phi_{m,t} = \eta_t^{-1}\phi_t^{mkt} - (\eta_t^{-1} - 1)\phi_{d,t} \tag{OA.171}$$

$$= \eta_t^{-1}\phi_t^{mkt} - (\eta_t^{-1} - 1)\frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f + \frac{1}{2}v_t). \tag{OA.172}$$

Plugging (OA.172) into (OA.170) and rearranging terms leads to

$$\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t = \gamma\Sigma_t\phi_t^{mkt} + \eta_t\gamma\mathcal{B}_t. \tag{OA.173}$$

Therefore, 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 market return, denoted by r_{t+1}^{mkt}, and the covariance with common fund flow, denoted by $flow_{t+1}$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\text{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_t^{mkt})\right] + \eta_t\gamma\text{Cov}_t\left[r_{t+1}(\phi), flow_{t+1}\right]. \tag{OA.174}$$

3.10 Proof of Corollary 3.1

According to Proposition 2.4 and Theorem 1, when $\lambda = 0$, $q_t = 0$ and thus $\eta_t = 0$. Therefore, Theorem 2 implies the conditional CAPM when $\lambda = 0$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\text{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_t^{mkt})\right] \tag{OA.175}$$

$$= \gamma\text{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi_t^{mkt})\right] \tag{OA.176}$$

with $\hat{r}_{t+1}(\phi_t^{mkt}) \equiv r_{t+1}(\phi_t^{mkt}) - \mathbb{E}_t r_{t+1}(\phi_t^{mkt})$.

When $\lambda = 0$, the market portfolio is the mean-variance efficient portfolio:

$$\phi_t^{mkt} = \phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t) \tag{OA.177}$$

$$= \frac{1}{\gamma}\Sigma^{-1}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]. \tag{OA.178}$$

Thus, ϕ_t^{mkt} has constant portfolio weights, denoted by ϕ^{mkt}.

Further, according to (OA.176), it holds that

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]\frac{\text{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi^{mkt})\right]}{Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]} \tag{OA.179}$$

$$= \gamma Var_t\left[\hat{r}_{t+1}(\phi^{mkt})\right]\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}}. \tag{OA.180}$$

Taking unconditional expectations on both sides leads to

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \Lambda\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}} \tag{OA.181}$$

where $\Lambda \equiv \gamma\bar{h}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]^T\Sigma^{-1}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]$.

Lastly, $\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}}$ is actually the unconditional CAPM beta:

$$\frac{\phi^T\Sigma\phi^{mkt}}{(\phi^{mkt})^T\Sigma\phi^{mkt}} = \beta^{mkt}(\phi) \equiv \frac{\text{Cov}\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi^{mkt})\right]}{Var\left[\hat{r}_{t+1}(\phi^{mkt})\right]}. \tag{OA.182}$$

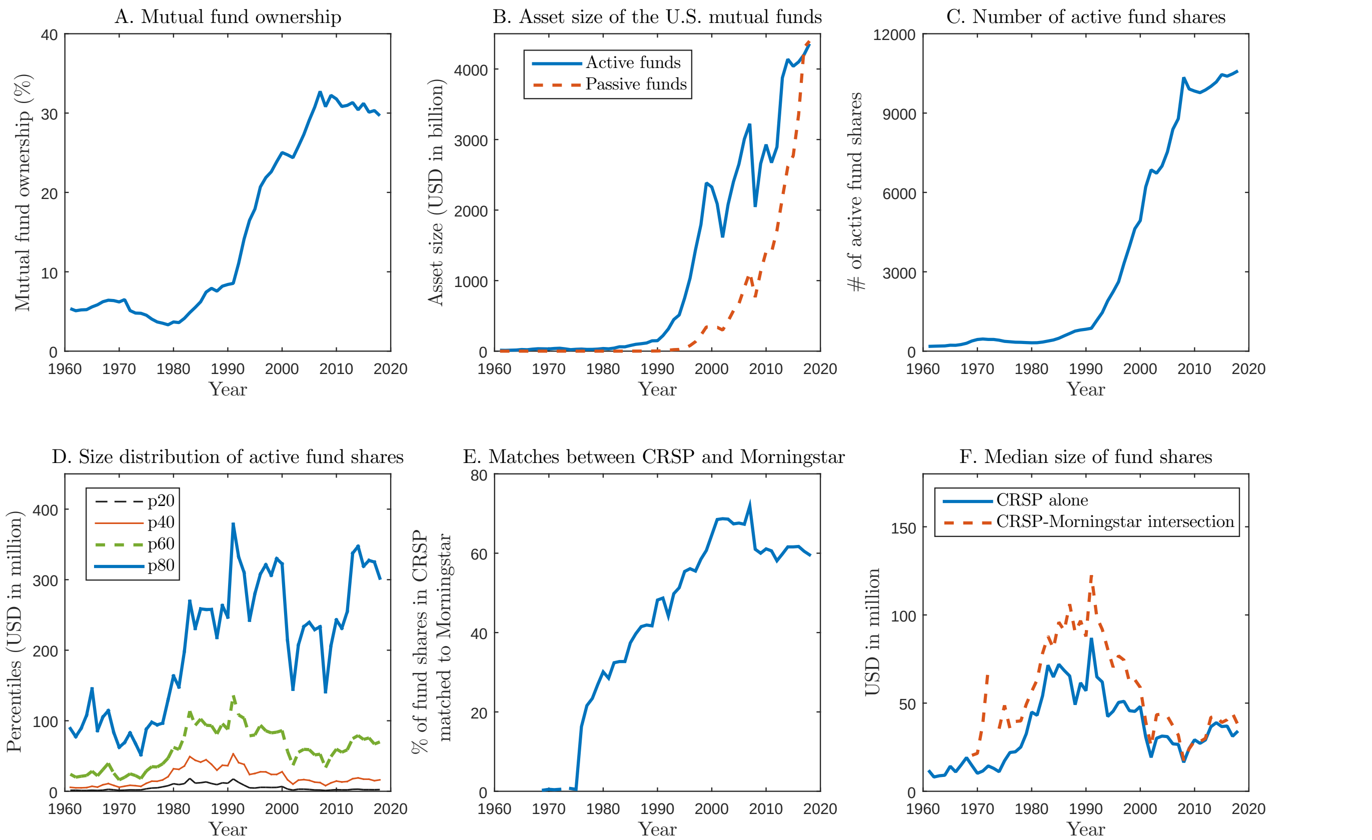
Therefore, the unconditional CAPM holds:

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \beta^{mkt}(\phi)\Lambda. \tag{OA.183}$$

4 Supplementary Empirical Results

4.1 Additional Description of Mutual Fund Data

Figure OA.1 provides additional facts and description of the mutual fund data. Panel A plots the percentage of the US corporate equity market held by mutual funds. Panel B plots the aggregate asset size of the active US mutual funds and passive US mutual funds in the CRSP mutual fund data, covering 25,459 unique fund shares from 5,875 unique funds over the period from 1961 to 2018. Panel C plots the number of fund shares of the active US mutual funds covered by the CRSP



Note: Panel A plots the percentage of the US corporate equity market held by mutual funds. The dollar value of the aggregate US corporate equities owned by mutual funds is obtained from the flow of funds accounts of the Federal Reserve Board. The market value of the aggregate US corporate equities is obtained from CRSP. Panel B plots the aggregate asset size of active US mutual funds and passive US mutual funds in the CRSP mutual fund data. Panel C plots the number of fund shares of the active US mutual funds covered by the CRSP mutual fund data. Panel D plots the 20th, 40th, 60th, and 80th percentiles of the asset size for fund shares of active US mutual funds covered by the CRSP mutual fund data. Panel E plots the percentage of fund shares in the CRSP mutual fund data that can be matched to the Morningstar mutual fund data. Panel F plots the median size of fund shares in the CRSP mutual fund data and the CRSP-Morningstar intersection data.

Figure OA.1: Mutual fund data.

mutual fund data over time. Panel D plots the 20th, 40th, 60th, and 80th percentiles of the asset size for active US mutual funds covered by the CRSP mutual fund data.

Following Berk and van Binsbergen (2015) and Pástor, Stambaugh and Taylor (2015), we use the Morningstar mutual fund data to cross-check the accuracy of the fund returns and asset size in the CRSP data. Specifically, we define a share class as well matched if and only if (a) 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 five basis points, and (b) the 60th percentile of the absolute value of the difference between the CRSP and Morningstar monthly TNA is less than $100,000. Panel E of Figure OA.1 plots the percentage of fund shares in the CRSP mutual fund data that can be matched to the Morningstar mutual fund data. The percentage of matching increases over time because of expanded coverage of the Morningstar data. The analysis of our paper focuses on the period from 1991 to 2018, in which we have monthly asset data to compute fund flows. During this sample period, 13,519 out of 24,823 active fund shares in the CRSP mutual fund data can be matched to Morningstar, while 1,407,627 out of 2,226,748 fund share-month observations in the CRSP mutual fund data can be matched to Morningstar. The matching rate is 54.46% at the fund share level and is 63.21% at the fund share-month level. Around 2% of share-month observations in the CRSP panel data are not matched with the Morningstar data because of the discrepancies in reported returns and TNA across the two datasets. The remaining 35% of share-month observations in the CRSP panel data are not matched because of no coverage in the Morningstar data. The above summary statistics for the matching percentage are similar to those in Pástor, Stambaugh and Taylor (2015). Panel F of Figure OA.1 plots the median size of fund shares in the CRSP mutual fund data and the CRSP-Morningstar intersection data. The median fund shares covered by the CRSP-Morningstar intersection sample are slightly larger than those covered by the CRSP mutual fund sample, but the difference has diminished since 2000.

4.2 Systematic Volatility of Fund-Level Flows and Returns

We compute the yearly flow volatility and return volatility for fund portfolios sorted on asset size and age. We focus on the volatility of the systematic component of fund flow shocks and returns. Specifically, we regress the fund flow of each fund portfolio on the common fund flows and compute the yearly volatility of the explained component. Similarly, we regress the returns of each fund portfolio on the market returns and compute the yearly volatility of the explained component.[12] The results are tabulated in Table OA.1 and plotted in Figure OA.2. Fund flow volatility is higher for smaller and younger funds. The average flow volatility is around 20% of the average return volatility for fund portfolios sorted on asset size and age. This finding shows

[12]We compute the fund flow and returns of each fund portfolio using the equal-weighted average of the fund flows and returns of all funds in the portfolio. This is because the goal here is to examine the systematic component of fund flow shocks and returns for an average fund. The results in Table OA.1 and Figure OA.2 are similar if we use value-weighted average across funds to compute fund flow and returns for each fund portfolio.

Table OA.1: Flow volatility and return volatility.

Panel A: Yearly flow volatility and return volatility across fund portfolios sorted on asset size				
	CRSP mutual funds alone		CRSP-Morningstar intersection	
Asset size quintiles	Flow volatility	Return volatility	Flow volatility	Return volatility
Q1	0.048	0.158	0.063	0.159
Q2	0.044	0.162	0.047	0.162
Q3	0.035	0.167	0.039	0.167
Q4	0.025	0.172	0.026	0.172
Q5	0.022	0.173	0.025	0.174
Average	0.035	0.166	0.040	0.167
Avg flow vol/avg return vol	21.0%		23.9%	

Panel B: Yearly flow volatility and return volatility across fund portfolios sorted on age				
	CRSP mutual funds alone		CRSP-Morningstar intersection	
Age quintiles	Flow volatility	Return volatility	Flow volatility	Return volatility
Q1	0.064	0.166	0.61	0.173
Q2	0.037	0.172	0.042	0.170
Q3	0.038	0.170	0.040	0.169
Q4	0.036	0.164	0.030	0.162
Q5	0.023	0.163	0.021	0.165
Average	0.039	0167	0.039	0.168
Avg flow vol/avg return vol	23.6%		23.3%	

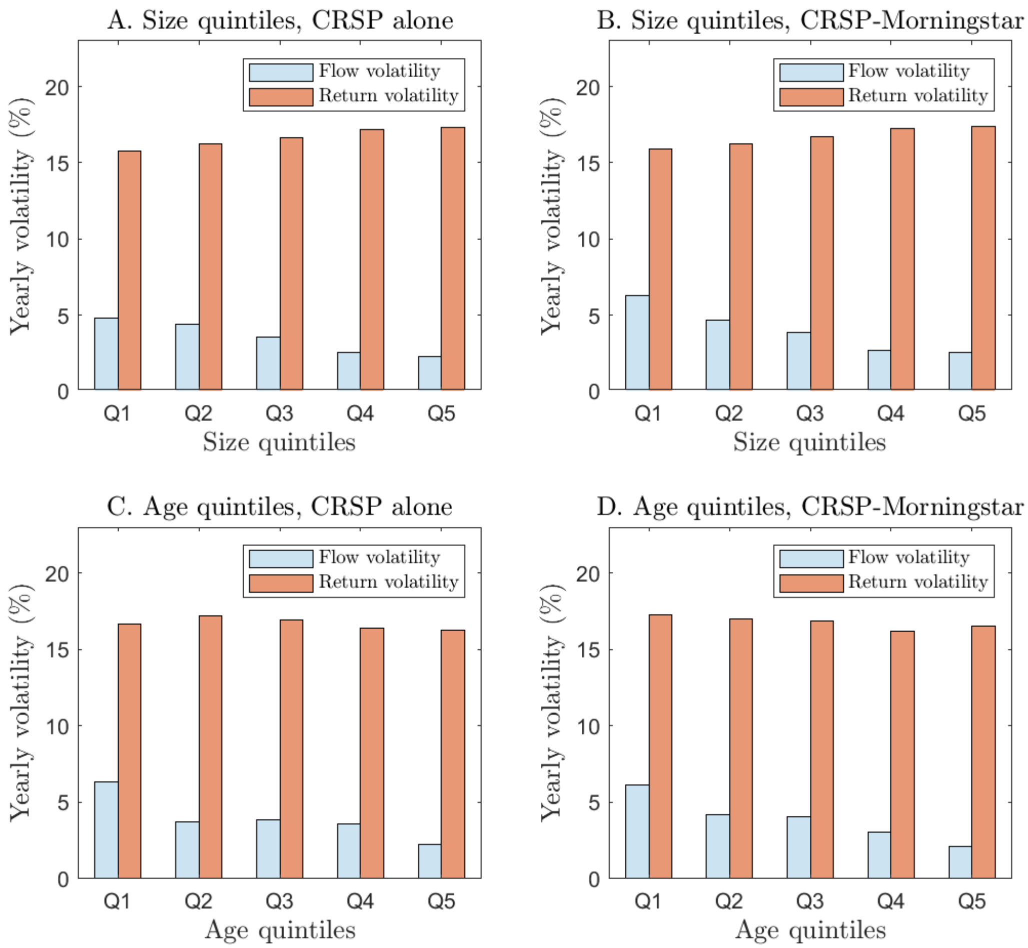
Note: Panel A tabulates the yearly flow volatility and return volatility for fund portfolios sorted on asset size. Panel B tabulates the yearly flow volatility and return volatility for fund portfolios sorted on age. Flow volatility of each fund portfolio is the volatility of the part of fund flows that can be explained by common fund flows. Return volatility of each fund portfolio is the part of fund returns that can be explained by the market returns.

that a substantial amount of variation in AUM comes from fund flows instead of price changes of the underlying stocks, which suggests that fund managers should indeed care about fund flows.

4.3 Additional Results on Common Flows and Economic Uncertainty

Time-Series Comovements. Figure OA.3 plots the quarterly average common fund flow (level) against the quarterly average economic uncertainty (level). It is clear that the quarterly average common fund flow (level) comoves negatively with both the quarterly average economic uncertainty (level) and average market volatility (level).

Fama-MacBeth Regressions for Economic Uncertainty Betas. In Table OA.2, we perform the Fama-MacBeth tests which regress stock returns on the betas to the various economic uncertainty measures, including the macro uncertainty measure (Jurado, Ludvigson and Ng, 2015; Ludvigson, Ma and Ng, 2021), the economic policy uncertainty measure (Baker, Bloom and Davis, 2016), the



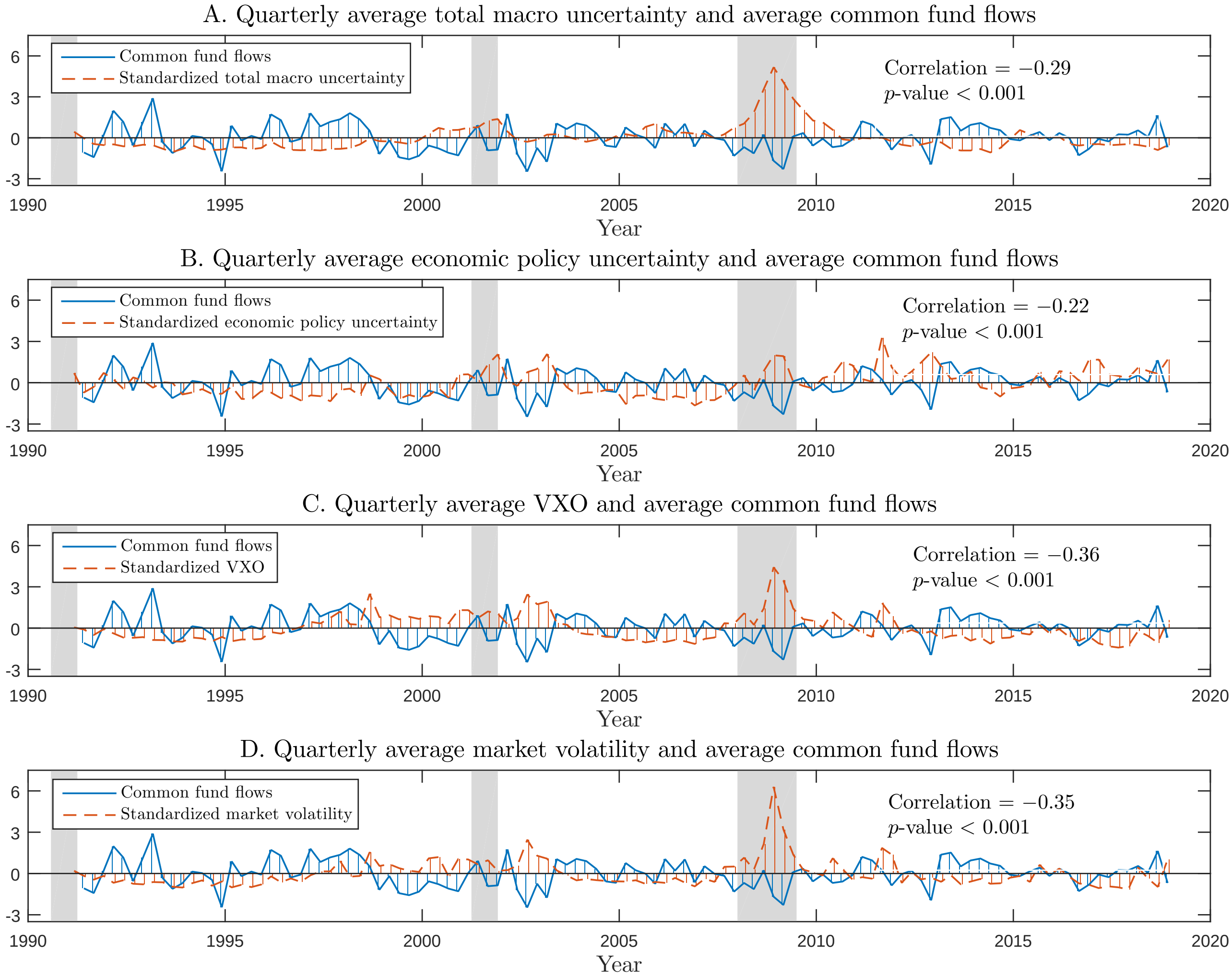
Note: Panels A and B plot the yearly flow volatility and return volatility for fund portfolios sorted on asset size. Panels C and D plot the yearly flow volatility and return volatility for fund portfolios sorted on age. Flow volatility and return volatility are computed based on the CRSP mutual fund data in panels A and C and based on the CRSP-Morningstar intersection data in panels B and D.

Figure OA.2: Flow volatility and return volatility.

VXO index, and the realized market volatility. Consistent with previous studies (e.g., Brogaard and Detzel, 2015; Bali, Brown and Tang, 2017), we find that the betas to the economic uncertainty measures are negatively priced at the cross section of stocks. The coefficient of the betas to the four economic uncertainty measures are all statistically and economically significant.

4.4 Alternative Measures for Common Fund Flows

Besides asset size and age, we also construct common fund flows based on other fund characteristics. Figures OA.4 and OA.5 plot fund flow shocks across fund quintiles sorted on industry



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

Figure OA.3: Average common fund flows and economic uncertainty.

concentration (Kacperczyk, Sialm and Zheng, 2005), and portfolio liquidity (Pástor, Stambaugh and Taylor, 2020), respectively. Similar to asset size and age, we find that fund flow shocks sorted on these characteristics also share common time-series variation. The common fund flows constructed based on asset size, age, industry concentration, and portfolio liquidity are highly correlated with each other. The correlation coefficients range from 0.87 to 0.96 (see Table OA.3 for

Table OA.2: Fama-MacBeth regressions with the economic uncertainty betas.

	(1)	(2)	(3)	(4)
		$Ret_{i,t}$ (%)		
$\beta_{i,t-1}^{MacroUnc}$	-0.173^{**}			
	[−2.519]			
$\beta_{i,t-1}^{EPU}$		-0.098^{**}		
		[−2.054]		
$\beta_{i,t-1}^{VXO}$			-0.085^{*}	
			[−1.782]	
$\beta_{i,t-1}^{MktVol}$				-0.125^{**}
				[−1.985]
Constant	1.416^{***}	1.426^{***}	1.425^{***}	1.420^{***}
	[3.993]	[4.029]	[4.031]	[4.020]
Average obs./month	3036	3036	3036	3036
Average R-squared	0.001	0.001	0.002	0.002

Note: This table reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly stock returns ($ret_{i,t}$) on various economic uncertainty betas, which include betas to the shock to the macro uncertainty measure ($\beta_{i,t-1}^{MacroUnc}$), betas to the shock to the economic policy uncertainty measure ($\beta_{i,t-1}^{EPU}$), betas to the shock to the VXO index ($\beta_{i,t-1}^{VXO}$), and betas to the realized market volatility ($\beta_{i,t-1}^{MktVol}$). The economic uncertainty betas are standardized to have means of 0 and standard deviations of 1. Following Bali, Brown and Tang (2017), we estimate these uncertainty betas using a rolling window approach by regressing stock returns on economic uncertainty shocks controlling for market returns, size and value factors (Fama and French, 1993), momentum factor (Carhart, 1997), liquidity factor (Pástor and Stambaugh, 2003), investment and profitability factors (Fama and French, 2015; Hou, Xue and Zhang, 2015). The sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We compute standard errors using the Newey-West estimator with 1-month lag allowing for serial correlation in returns. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. The sample period spans from 1991 to 2018.

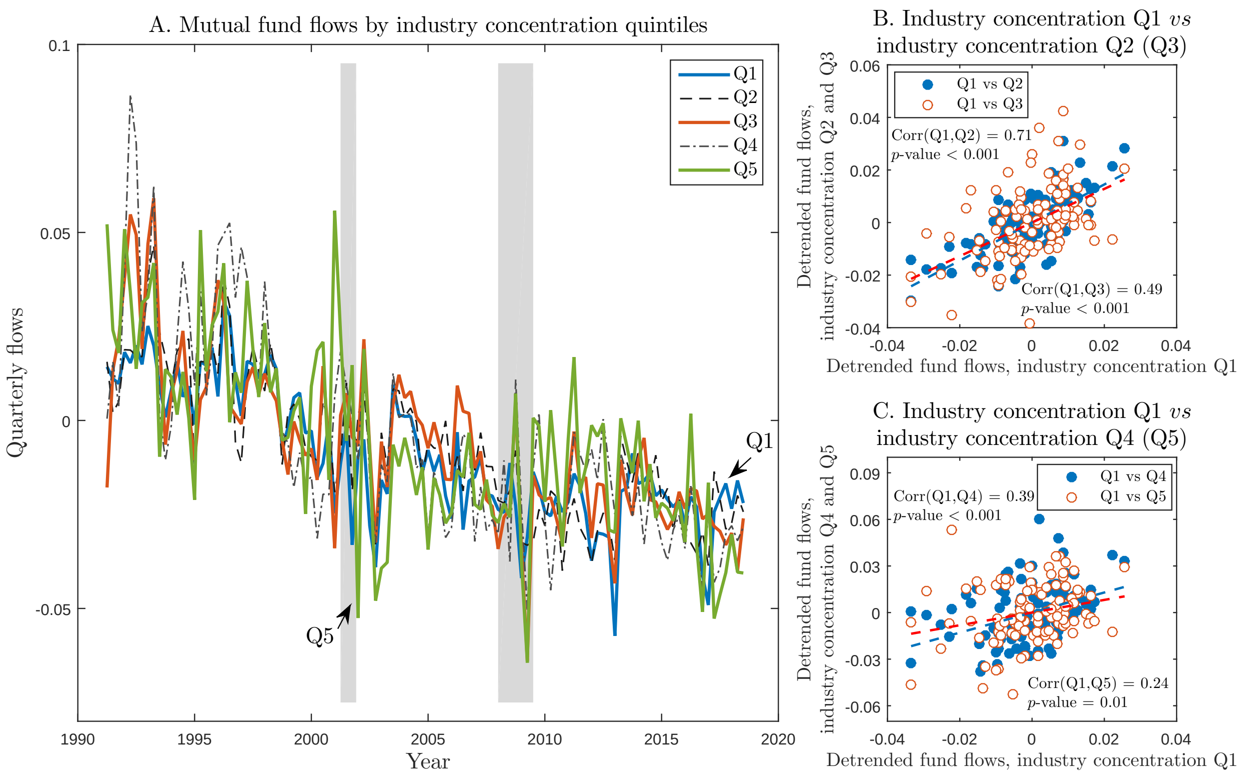
Table OA.3: Correlation among the common fund flows constructed based on various fund share characteristics.

Panel A: Correlation in the CRSP mutual funds data				
Fund characteristics	Asset size	Age	Industry concentration	Portfolio liquidity
Asset size	1			
Age	0.87	1		
Industry concentration	0.89	0.95	1	
Portfolio liquidity	0.91	0.91	0.94	1
Panel B: Correlation in the CRSP-Morningstar intersection data				
Fund characteristics	Asset size	Age	Industry concentration	Portfolio liquidity
Asset size	1			
Age	0.91	1		
Industry concentration	0.91	0.95	1	
Portfolio liquidity	0.93	0.92	0.96	1

details).

4.5 Common Fund Flows, Discount Rates, and Sentiments.

We test the relation between common fund flows and shocks to the discount rates and sentiments. We measure discount rates using the dividend-to-price ratio and the smoothed earnings-price ratio

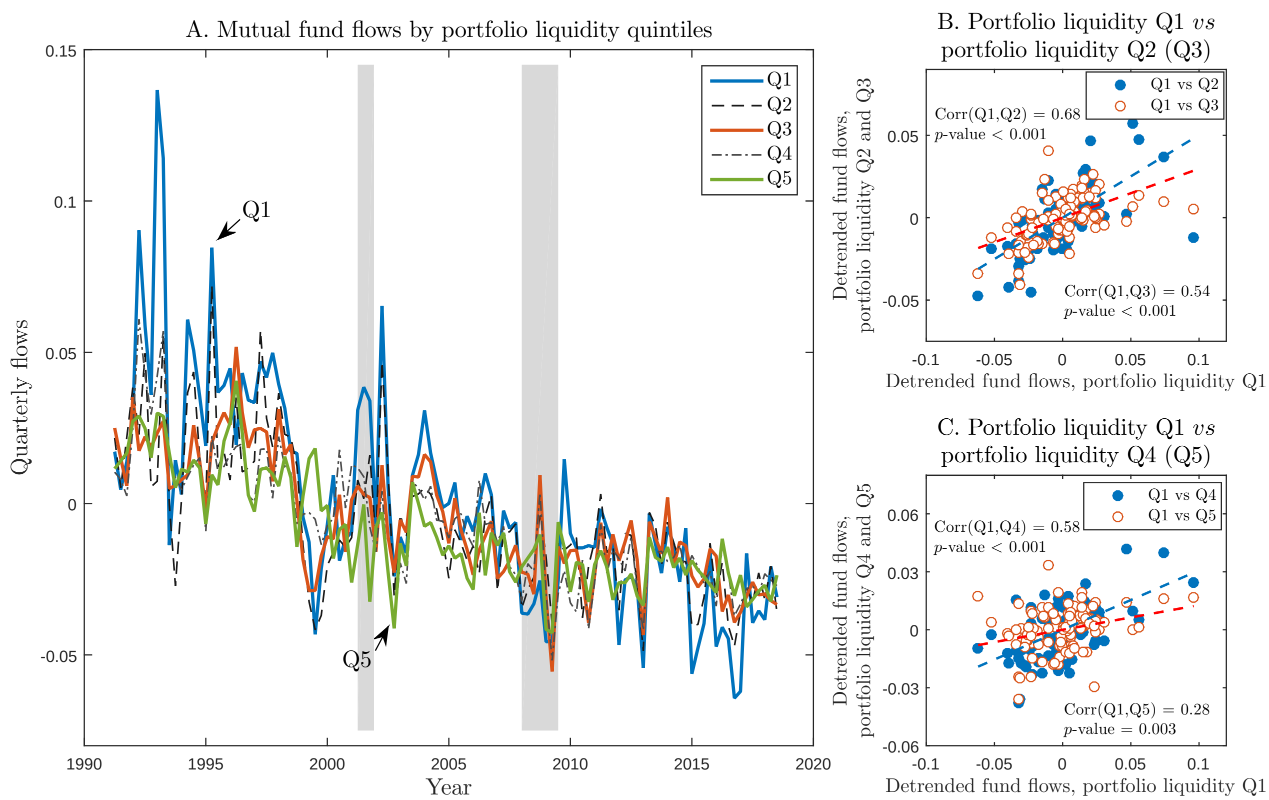


Note: Panel A plots active mutual fund flows by quintiles sorted on the industry concentration of funds (Kacperczyk, Sialm and Zheng, 2005) after removing relative performance. We control for the flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the NBER recession periods. Panels B and C plot the detrended flows of funds with lowest industry concentration (Q1) against the detrended flows of other industry concentration groups.

Figure OA.4: Mutual fund flows by industry concentration after removing relative performance.

(Campbell and Shiller, 1988, 1998), and we measure sentiments using the investor sentiment index of Baker and Wurgler (2006). We regress common fund flows on the contemporaneous shocks to the measures of discount rates and sentiments estimated using an AR(1) model. As shown in panel A of Table OA.4, active mutual funds experience common outflows when contemporaneous discount rate increases. The relation is both statistically and economically significant. Active mutual funds experience common inflows when contemporaneous sentiment increases, but this relation is statistically insignificant. In panel B, we find similar results for common fund flows constructed from the CRSP-Morningstar intersection data.

Common Flows of Index Funds and Hedge Funds. We perform portfolio-sorting analysis based on the betas to the common flows of the US index funds. Specifically, we sort index funds to



Note: Panel A plots active mutual fund flows by quintiles sorted on the portfolio liquidity of fund (Pástor, Stambaugh and Taylor, 2020) after removing relative performance. We control for the flow-performance sensitivity at the fund level. The lines represent the asset-value-weighted fund flows of individual quintiles. Gray areas represent the NBER recession periods. Panels B and C plot the detrended flows of the fund with lowest portfolio liquidity (Q1) against the detrended flows of other portfolio liquidity groups.

Figure OA.5: Mutual fund flows by portfolio liquidity after removing relative performance.

quintiles based on asset size and then compute the value-weighted flow of each quintile after removing relative performance. We then detrend the flow and extract the principal components. We standardize the first principal component and define it as the common flows of index funds. We estimate the betas to common flows of index funds using a 3-year rolling window. Unlike betas to the common flows of active mutual funds, betas to the common flows of index funds are not positively priced at the cross section of stocks. As shown in Table OA.5, the long-short portfolios sorted on the betas to the common flows of index funds have insignificant average excess returns and CAPM alphas.

Similarily, we perform portfolio-sorting analysis based on the betas to the common flows of the US hedge funds. We construct the common flows using the first principal component of the hedge fund portfolios sorted on both asset size and fund age. As shown in Table OA.6, the long-short

Table OA.4: Common fund flows, discount rates, and sentiments.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. CRSP mutual funds alone			Panel B. CRSP-Morningstar intersection		
	$Common\_flows_t$			$Common\_flows_t$		
DP_shock_t	-0.255^{***}			-0.303^{***}		
	[−3.865]			[−4.355]		
$SmoothEP\_shock_t$		-0.260^{***}			-0.315^{***}	
		[−4.010]			[−4.561]	
$Sentiment\_shock_t$			0.076			0.015
			[1.253]			[0.259]
$Common\_flows_{t-1}$	0.079	0.073	0.104^{*}	0.191^{***}	0.184^{***}	0.218^{***}
	[1.397]	[1.302]	[1.807]	[3.583]	[3.471]	[3.986]
Observations	334	334	334	334	334	334
R-squared	0.07	0.07	0.02	0.13	0.14	0.05

Note: This table shows the relation between common fund flows ($Common\_flows_t$) and the shocks to discount rates and sentiments. DP_shock_t is the shock to the dividend-to-price ratio in month t estimated by an AR(1) model. $SmoothEP\_shock_t$ is the shock to smoothed earnings-price ratio (Campbell and Shiller, 1988, 1998) in month t estimated by an AR(1) model. $Sentiment\_shock_t$ is the shock to the investor sentiment index (Baker and Wurgler, 2006) in month t estimated by an AR(1) model. All variables are standardized to have means of 0 and standard deviations of 1. The constant term is omitted for brevity. The analysis is performed at a monthly frequency. Standard errors are computed using the Newey-West estimator with one lag allowing for serial correlation in returns. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1991 to 2018.

Table OA.5: Portfolio-sorting analysis based on the betas to the common flows of index funds.

	CRSP mutual funds alone		CRSP-Morningstar intersection	
$\beta_i^{indexflow}$ quintiles	Excess returns	CAPM alphas	Excess returns	CAPM alphas
Q1	8.60^{***}	0.70	9.14^{***}	1.86
	[2.81]	[0.49]	[3.09]	[1.17]
Q2	8.57^{***}	1.29^{*}	8.68^{***}	2.36^{**}
	[3.27]	[1.67]	[3.63]	[2.37]
Q3	8.90^{***}	1.45	9.11^{***}	0.92
	[3.26]	[1.54]	[3.10]	[1.10]
Q4	10.81^{***}	1.88	9.56^{**}	−1.10
	[3.22]	[1.38]	[2.35]	[−0.62]
Q5	10.26^{**}	−2.48	10.46^{*}	−2.70
	[2.05]	[−1.01]	[1.95]	[−0.93]
Q5 − Q1	1.66	−3.18	1.31	−4.55
	[0.50]	[−1.10]	[0.32]	[−1.26]

Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on betas to the common fund flows of index funds ($\beta_i^{indexflow}$). In June of year t, we sort firms into quintiles based on their $\beta_i^{indexflow}$. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Our sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We annualize the 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.

portfolios sorted on the betas to the common flows of hedge funds also have insignificant average excess returns and CAPM alphas.

Table OA.6: Portfolio-sorting analysis based on the betas to the common flows of hedge funds.

	Common flows constructed from asset size quintiles		Common flows constructed from fund age quintiles	
β_i^{hfflow} quintiles	Excess returns	CAPM alphas	Excess returns	CAPM alphas
Q1	9.82***	2.82**	8.60***	1.66
	[3.60]	[2.18]	[2.81]	[0.50]
Q2	7.31***	0.48	8.57***	1.29*
	[2.94]	[0.58]	[3.27]	[1.67]
Q3	9.30***	0.47	8.90***	1.45
	[2.90]	[0.45]	[3.26]	[1.54]
Q4	10.46**	−0.42	10.81***	1.88
	[2.52]	[−0.23]	[3.22]	[1.38]
Q5	10.58*	−3.00	10.26**	−2.48
	[1.93]	[−1.04]	[2.05]	[−1.01]
Q5 − Q1	0.75	−5.82	1.66	−3.18
	[0.18]	[−1.53]	[0.50]	[−1.10]

Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on betas to the common fund flows of hedge funds (β_i^{hfflow}). We construct the common flows using the first principal component of the hedge fund portfolios sorted on both asset size and fund age. Hedge fund flows are computed based on hedge fund returns and AUM from the Thomson Reuters Lipper Hedge Fund Database (TASS). In June of year t, we sort firms into quintiles based on their β_i^{hfflow}. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. Our sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We annualize the 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.

4.6 Stock Characteristics Across Portfolios Sorted on Flow Betas.

In Table OA.7, we tabulate the mean values of the stock characteristics across stock quintile portfolios sorted on common flow betas. We show that stocks with higher flow betas tend to have lower market cap, higher book-to-market ratios, higher historical liquidity betas, higher Amihud illiquidity measure, higher price impact measures, and higher cash flow betas.

4.7 Risk-Adjusted Excess Returns of Portfolios Sorted on Flow Betas

In Table 7 of the main text, we have shown that stocks with higher flow betas tend to be small, value and illiquid stocks. Although our model has no prediction over the alphas of multifactor models controlling for additional empirical risk factors, such as SMB, HML, and the liquidity factor, it is empirically interesting to test whether controlling for these additional risk factors can explain the asset pricing implications of common flow betas. Thus, we regress the excess returns of the long-short portfolio sorted on the common flow betas on market excess returns and additional empirical risk factors. Table OA.8 presents the results from the regressions. Although

Table OA.7: Stock characteristics across portfolios sorted on common flow betas.

	Panel A: Summary statistics of the stock characteristics				
	Mean	Median	Standard deviation	p25	p75
$Lnsize_{i,t}$	5.493	5.401	2.162	3.971	6.937
$Lnsize_{i,t} - Lnsize_t^{median}$	0.244	0	2.071	−1.213	1.612
$LnBEME_{i,t}$	−0.386	−0.404	1.180	−0.968	0.096
$Liqbeta_{i,t}$	0.164	0.139	0.634	−0.079	0.414
$AIM_{i,t}$	3.819	0.026	20.111	0.002	0.408
$FIT_{i,t}(\%)$	0.772	−0.335	9.591	−2.517	2.533
$PI\_MF_{i,t}$	0.036	0.028	0.036	0.015	0.046
$PI\_HH_{i,t}$	1.549	1.411	0.921	0.836	2.150
$PI\_IA_{i,t}$	0.023	0.013	0.037	0.006	0.026
$PI\_PF_{i,t}$	0.011	0.006	0.027	0.003	0.009
$CFbeta_{i,t}$	0.027	0.013	0.435	−0.088	0.143

	Panel B: Stock characteristics across portfolios sorted on common flow betas									
	CRSP mutual funds alone					CRSP-Morningstar intersection				
β_i^{flow} quintiles	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
$Lnsize_{i,t}$	5.218	5.687	5.800	5.787	4.965	5.261	5.757	5.804	5.716	4.919
$Lnsize_{i,t} - Lnsize_t^{median}$	−0.032	0.439	0.552	0.539	−0.284	0.012	0.509	0.556	0.468	−0.331
$LnBEME_{i,t}$	−0.542	−0.335	−0.311	−0.343	−0.382	−0.506	−0.335	−0.312	−0.341	−0.421
$Liqbeta_{i,t}$	0.068	0.109	0.133	0.180	0.331	0.049	0.096	0.134	0.191	0.348
$AIM_{i,t}$	4.756	2.489	2.279	2.948	6.659	4.448	2.384	2.398	3.219	6.680
$FIT_{i,t}(\%)$	0.699	0.804	0.846	0.829	0.676	0.779	0.733	0.900	0.826	0.613
$PI\_MF_{i,t}$	0.038	0.036	0.035	0.036	0.037	0.037	0.035	0.036	0.037	0.038
$PI\_HH_{i,t}$	1.593	1.493	1.474	1.479	1.679	1.598	1.477	1.473	1.485	1.686
$PI\_IA_{i,t}$	0.024	0.022	0.021	0.022	0.024	0.023	0.021	0.022	0.023	0.025
$PI\_PF_{i,t}$	0.012	0.010	0.010	0.011	0.012	0.011	0.010	0.010	0.011	0.012
$CFbeta_{i,t}$	0.027	0.018	0.020	0.026	0.040	0.018	0.019	0.021	0.030	0.043

Note: Panel A tabulates summary statistics of the stock characteristics. P25 and p75 are the 25^{th} and 75^{th} percentiles. Panel B tabulates the mean values of the stock characteristics across stock quintile portfolios sorted on the common flow betas. The sorting is performed at quarterly frequency. $Lnsize_t^{median}$ represents the median stock size (natural log of market cap) in each quarter. Sample period spans from 1992 to 2018.

the magnitude of the alpha of the long-short portfolio sorted on the common flow betas reduces after controlling for additional empirical risk factors, we find that the alpha remains economically and statistically significant.

4.8 Relation Between Flow Betas and the Flow-Induced Trading Pressure

In Table 1 of the main text, we show that stocks with high flow betas are associated with higher average excess returns and higher CAPM alphas. One potential concern is that this empirical pattern could simply be driven by the flow-induced trading pressures (FIT). Indeed, a large literature has documented that aggregate fund flows can exert a substantial price impact on short-term stock returns, which reverts over a longer horizon (e.g., Coval and Stafford, 2007;

Table OA.8: Alphas of the multifactor models.

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. CRSP mutual funds alone			Panel B. CRSP-Morningstar intersection		
	Long-short flow beta spread (%)			Long-short flow beta spread (%)		
$MktRf_t$	−0.06	−0.06	−0.00	0.19**	0.19**	0.21**
	[−0.84]	[−0.70]	[−0.02]	[2.24]	[2.21]	[2.38]
SMB_t	0.09	0.10	0.08	0.33***	0.33***	0.32***
	[1.16]	[1.19]	[0.98]	[3.46]	[3.51]	[3.53]
HML_t	0.46***	0.46***	0.50***	0.21	0.20	0.22
	[3.33]	[3.30]	[3.60]	[1.40]	[1.39]	[1.45]
PS_t		−0.05	−0.06		−0.02	−0.02
		[−0.66]	[−0.75]		[−0.26]	[−0.29]
MOM_t			0.15**			0.05
			[2.17]			[0.53]
Annualized alpha	6.00**	6.23**	4.86*	5.80*	5.89*	5.46*
	[2.00]	[2.08]	[1.83]	[1.90]	[1.92]	[1.81]
Observations	312	312	312	312	312	312
R-squared	0.09	0.09	0.11	0.08	0.08	0.08

Note: This table shows the alphas of various multifactor models for the value-weighted long-short portfolio sorted on the 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 $t+1$. $MktRf_t$ is the excess market returns. SMB_t and HML_t are the size and value factors (Fama and French, 1993). PS_t is the liquidity factor (Pástor and Stambaugh, 2003). MOM_t is the momentum factor (Carhart, 1997). 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 alphas by multiplying them by 12. The sample period spans from July 1992 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

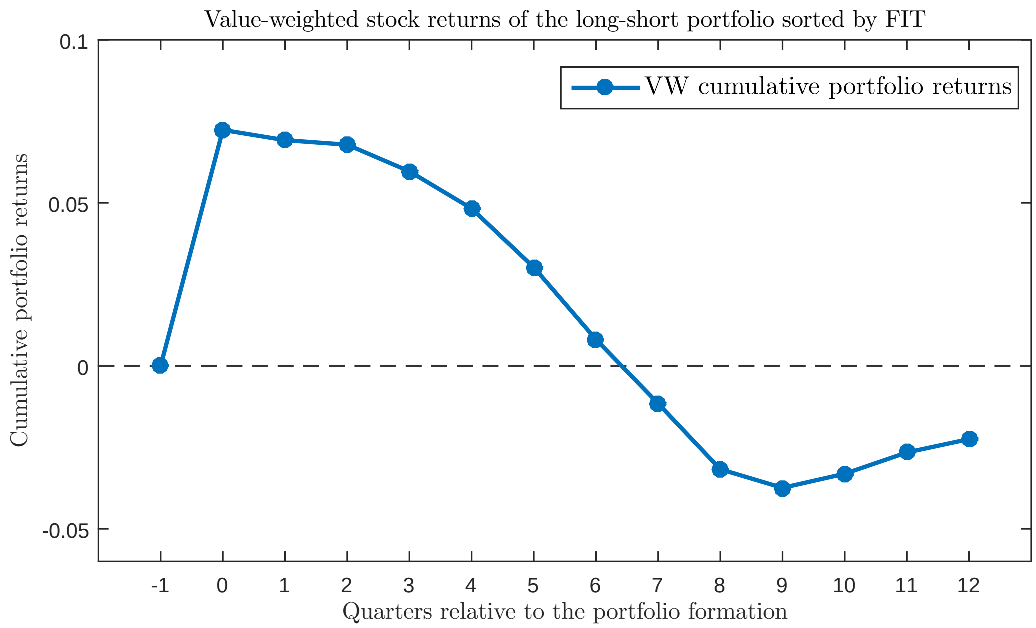
Frazzini and Lamont, 2008; Lou, 2012).

Because flow betas are estimated based on the past-36-month covariance between stock returns and common fund flows, it is possible that stocks in different flow beta quintiles have experienced different flow-driven trading, or they are at different stages of the flow-driven price-pressure cycles. Thus, to test this slow-moving capital story, we construct the FIT measure following Lou (2012) and examine its relation with flow betas. Specifically, we define the FIT for each stock i in each quarter t as:

$$FIT_{i,t} = \frac{\sum_j shares_{i,j,t-1} \times flow_{j,t} \times PSF_{j,t-1}}{\sum_j shares_{i,j,t-1}}, \quad \text{(OA.184)}$$

where $flow_{j,t}$ is the flow of active mutual fund j in quarter t, and $shares_{i,j,t-1}$ is the number of shares held by mutual fund j at the end of the previous quarter. $PSF_{j,t-1}$ is the partial scaling factor, which is estimated by regressing the trade of mutual funds on the fund flows. We follow Lou (2012) to set $PSF_{j,t-1}$ to 0.970.

Lou (2012) examines the cumulative portfolio returns of the long-short portfolio sorted by FIT using the mutual fund holding data from 1980 to 2006. Figure 1 of his paper shows that in



Note: This figure replicates Figure 1 of Lou (2012) using the data from 1980 to 2018, and it shows the value-weighted cumulative returns of the long-short portfolio that longs Decile 10 and shorts Decile 1 stocks sorted by FIT.

Figure OA.6: Cumulative portfolio returns of the long-short portfolio sorted by the flow-induced trading pressure.

the portfolio formation quarter, stock returns of the long-short portfolio are positive and such positive returns are reversed by the end of year three. We extend the data to 2018 and replicate the findings of Lou (2012). Figure OA.6 shows the cumulative returns to the long-short portfolio that longs Decile 10 and shorts Decile 1 stocks sorted by FIT. We find that the stock return patterns associated with FIT documented by Lou (2012) remain robust in the extended time window.

Next, we examine the cross-sectional relation between flow betas and FIT using panel regressions with time fixed effects. Besides computing the contemporaneous and lagged FIT, we also accumulate the FIT measure across different past time horizons (i.e., past two quarters, one year, two years, and three years) because flow betas are estimated based on returns of past 36 months. As shown in Table OA.9, flow betas have insignificant correlation with the contemporaneous FIT, lagged FIT, and FIT accumulated across different time horizons. In Panel A of Table 8 in the main text, we further show that the flow betas remain positively priced in the cross section of stocks after controlling for FIT. The above findings collectively suggest that the asset pricing implications of the flow betas are very unlikely a side effect of the flow-induced trading pressures.

Table OA.9: Relation between flow betas and the flow-induced trading pressure.

	Panel A: Flow betas and lagged FIT									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CRSP mutual funds alone $\beta_{i,t}^{flow}$					CRSP-Morningstar intersection $\beta_{i,t}^{flow}$				
$FIT_{i,t-h}$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$	$h=0$	$h=1$	$h=2$	$h=3$	$h=4$
	−0.002	−0.005	−0.007	−0.009	−0.008	−0.003	−0.004	−0.005	−0.004	−0.003
	[−0.168]	[−0.570]	[−0.734]	[−1.100]	[−1.281]	[−0.379]	[−0.508]	[−0.702]	[−0.737]	[−0.566]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	351835	343766	337483	332077	327148	351835	343766	337483	332077	327148
R-squared	0.16	0.16	0.17	0.17	0.17	0.19	0.19	0.19	0.19	0.20

	Panel B: Flow betas and FIT cummulated across different time horizon							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone $\beta_{i,t}^{flow}$				CRSP-Morningstar intersection $\beta_{i,t}^{flow}$			
$\sum_{k=0}^{h} FIT_{i,t-k}$	$h=1$	$h=3$	$h=7$	$h=11$	$h=1$	$h=3$	$h=7$	$h=11$
	−0.004	−0.010	−0.015	−0.013	−0.004	−0.007	−0.005	0.006
	[−0.417]	[−0.899]	[−1.506]	[−1.427]	[−0.486]	[−0.836]	[−0.571]	[0.689]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	342890	327881	303235	280873	342890	327881	303235	280873
R-squared	0.16	0.17	0.17	0.18	0.19	0.19	0.20	0.21

Note: Panel A of this table shows the relation between common flow betas and lagged FIT. Panel B of this table shows the relation between common flow betas and FIT cummulated across different time horizons. The analysis is performed at the quarterly frequency. $\beta_{i,t}^{flow}$ is the common flow beta for stock i in quarter t. $FIT_{i,t}$ is the flow-induced trading pressure for stock i in quarter t, which is computed following Lou (2012). All variables are standardized to have means of 0 and standard deviations of 1. We include t-statistics in brackets. Standard errors are double clustered at the stock and quarter levels. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1992 to 2018.

4.9 Predicted Flow Betas

Because flow betas are closely associated with stock characteristics, we further strengthen our asset pricing results using the predicted beta approach following the literature.[13] In particular, we use lagged market caps, lagged book-to-market ratios, lagged historical liquidity betas, lagged Amihud illiquidity measures, lagged price impact measures, lagged cash flow betas, and lagged flow betas to predict flow betas. The predicted flow betas are negatively associated with market caps and positively correlated with book-to-market ratios, historical liquidity betas, Amihud illiquidity measures, price impact measures, and cash flow betas (see Table OA.10).

Specifically, we model each stock's predicted flow beta as a linear function of observable variables:

$$\beta_{i,t-1}^{flow} = a_{0,i} + a_{1,i}^{T} Z_{i,t-1}. \quad \text{(OA.185)}$$

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

Table OA.10: Predicted common flow betas and stock characteristics.

	CRSP mutual funds alone					CRSP-Morningstar intersection				
$Predicted\_\beta_{i,t}^{flow}$ quintiles	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
$Lnsize_{i,t}$	6.361	6.317	6.005	5.653	4.743	7.249	6.566	5.918	5.204	4.142
$Lnsize_{i,t} - Lnsize_t^{median}$	0.663	0.619	0.307	−0.045	−0.955	1.551	0.868	0.220	−0.494	−1.556
$LnBEME_{i,t}$	−1.216	−0.731	−0.484	−0.312	−0.105	−0.804	−0.613	−0.505	−0.455	−0.468
$Liqbeta_{i,t}$	0.076	0.168	0.216	0.281	0.459	0.063	0.149	0.220	0.296	0.473
$AIM_{i,t}$	0.485	0.565	0.811	1.375	9.634	0.263	0.405	0.721	1.569	9.911
$PI\_HH_{i,t}$	1.145	1.219	1.367	1.520	1.722	1.192	1.227	1.323	1.488	1.745
$CFbeta_{i,t}$	−0.093	0.008	0.026	0.054	0.152	−0.110	−0.012	0.016	0.060	0.193

Note: This table shows the stock characteristics across stock portfolios sorted on the predicted common flow betas. The characteristics are raw values without standardization. Sample period spans from 1995 to 2018.

Vector $Z_{i,t-1}$ contains seven characteristics: lagged firm size, lagged book-to-market ratio, lagged historical liquidity betas, lagged Amihud illiquidity measure, lagged price impact of household, lagged cash flow betas, and lagged common flow betas estimated by equation (2.5) using all data available from month $t-36$ through $t-1$. Substituting the right side of equation (OA.185) for β_i^{flow} in equation (2.5), we obtain:

$$ret_{i,t} = a + a_{0,i} \times \text{common flow}_t + a_{1,i}^T Z_{i,t-1} \times \text{common flow}_t + \varepsilon_{i,t}. \tag{OA.186}$$

The above regression for stock i contains eight independent variables, seven of which are cross-products of the elements of $Z_{i,t-1}$ with common flow$_t$. Following Pástor and Stambaugh (2003), we use an expanding window to run the above regression to obtain $\hat{a}_{0,i}$ and $\hat{a}_{1,i}^T$ using all data available up to the current month-end. We then predict flow betas based on the estimated coefficients:

$$Predicted\_\beta_{i,t-1}^{flow} = \hat{a}_{0,i} + \hat{a}_{1,i}^T Z_{i,t-1}. \tag{OA.187}$$

The predicted common flow betas exhibit many properties that are similar to those of the common flow betas. First, Table OA.10 shows that the predicted common flow betas are negatively correlated with stock size and positively correlated with book-to-market ratio, historical liquidity betas, Amihud illiquidity measure, price impact of household, and the cash flow betas. This result is consistent with the relation between common flow betas and stock characteristics shown in Table 7 in the main text.

Table OA.11: Portfolio holdings of active mutual funds and predicted common flow betas.

	Panel A: Relation between predicted common flow betas and stock returns (Fama-MacBeth regressions)			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$Ret_{i,t}$ (%)		$Ret_{i,t}$ (%)	
$Predicted\_\beta^{flow}_{i,t-1}$	0.347**	0.353**	0.526***	0.537***
	[2.185]	[2.214]	[3.147]	[3.372]
$\beta^{M}_{i,t-1}$		0.056		0.001
		[0.402]		[0.008]
Constant	1.304***	1.305***	1.235***	1.208***
	[3.459]	[3.421]	[3.384]	[3.184]
Average obs./month	2538	2538	2538	2538
Average R-squared	0.01	0.02	0.01	0.02

	Panel B: Active mutual funds tilt their holdings away from stocks with high predicted common flow betas				
	(1)	(2)		(3)	(4)
	Panel regressions with time FE			Fama-MacBeth regressions	
	CRSP	CRSP-MS		CRSP	CRSP-MS
	$w^{MF}_{i,t} - w^{M}_{i,t}$			$w^{MF}_{i,t} - w^{M}_{i,t}$	
$Predicted\_\beta^{flow}_{i,t-1}$	−0.200***	−0.342**	$Predicted\_\beta^{flow}_{i,t-1}$	−0.222***	−0.407***
	[−10.004]	[−14.367]		[−13.177]	[−17.947]
$\beta^{M}_{i,t-1}$	0.037***	0.088***	$\beta^{M}_{i,t-1}$	0.048***	0.082***
	[3.627]	[7.899]		[6.336]	[9.114]
Quarter FE	Yes	Yes			
Observations	241135	241135	Avg. obs./quarter	2254	2254
R-squared	0.03	0.04	Avg. R-squared	0.04	0.05

Note: Panel A reports the slope coefficients and test statistics from Fama-MacBeth regressions that regress monthly stock returns ($ret_{i,t}$) on the predicted common flow betas ($predicted\_\beta^{flow}_{i,t-1}$) and market betas ($\beta^{M}_{i,t-1}$). $predicted\_\beta^{flow}_{i,t-1}$ and $\beta^{M}_{i,t-1}$ are standardized to have means of 0 and standard deviations of 1. Panel B studies the relation between predicted common flow betas and active mutual funds' weight deviation from the market ($w^{MF}_{i,t} - w^{M}_{i,t}$). We control for the market betas in the regressions. $w^{MF}_{i,t} - w^{M}_{i,t}$, $predicted\_\beta^{flow}_{i,t-1}$, and $\beta^{M}_{i,t-1}$ are standardized to have means of 0 and standard deviations of 1. The analysis is performed at quarterly frequency. We perform panel regressions with quarter fixed effects in columns (1) and (2), and Fama-MacBeth regressions in columns (3) and (4). Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE is fixed effects. Sample period spans from 1995 to 2018. Standard errors are double-clustered at the stock and quarter levels. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Next, in panel A of Table OA.11, using the Fama-MacBeth regressions, we show that the predicted flow betas are also positively priced in the cross section. Specifically, we find that the predicted common flow betas are also positively priced in the cross-section of stocks. Finally, in panel B of Table OA.11, we examine the relation between the portfolio weight deviation of active mutual funds and the predicted flow betas. We find that active mutual funds tilt their portfolio holdings away from the stocks with high predicted common flow betas.

Table OA.12: Active mutual funds tilt their holdings away from stocks with high flow betas: analysis with rescaled portfolio weights.

Panel A: Panel regressions with time FE						
	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
	$rescaled\_w^{MF}_{i,t} - rescaled\_w^{M}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$	
Benchmarks	Market portfolio		S&P 500 portfolio		Russell 1000 growth portfolio	
$\beta^{flow}_{i,t-1}$	-0.028^{***}	-0.024^{***}	-0.092^{***}	-0.061^{**}	-0.068^{***}	-0.061^{***}
	[−5.872]	[−5.427]	[−3.648]	[−2.307]	[−3.616]	[−3.257]
$\beta^{M}_{i,t-1}$	0.074^{***}	0.076^{***}	0.112^{***}	0.113^{***}	0.083^{***}	0.091^{***}
	[10.614]	[10.970]	[3.310]	[3.179]	[4.241]	[4.303]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	413321	413321	26208	26208	30780	30780
R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Panel B: Fama-MacBeth regressions						
	(1)	(2)	(3)	(4)	(5)	(6)
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
	$rescaled\_w^{MF}_{i,t} - rescaled\_w^{M}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$	
Benchmarks	Market portfolio		S&P 500 portfolio		Russell 1000 growth portfolio	
$\beta^{flow}_{i,t-1}$	-0.034^{***}	-0.021^{***}	-0.100^{***}	-0.060^{***}	-0.094^{***}	-0.078^{***}
	[−8.882]	[−5.377]	[−9.581]	[−4.135]	[−9.030]	[−7.849]
$\beta^{M}_{i,t-1}$	0.087^{***}	0.085^{***}	0.109^{***}	0.106^{***}	0.097^{***}	0.100^{***}
	[16.138]	[16.101]	[15.432]	[11.937]	[15.982]	[15.417]
Avg. obs./quarter	3863	3863	437	437	513	513
Avg. R-squared	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table studies the relation between common flow betas ($\beta^{flow}_{i,t-1}$) and active mutual funds' weight deviation from the benchmark portfolios. Our analysis is the same as in Table 3 in the main text, except that we rescale the stock weights in the aggregate mutual fund portfolio, the market portfolio, and the self-disclosed benchmark portfolios to make sure the sum of the weights for the stocks included in the analysis is 1 in each quarter. In columns (1) and (2), for a given quarter t, we include stocks with positive aggregate mutual fund holdings in this quarter, and stocks with zero aggregate mutual fund holdings in quarter t but non-zero aggregate mutual fund holdings in any of the quarters from quarter $t-8$ to $t-1$. In columns (3) to (6), we further require that the stocks in our analysis to be part of the self-disclosed benchmark portfolios. We perform panel regressions with quarter fixed effects in panel A, and Fama-MacBeth regressions in panel B. Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

4.10 Portfolio Tilts with Rescaled Weights

In Table 3 in the main text, we show that active mutual funds tilt their portfolios away from stocks with high flow betas using the raw stock weights to compute the deviations of mutual fund portfolios from benchmark portfolios. In Table OA.12, we perform a robustness check by rescaling the stock weights in the aggregate mutual fund portfolio, the market portfolio, and the self-disclosed benchmark portfolios to make sure the sum of the weights for the stocks included in the analysis is 1 in each quarter. In columns (1) and (2) of Table OA.12, for a given quarter t, we include stocks with positive aggregate mutual fund holdings in this quarter, and stocks with zero

Table OA.13: Relation between the observed tilt and the model-implied tilt.

	Panel A: Panel regressions with time FE			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$w_{i,t}^{MF} - w_{i,t}^{M}$		$w_{i,t}^{MF} - w_{i,t}^{M}$	
$-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{flow}$	0.017***	0.017***	0.015***	0.015***
	[3.536]	[3.535]	[3.394]	[3.393]
$-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{M}$		−0.001		−0.001
		[−0.077]		[−0.348]
Quarter FE	Yes	Yes	Yes	Yes
Observations	408054	408054	408054	408054
R-squared	0.01	0.01	0.01	0.01

	Panel B: Fama-MacBeth regressions			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$w_{i,t}^{MF} - w_{i,t}^{M}$		$w_{i,t}^{MF} - w_{i,t}^{M}$	
$-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{flow}$	0.050***	0.050***	0.037***	0.037***
	[6.675]	[6.694]	[5.252]	[5.307]
$-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{M}$		0.013		0.013
		[1.284]		[1.328]
Avg. obs./quarter	3814	3814	3814	3814
Avg. R-squared	0.01	0.01	0.01	0.01

Note: This table investigates the relation between the observed portfolio tilt and the model-implied portfolio tilt. $w_{i,t}^{MF}$ is the weight of the aggregate active mutual fund portfolio for stock i in quarter t, and $w_{i,t}^{M}$ is the weight of the market portfolio for stock i. $w_{i,t}^{MF} - w_{i,t}^{M}$ represents the observed portfolio tilt. Independent variable $-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{flow}$ represents the lagged model-implied portfolio tilt. We include stocks with zero aggregate mutual fund weight conditional on these stocks have non-zero aggregate mutual fund weight in any of the quarters in the previous 2 years. $-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{flow}$, $-\Sigma_{t-1}^{-1}\beta_{i,t-1}^{M}$, and $w_{i,t}^{MF} - w_{i,t}^{M}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at a quarterly frequency. We perform panel regressions with quarter fixed effects in panel A, and Fama-MacBeth regressions in panel B. FE stands for fixed effects. Standard errors for the panel regressions are double clustered at the stock and quarter levels. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1992 to 2018.

aggregate mutual fund holdings in quarter t but non-zero aggregate mutual fund holdings in any of the quarters from quarter $t-8$ to $t-1$. In columns (3) to (6) of Table OA.12, we further require the stocks in our analysis to be part of the self-disclosed benchmark portfolios. Our results remain robust to the usage of the rescaled portfolio weights.

4.11 Model-Implied Portfolio Tilt

In equilibrium, the portfolio tilt is equal to

$$\Sigma_t^{-1}\mathcal{B}_t = \left(v^2 I_n + KK^T\right)^{-1}\mathcal{B} \tag{OA.188}$$

$$= v^{-2}\left[I_n - K\left(v^2 I_k + K^T K\right)^{-1} K^T\right]\mathcal{B}. \tag{OA.189}$$

The first equality is caused by the equilibrium covariance matrix of log returns $\Sigma = v^2 I_n + KK^T$ and the cancelation of $\sqrt{h_t}$. The second equality is because of the Woodbury identity.

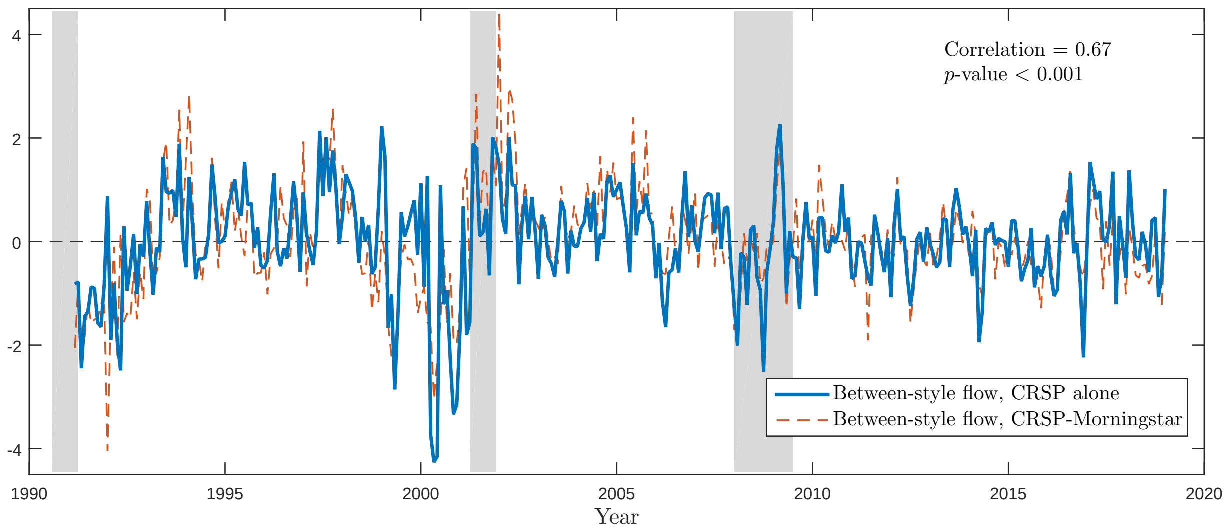
We empirically estimate Σ_t^{-1} using equation (OA.189). We estimate the factor structure of stock returns using the Fama-French three-factor model with a 3-year rolling window. Matrix K_t is the loading matrix of the three factors. Scalar v_t is the average idiosyncratic volatility across all stocks. Consistent with Corollary 2.2, we find that the theoretical tilts (i.e., $\Sigma_t^{-1}\mathcal{B}_t$) are highly correlated with the flow betas (i.e., $\mathcal{B}_t$). The correlation is 0.70 in the CRSP mutual fund data and is 0.69 in the CRSP-Morningstar intersection sample. In Table OA.13, we regress the deviation of mutual fund holdings from the market portfolios on the lagged theoretical portfolio tilt. We find that active mutual funds systematically tilt their holdings away from the stocks with higher theoretical portfolio tilts. This result provides strong support to Theorems 1 and 1 of our model.

4.12 Evidence from Portfolio Tilts and Between-Style Flow Betas

We have shown above that active equity funds tilt away from stocks with high flow betas. A salient feature of the delegated asset management industry is that it offers different styles of investing such as value and growth. Funds should also have incentives to hedge against the risk associated with the between-style flows (e.g., fund flows from growth to value funds). For example, we expect value equity funds to tilt their holdings away from stocks that perform poorly when clients direct funds from value to growth funds; on the contrary, we expect growth equity funds to tilt their holdings toward the stocks with the same property.

The key difference between the between-style flows and common fund flows in their asset pricing implications. Unlike the common fund flows, it is less likely that the between-style flow shocks would be priced in the cross section of stocks, because the two styles of funds tilt their portfolios in the opposite directions, thereby helping absorb each other's hedging demand. In this subsection, we test the predictions on the portfolio tilts and asset pricing implications related to the between-style flows to further support the economic mechanism of flow hedging.

To construct the between-style fund flows, we estimate the fund-level flow shock of value funds



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

Figure OA.7: Between-style fund flows.

and growth funds using regression specifications (2.2) and (2.3). We then sort the value funds and growth funds into five groups separately based on asset size and compute the value-weighted average fund flow shocks for each group.[14] To make sure the between-style fund flows capture flows between fund styles within the mutual fund sector rather than the flows in and out of the mutual fund sector, we regress the fund flow shocks of the ten fund groups on the common fund flows and take the residuals. Finally, we extract the PC1 of the residuals of the ten fund groups. The PCA loadings of the PC1 are positive for all five groups of value funds and are negative for all five groups of growth funds. Specifically, when using the CRSP alone data, the PCA loadings for the five groups of value funds are $[0.2359, 0.1248, 0.3607, 0.3956, 0.4210]$ from the smallest asset size group to the largest asset size group, while the PCA loadings for the five groups of growth funds are $[-0.1114, -0.3101, -0.2533, -0.4157, -0.3454]$. We find similar pattern for the PCA loadings when using the CRSP-Morningstar intersection data. We define the PC1 as the between-style fund flow and it reflects the flows from growth funds to value funds. Figure OA.7 plots the monthly

[14]Following Lettau, Ludvigson and Manoel (2018), we classify active mutual funds into growth, value, and other funds based on fund names. We use the CRSP, Lipper, Wiesenberger, and Strategic Insight objective codes to further classify mutual funds that cannot be identified by their names.

Table OA.14: Between-style flows and portfolio tilts of value and growth funds.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
		CRSP			CRSP-MS			CRSP			CRSP-MS	
	Panel A: Panel regressions with time FE											
	$w_{i,t}^{V} - w_{i,t}^{mkt,V}$			$w_{i,t}^{V} - w_{i,t}^{mkt,V}$			$w_{i,t}^{G} - w_{i,t}^{mkt,G}$			$w_{i,t}^{G} - w_{i,t}^{mkt,G}$		
$\beta_{i,t-1}^{G\to V}$	-0.085^{***}	-0.079^{***}	-0.044^{***}	-0.045^{***}	-0.045^{***}	-0.030^{***}	0.077^{***}	0.076^{***}	0.047^{***}	0.041^{***}	0.040^{***}	0.032^{**}
	[−12.103]	[−11.055]	[−7.427]	[−6.416]	[−5.763]	[−4.218]	[11.446]	[10.913]	[7.048]	[6.346]	[5.796]	[5.337]
$\beta_{i,t-1}^{mkt}$	0.006	0.009	0.010	-0.020^{***}	-0.017^{***}	−0.000	0.070^{***}	0.062^{***}	0.066^{***}	0.096^{***}	0.088^{***}	0.078^{***}
	[0.935]	[1.219]	[1.331]	[−2.767]	[−2.191]	[−0.049]	[8.953]	[6.978]	[8.360]	[11.479]	[9.457]	[9.508]
$LnBEME_{i,t-1}$		0.081^{***}			0.085^{***}			-0.117^{***}			-0.121^{***}	
		[7.938]			[8.309]			[−10.216]			[−10.522]	
$\beta_{i,t-1}^{HML}$			0.089^{***}			0.110^{***}			-0.069^{***}			-0.090^{***}
			[10.174]			[12.806]			[−8.839]			[−11.444]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	335910	305276	335910	335910	305276	335910	336657	301087	336657	336657	301087	336657
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.01	0.02	0.02
	Panel B: Fama-MacBeth regressions											
	$w_{i,t}^{V} - w_{i,t}^{mkt,V}$			$w_{i,t}^{V} - w_{i,t}^{mkt,V}$			$w_{i,t}^{G} - w_{i,t}^{mkt,G}$			$w_{i,t}^{G} - w_{i,t}^{mkt,G}$		
$\beta_{i,t-1}^{G\to V}$	-0.104^{***}	-0.102^{***}	-0.063^{***}	-0.024^{***}	-0.029^{***}	-0.024^{***}	0.073^{***}	0.074^{***}	0.050^{***}	0.042^{***}	0.044^{***}	0.040^{***}
	[−14.879]	[−12.958]	[−13.749]	[−5.436]	[−6.320]	[−7.601]	[11.685]	[11.961]	[8.114]	[6.258]	[6.096]	[6.115]
$\beta_{i,t-1}^{mkt}$	0.021^{***}	0.030^{***}	0.050^{***}	-0.015^{***}	−0.008	0.034^{***}	0.089^{***}	0.085^{***}	0.078^{***}	0.113^{***}	0.111^{***}	0.098^{***}
	[4.221]	[5.246]	[8.891]	[−2.880]	[−1.474]	[5.234]	[11.659]	[9.512]	[9.739]	[13.882]	[11.505]	[12.105]
$LnBEME_{i,t-1}$		0.094^{***}			0.098^{***}			-0.106^{***}			-0.111^{***}	
		[15.872]			[16.381]			[−17.698]			[−19.426]	
$\beta_{i,t-1}^{HML}$			0.108^{***}			0.155^{***}			-0.059^{***}			-0.083^{***}
			[13.072]			[17.469]			[−9.925]			[−15.063]
Avg. obs/quarter	3139	2853	3139	3139	2853	3139	3146	2814	3146	3146	2814	3146
Avg. R-squared	0.01	0.02	0.01	0.01	0.01	0.01	0.02	0.03	0.02	0.02	0.03	0.02

Note: This table investigates the relation between the between-style flow beta $\beta_{i,t-1}^{G\to V}$ and the portfolio tilt of the value funds and growth funds, relative to the market portfolio. We control for the market beta $\beta_{i,t-1}^{mkt}$ in the regressions. We also control for the book-to-market ratio $LnBEME_{i,t-1}$ and the HML beta $\beta_{i,t-1}^{HML}$ of the stocks. We perform panel regressions with quarter fixed effects in panel A and Fama-MacBeth regressions in panel B. $w_{i,t}^{V}$ and $w_{i,t}^{G}$ are the portfolio weights for stock i in the aggregate portfolio holdings of value funds and growth funds in quarter t, respectively. $w_{i,t}^{mkt,V}$ and $w_{i,t}^{mkt,G}$ is the weight for stock i in the market portfolio for the stocks invested by value funds and growth funds from quarter $t-7$ to quarter t, respectively. We normalize the market weights to make sure that the sum of the weights is 1 each quarter. $w_{i,t}^{V} - w_{i,t}^{mkt,V}$, $w_{i,t}^{G} - w_{i,t}^{mkt,G}$, $\beta_{i,t-1}^{G\to V}$, $\beta_{i,t-1}^{mkt}$, $LnBEME_{i,t-1}$, and $\beta_{i,t-1}^{HML}$ are standardized to have means of 0 and standard deviations of 1. The analysis here is performed at quarterly frequency. Sample period spans from 1992 to 2018. Standard errors for the panel regressions are double clustered at the stock and quarter levels. FE stands for fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

between-style fund flows constructed using the CRSP alone and CRSP-Morningstar intersection data. The two monthly time series are highly correlated with the correlation of 0.67 (p-value $<$ 0.001). The between-style fund flows are negative during the dot-com bubble period and are positive after the subsequent bust, suggesting that money flows into growth funds during the dot-com bubble period and then flows out after the bust.

We expect that value funds tilt holdings away from stocks with high between-style betas. This is because value fund managers dislike stocks that have bad performance when money flows

Table OA.15: Excess returns and alphas of portfolios sorted on between-style flow betas.

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

Note: This table shows the value-weighted average excess returns and alphas for stock portfolios sorted on between-style flow betas. In June of year t, we sort firms into quintiles based on their average between-style betas from January to June of year t. Once the portfolios are formed, their monthly returns are tracked from July of year t to June of year $t+1$. We estimate the portfolio alphas using both the CAPM model and the Fama-French three-factor model. Our sample includes the firms listed on the NYSE, NASDAQ, and Amex with share codes 10 and 11. We exclude financial firms and utility firms from the analysis. We annualize the average excess returns and CAPM alphas by multiplying them by 12. The sample period spans from July 1992 to June 2018. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

from value funds to growth funds (i.e., negative between-style fund flows). On the other hand, we expect that growth funds to show the opposite tilt. To test this hypothesis, we estimate the between-style flow beta of each stock using regression specification (2.5) by replacing the common fund flows with the between-style flows on the right-hand side. We then examine the relation between the between-style flow beta and the portfolio tilt of the value funds and growth funds relative to the market portfolio in Table OA.14. Consistent with our hypotheses, we find that value funds indeed tilt their holdings away from stocks with high between-style betas (Columns 1 to 6), while growth funds do the opposite (Columns 7 to 12). These findings are robust after controlling for the book-to-market ratios and the HML betas of the stocks to account for the difference in investment style. The findings are also robust to the choice of the data samples we use to construct the between-style betas (i.e., CRSP alone and CRSP-Morningstar intersection) and the regression specifications (i.e., panel regressions and Fama-MacBeth regressions).

Because value and growth funds tilt their holdings in the opposite directions for stocks with high between-style betas, we do not expect that the between-style betas to be priced in the cross section of stocks. To test this hypothesis, we perform portfolio sorting analyses. Table OA.15 shows the average excess returns and alphas of the long-short portfolios sorted on the between-style flow betas. Unlike the flow betas, we find that stocks with higher between-style flow betas are not associated with significantly higher excess returns or risk-adjusted alphas.

5 Additional (Quasi) Natural Experiments

5.1 Additional Analysis of Natural Disaster Experiments

Natural Disaster Shocks Measured Using Establishment-Level Data. In Table OA.16, we use establishment-level data from Infogroup Historical Business Database to map firms to natural disaster losses. Infogroup Historical Business Database records and updates all business locations in the US starting from 1997. Infogroup gathers geographic location-related business and residential data from various public data sources, such as local yellow pages, credit card billing data, etc. The data contain addresses, sales, and number of employees at the establishment level. We merge Infogroup to Compustat-CRSP based on tickers and the names of the parent firms.

We define a stock as being negatively affected by natural disasters if it is a nonfinancial 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. We find that active mutual funds with heavy exposures to the stocks that are affected by natural disasters experience outflows in the next few quarters (see panel A of Table OA.16). To hedge against the increased outflow risk, these mutual funds tilt their holdings of the stocks that are unaffected by natural disasters toward low-flow-beta stocks relative to other funds (see panel B of Table OA.16). These findings are consistent with those in the main text in which we measure natural disaster shocks using the headquarter-level data.

Response of the Benchmarked Returns of Active Mutual Funds to Natural Disasters. We examine the responses of relative performance of active mutual funds to natural disasters. Specifically, we regress the returns of active mutual funds benchmarked by the market returns on the fund-level exposure to natural disasters. As we show in Table OA.17, the benchmarked performance of active

Table OA.16: Mutual funds' rebalancing of unaffected stocks following natural disaster shocks measured with establishment-level data.

	Panel A: Abnormal fund flows around natural disaster shocks							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone				CRSP-Morningstar intersection			
	$Abflow_{f,t}$	$Abflow_{f,t+1}$	$Abflow_{f,t+2}$	$Abflow_{f,t+3}$	$Abflow_{f,t}$	$Abflow_{f,t+1}$	$Abflow_{f,t+2}$	$Abflow_{f,t+3}$
$ND_{f,t}$	-0.049^{***}	-0.039^{***}	-0.029^{***}	-0.021^{***}	-0.040^{***}	-0.031^{***}	-0.022^{***}	-0.012^{*}
	[−7.381]	[−5.913]	[−4.573]	[−3.197]	[−5.625]	[−4.215]	[−3.111]	[−1.688]
Observations	174984	170928	166856	162733	141530	137756	134611	131575
R-squared	0.002	0.002	0.001	0.001	0.002	0.001	0.001	0.001

	Panel B: Rebalancing of stocks unaffected by natural disasters							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				CRSP-Morningstar intersection $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-0.018^{*}	-0.022^{**}	-0.023^{**}	-0.027^{**}	-0.021^{**}	-0.022^{**}	-0.027^{**}	-0.028^{**}
	[−1.897]	[−1.990]	[−2.054]	[−2.323]	[−2.042]	[−2.052]	[−2.231]	[−2.273]
$\beta^{flow}_{i,t-1}$	0.035^{***}	0.058^{***}	0.067^{***}	0.093^{***}	0.015	0.036^{***}	0.050^{***}	0.066^{***}
	[3.791]	[5.285]	[5.855]	[6.576]	[1.643]	[3.054]	[4.151]	[4.128]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.005	0.019^{*}	0.014	0.024^{**}	0.008	0.021^{*}	0.018	0.027^{**}
	[0.463]	[1.730]	[1.159]	[2.001]	[0.737]	[1.861]	[1.424]	[2.143]
$\beta^{M}_{i,t-1}$	0.004	-0.014^{*}	0.041^{***}	0.017	0.006	-0.015^{*}	0.040^{***}	0.016
	[0.458]	[−1.777]	[3.199]	[1.197]	[0.708]	[−1.813]	[3.012]	[1.081]
$ND_{f,t}$	-0.082^{***}	-0.409^{***}	-0.181^{***}	-0.409^{***}	-0.084^{***}	-0.409^{***}	-0.183^{***}	-0.410^{***}
	[−5.918]	[−15.438]	[−11.314]	[−15.577]	[−6.010]	[−15.419]	[−11.476]	[−15.599]
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	6428819	6428819	6428513	6428513	6428819	6428819	6428513	6428513
R-squared	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.02

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disasters following natural disaster shocks. The variables are explained in Tables 13 and 14 in the main text. Different from these two tables in which firms are mapped to natural disaster losses based on headquarter-level information, we define a stock as being negatively affected by natural disasters if it is a nonfinancial 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. The establishment-level data are from Infogroup. 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.

mutual funds is more negative when they have higher exposure to natural disasters.

Evidence Supporting the Exclusion Restriction Condition in the Natural Disaster Setting. In Table 14 in the main text, we examine how mutual funds rebalance stocks unaffected by natural disasters. We find that active funds tilt their holdings further away from stocks with high flow betas. In this analysis, we focus on firms that are not affected by natural disasters. However, one may still argue that the exclusion restriction could be violated if the spillover effect through the supplier-customer linkage (e.g., Barrot and Sauvagnat, 2016) is prevalent. To address this potential concern, we further drop the suppliers and customers of the affected firms from our analysis. As

Table OA.17: Response of the benchmarked returns of active mutual funds to natural disasters.

	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
Natural disaster data:	Headquarter-level	Establishment-level	Headquarter-level	Establishment-level
	$AbRet_{f,t}$ (%)		$AbRet_{f,t}$ (%)	
$ND_{f,t}$	-1.362^{**}	-1.748^{**}	-1.119^{**}	-0.924^{*}
	[−2.256]	[−2.028]	[−1.968]	[−1.795]
Fund FE	Yes	Yes	Yes	Yes
Observations	172238	172238	139692	139692
R-squared	0.05	0.05	0.03	0.03

Note: This table shows the response of the benchmarked returns of active mutual funds to natural disasters. $AbRet_{f,t}$ is the active mutual funds' annualized returns benchmarked by the market returns. Independent variable $ND_{f,t}$ is the portfolio weight of the stocks affected by natural disasters in fund f, and it is standardized to have a mean of zero and a standard deviation of one. FE is fixed effects. We cluster standard errors at both the fund level and at the quarter level. 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.

shown in Table OA.18, our findings remain robust in this test.

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

Next, we explore the possibility that natural disaster shocks and fund rebalancing may be correlated because funds' exposures to disasters are dependent on certain characteristics of their portfolios, which may be correlated with future changes in the portfolios in the direction related to stocks' flow betas. In other words, although disasters themselves are largely unpredictable, there may still be variation in the conditional mean of the ND variable we construct, driven by the composition of the funds' portfolios.

To address this possibility in our empirical tests, we control for a list of portfolio characteristics (i.e., average size, average book-to-market ratio, average historical liquidity betas, and average Amihud illiquidity measure of the stocks held by the fund) and their interaction with flow betas in Table OA.20 – these are the characteristics we have shown to be correlated with flow betas at the individual stock level (see Table 7 in the main text). Clearly, this list of characteristics is not exhaustive, but this test helps us evaluate how likely our results are to be driven by the covariance of the conditional expectations of disaster shocks and portfolio changes, as we describe above.

Table OA.18: Exclusion of suppliers and customers of the firms affected by natural disasters.

	Panel A: Natural disaster shocks defined using headquarter-level information							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				CRSP-Morningstar intersection $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	−0.034***	−0.040***	−0.037***	−0.043***	−0.028***	−0.034***	−0.034***	−0.039***
	[−3.589]	[−4.041]	[−3.563]	[−3.910]	[−2.705]	[−3.129]	[−3.089]	[−3.333]
$\beta^{flow}_{i,t-1}$	0.028***	0.059***	0.047***	0.083***	0.011	0.042***	0.033***	0.062***
	[4.069]	[7.595]	[5.409]	[7.955]	[1.641]	[5.061]	[3.622]	[5.442]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.013	0.027**	0.017	0.028**	0.016	0.030***	0.021*	0.032***
	[1.197]	[2.480]	[1.476]	[2.383]	[1.436]	[2.750]	[1.768]	[2.631]
$\beta^{M}_{i,t-1}$	0.012*	−0.009	0.059***	0.033***	0.014**	−0.011*	0.058***	0.030***
	[1.941]	[−1.515]	[6.332]	[3.255]	[2.254]	[−1.795]	[6.161]	[2.945]
$ND_{f,t}$	−0.069***	−0.252***	−0.114***	−0.255***	−0.071***	−0.253***	−0.116***	−0.257***
	[−6.930]	[−13.112]	[−10.317]	[−13.050]	[−7.109]	[−13.189]	[−10.481]	[−13.138]
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	6222587	6222587	6222285	6222285	6222587	6222587	6222285	6222285
R-squared	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.02

	Panel B: Natural disaster shocks defined using establishment-level information							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	CRSP mutual funds alone $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				CRSP-Morningstar intersection $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	−0.023**	−0.028**	−0.024*	−0.027**	−0.027**	−0.032**	−0.030**	−0.033**
	[−1.992]	[−2.370]	[−1.929]	[−2.151]	[−2.270]	[−2.545]	[−2.342]	[−2.527]
$\beta^{flow}_{i,t-1}$	0.017**	0.050***	0.035***	0.069***	0.001	0.034***	0.023**	0.051***
	[2.216]	[5.353]	[3.746]	[5.816]	[0.099]	[3.331]	[2.168]	[3.798]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.004	0.019	0.011	0.023	0.008	0.023*	0.016	0.027*
	[0.342]	[1.497]	[0.813]	[1.616]	[0.645]	[1.751]	[1.132]	[1.891]
$\beta^{M}_{i,t-1}$	0.008	−0.013*	0.051***	0.026**	0.012*	−0.014*	0.051***	0.025**
	[1.098]	[−1.745]	[4.408]	[2.160]	[1.650]	[−1.801]	[4.536]	[2.108]
$ND_{f,t}$	−0.084***	−0.389***	−0.183***	−0.388***	−0.086***	−0.390***	−0.185***	−0.390***
	[−6.094]	[−12.143]	[−10.858]	[−11.990]	[−6.236]	[−12.150]	[−10.953]	[−12.021]
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	4638090	4638090	4637812	4637812	4638090	4638090	4637812	4637812
R-squared	0.01	0.01	0.02	0.02	0.01	0.01	0.02	0.02

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disasters after natural disaster shocks. We exclude from the sample (i.e., unaffected firms) the suppliers and customers of the firms affected by natural disasters. The variables are explained in Tables 13 and 14 in the main text. In panel A, we map firms to natural disaster shocks based on headquarter-level information as done in Table 14. In panel B, we map firms to natural disaster shocks based on establishment-level information as done in panel B of Table OA.16. 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.

We find that our results remain essentially unchanged, with flow betas predicting portfolio tilt in relation to natural disaster shocks.

Table OA.19: Control for stock liquidity and its interaction with flow betas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				Panel B. CRSP-Morningstar intersection $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-0.030^{***}	-0.033^{***}	-0.035^{***}	-0.040^{***}	-0.023^{**}	-0.026^{**}	-0.030^{***}	-0.033^{***}
	[−3.310]	[−3.343]	[−3.549]	[−3.747]	[−2.412]	[−2.404]	[−2.871]	[−2.894]
$\beta^{flow}_{i,t-1}$	0.040^{***}	0.062^{***}	0.062^{***}	0.090^{***}	0.023^{***}	0.044^{***}	0.045^{***}	0.065^{***}
	[5.654]	[7.672]	[6.798]	[8.392]	[3.419]	[5.110]	[5.142]	[5.743]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.022^{**}	0.034^{***}	0.027^{**}	0.038^{***}	0.024^{**}	0.036^{***}	0.030^{***}	0.041^{***}
	[2.288]	[3.407]	[2.566]	[3.488]	[2.362]	[3.370]	[2.680]	[3.470]
$\beta^{M}_{i,t-1}$	0.005	-0.012^{**}	0.052^{***}	0.024^{**}	0.005	-0.015^{**}	0.050^{***}	0.022^{**}
	[0.861]	[−1.970]	[5.234]	[2.239]	[0.825]	[−2.340]	[5.079]	[2.016]
$AIM_{i,t-1} \times ND_{f,t}$	−0.003	0.008	0.003	0.009	−0.003	0.008	0.003	0.009
	[−0.474]	[1.043]	[0.356]	[1.208]	[−0.418]	[1.071]	[0.422]	[1.246]
$AIM_{i,t-1}$	-0.047^{***}	0.010	-0.020^{***}	0.005	-0.047^{***}	0.010	-0.020^{***}	0.005
	[−8.926]	[1.552]	[−3.521]	[0.815]	[−8.858]	[1.556]	[−3.499]	[0.848]
$ND_{f,t}$	-0.058^{***}	-0.258^{***}	-0.094^{***}	-0.258^{***}	-0.060^{***}	-0.259^{***}	-0.096^{***}	-0.259^{***}
	[−5.792]	[−15.139]	[−8.509]	[−15.458]	[−5.981]	[−15.203]	[−8.733]	[−15.559]
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9477152	9477152	9476833	9476833	9477152	9477152	9476833	9476833
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disasters after natural disaster shocks. We control for stock liquidity and its interaction with flow betas. We measured stock liquidity using the Amihud illiquidity measure ($AIM_{i,t-1}$), which is standardized to have a mean of 0 and standard deviation of 1. Other variables are explained in Table 14 in the main text. 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.

Active Mutual Funds Hedge at the Expense of Fund Performance. We show that active mutual funds hedge at the expense of their fund performance. Specifically, in each quarter t, we consider a counterfactual world in which active mutual funds keep relative portfolio weights the same as those in quarter $t-1$. In the first row of Table OA.21, we focus on the holdings of the stocks unaffected by natural disasters. We find that, relative to the counterfactual world, 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. In the second row of Table OA.21, we consider the fund quarters with higher-than-median-level exposure to natural disasters. We find that the loss in the annualized fund returns increases to 99 basis points ($p < 0.001$). In the third row of Table OA.21, we consider the fund quarters with lower-than-median-level exposure to natural disasters. We find that the loss in the annualized fund returns decreases to five basis points and becomes insignificant ($p = 0.586$). In the last row of Table OA.21, we compute the changes of fund returns based on their holdings of all stocks relative to the fund returns in the counterfactual

Table OA.20: Control for fund portfolio characteristics and their interaction with flow betas.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone				Panel B. CRSP-Morningstar intersection			
	$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	−0.028***	−0.028***	−0.033***	−0.036***	−0.024**	−0.024**	−0.029***	−0.031***
	[−3.073]	[−2.953]	[−3.411]	[−3.469]	[−2.484]	[−2.235]	[−2.877]	[−2.735]
$\beta^{flow}_{i,t-1} \times lnsize_{f,t-1}$	−0.008	−0.009	0.001	0.000	0.001	−0.007	0.006	−0.001
	[−0.709]	[−0.795]	[0.067]	[0.002]	[0.085]	[−0.700]	[0.553]	[−0.056]
$\beta^{flow}_{i,t-1} \times lnBEME_{f,t-1}$	−0.038***	−0.035***	−0.043***	−0.044***	−0.014	−0.014	−0.017	−0.019*
	[−3.424]	[−3.196]	[−3.593]	[−3.773]	[−1.357]	[−1.276]	[−1.542]	[−1.690]
$\beta^{flow}_{i,t-1} \times liqbeta_{f,t-1}$	−0.024***	−0.014*	−0.022**	−0.012	−0.010	−0.000	−0.007	0.004
	[−3.211]	[−1.750]	[−2.555]	[−1.328]	[−1.388]	[−0.016]	[−0.931]	[0.406]
$\beta^{flow}_{i,t-1} \times AIM_{f,t-1}$	0.019***	0.014**	0.020***	0.018***	0.012**	0.010	0.014**	0.013**
	[2.988]	[2.264]	[3.406]	[2.966]	[1.976]	[1.637]	[2.418]	[2.347]
$\beta^{flow}_{i,t-1}$	0.044***	0.062***	0.067***	0.092***	0.027***	0.044***	0.049***	0.067***
	[5.911]	[7.340]	[7.186]	[8.373]	[3.514]	[4.855]	[5.111]	[5.699]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.020**	0.032***	0.026**	0.036***	0.025**	0.036***	0.031***	0.041***
	[2.084]	[3.216]	[2.461]	[3.369]	[2.419]	[3.357]	[2.732]	[3.490]
$\beta^{M}_{i,t-1}$	0.007	−0.010	0.051***	0.024**	0.004	−0.016**	0.048***	0.019*
	[1.229]	[−1.587]	[5.144]	[2.224]	[0.671]	[−2.471]	[4.807]	[1.718]
$ND_{f,t}$	−0.069***	−0.258***	−0.101***	−0.258***	−0.067***	−0.260***	−0.100***	−0.260***
	[−6.688]	[−14.832]	[−9.048]	[−15.135]	[−6.564]	[−14.898]	[−9.046]	[−15.244]
$Lnsize_{f,t-1}$	0.044***	0.082*	0.038***	0.092**	0.042***	0.086*	0.036**	0.095**
	[3.179]	[1.859]	[2.710]	[2.060]	[2.970]	[1.953]	[2.470]	[2.123]
$LnBEME_{f,t-1}$	0.050**	−0.055	0.029	−0.056	0.049**	−0.059*	0.026	−0.060*
	[2.540]	[−1.628]	[1.451]	[−1.636]	[2.496]	[−1.755]	[1.335]	[−1.764]
$Liqbeta_{f,t-1}$	−0.023**	−0.004	−0.020**	−0.008	−0.019**	−0.003	−0.016	−0.007
	[−2.331]	[−0.192]	[−1.960]	[−0.404]	[−1.967]	[−0.155]	[−1.532]	[−0.345]
$AIM_{f,t-1}$	−0.046***	0.008	−0.025***	0.001	−0.046***	0.008	−0.024***	0.002
	[−6.112]	[0.879]	[−3.074]	[0.148]	[−5.986]	[0.946]	[−2.975]	[0.250]
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9477152	9477152	9476833	9476833	9477152	9477152	9476833	9476833
R-squared	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disasters after the natural disaster shocks. We control for lagged fund portfolio characteristics and its interaction with flow betas. The fund portfolio characteristics are computed based on value-weighted average of the characteristics of the stocks held by the mutual funds. These fund portfolio characteristics include fund-level average stock size ($lnsize_{f,t-1}$), average stock book-to-market ratio ($lnBEME_{f,t-1}$), average stock historical liquidity betas ($liqbeta_{f,t-1}$), and average Amihud illiquidity measure ($AIM_{f,t-1}$). All these fund portfolio characteristics are standardized to have means of 0 and standard deviations of 1. Other variables are explained in Table 14 in the main text. 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.

world. We find that the annualized fund returns is 49 basis points ($p < 0.001$) higher than those in the counterfactual world.

Table OA.21: Active mutual funds hedge at the expense of fund performance.

	Mean (%)	Standard error (%)	t-stat	# of funds
Unaffected stocks	-0.63^{***}	0.09	-6.99	5274
Unaffected stocks, fund quarters with high natural disaster exposure	-0.99^{***}	0.12	-8.48	5003
Unaffected stocks, fund quarters with low natural disaster exposure	-0.05	0.09	-0.54	5157
All stocks	0.49^{***}	0.07	6.83	5408

Note: This table shows that active mutual funds hedge at the expense of their fund performance by examining the changes of annualized fund performance relative to the counterfactual world. In the first row, we focus on the holdings of the stocks unaffected by natural disasters. 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 $t-1$. We denote the set of stocks unaffected by natural disasters as U_t. We denote the portfolio weights for stock i in fund f in quarter t within the unaffected stocks as $w^U_{i,f,t}$, which is computed as $\frac{w_{i,f,t}}{\sum_{i \in U_t} w_{i,f,t}}$. The portfolio weights for stock i in fund f in quarter t in the counterfactual portfolio weights is assumed to be the same as the weights in quarter $t-1$, which is denoted by $w^U_{i,f,t-1}$ and is computed as $\frac{w_{i,f,t-1}}{\sum_{i \in U_t} w_{i,f,t-1}}$. The changes of fund returns for fund f in quarter $t+1$ based on their holdings of the unaffected stocks relative to the fund returns in the counterfactual world are estimated as: $\Delta ret^U_{f,t+1} = \sum_{i \in U_t} w^U_{i,f,t} ret_{i,t+1} - \sum_{i \in U_t} w^U_{i,f,t-1} ret_{i,t+1}$, where $ret_{i,t+1}$ is the returns for stock i in quarter $t+1$. We average $\Delta ret^U_{f,t+1}$ at the fund level across all quarters in our sample and then present the summary statistics for the fund-level changes in fund returns ($\overline{\Delta ret}^U_f$) in the first row. The analysis in the second row and third row is the same as that in the first row, except that we limit the sample to the fund quarters that have higher and lower than the median level of natural disaster exposures, respectively. In the last row, we consider a counterfactual world in which active mutual funds keep the portfolio weights for all stocks the same as those in quarter $t-1$. The changes of fund returns for fund f in quarter $t+1$ relative to the fund returns in the counterfactual world are estimated as: $\Delta ret_{f,t+1} = \sum_i w_{i,f,t} ret_{i,t+1} - \sum_i w_{i,f,t-1} ret_{i,t+1}$. We average $\Delta ret_{f,t+1}$ at the fund level across all quarters in our sample and then present the summary statistics for the fund-level changes in fund returns ($\overline{\Delta ret}_f$) in the last row. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1994 to 2018.

5.2 Unexpected Announcement of the Possible US-China Trade War

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

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

Table OA.22: Changes in uncertainty betas and flow betas following the unexpected announcement of the possible US-China trade war.

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

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

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

The first public announcement of a possible US-China trade war shocked the market because it was from an unexpected personal Twitter post by the US president on March 2, 2018. A few days later, on March 22, the Trump administration issued a presidential memorandum proposing 25% tariffs on more than $50 billion worth of Chinese imports. Right after the unexpected announcement of the US-China trade war (i.e., March 2018), the monthly trade policy uncertainty index (Baker, Bloom and Davis, 2016) skyrocketed (see panel A of Figure OA.8). To justify the use of the trade-war announcement as a shifter of the flow beta of China-related stocks, we show that such stocks become significantly more sensitive to both economic uncertainty and common fund flows following the announcement. Specifically, we run the following regression to examine changes in stocks' uncertainty betas at a monthly frequency:

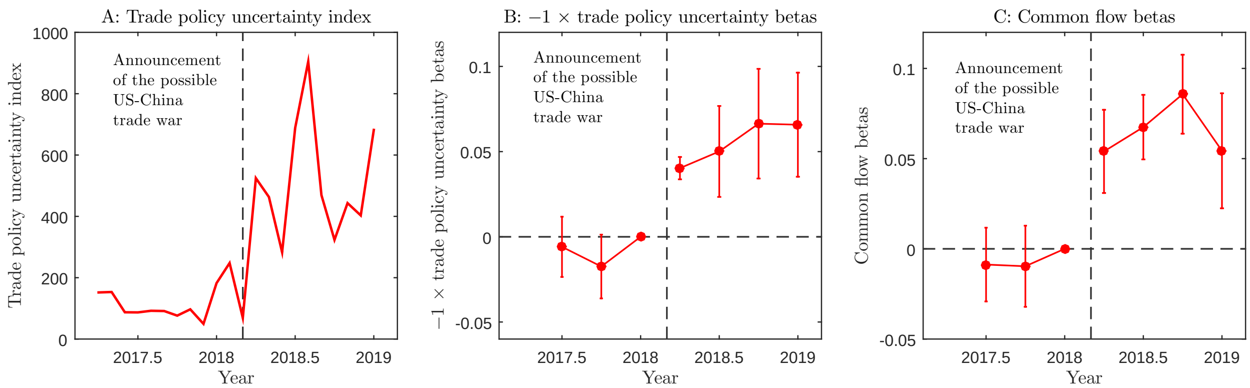
$$-1 \times \beta_{i,t}^{uncertainty} = b_1 \times China\_related_i \times \mathbf{1}_{\{t>March\_2018\}} + b_2 \times China\_related_i + b_3 \times \mathbf{1}_{\{t>March\_2018\}} + a_t + \varepsilon_{i,t}. \quad \text{(OA.190)}$$

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,[15] we multiply the trade policy uncertainty betas with -1 so that higher values of the left-hand side variable in specification (OA.190) 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).[16] 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 OA.22, coefficient b_1 is positive and statistically significant, suggesting that China-related stocks become more sensitive to economic uncertainty relative to

[15] 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).

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



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

Figure OA.8: Uncertainty betas and flow betas of China-related stocks around the unexpected announcement of a possible US-China trade war.

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:

$$-1 \times \beta_{i,t}^{uncertainty} = a + \sum_{\tau=-3}^{3} b_{1,\tau} \times China\_related_i \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} + b_2 \times China\_related_i + \sum_{\tau=-3}^{3} b_{3,\tau} \times \mathbf{1}_{\{t-\tau=Q1\_2018\}} + \varepsilon_{i,t}, \quad \text{(OA.191)}$$

where $\mathbf{1}_{\{t-\tau=Q1\_2018\}}$ is an indicator variable equal to 1 if and only if $t-\tau$ is the first quarter of 2018 — the time of the announcement by the Trump adminstration about a possible US-China trade war. When running the regression, we impose $b_{1,-1} = b_{3,-1} = 0$ to avoid collinearity in categorical regressions, and by doing this, we set the quarter right before the announcement quarter, namely the fourth quarter of 2017, as the benchmark. The sample period is from the second quarter of 2017 to the fourth quarter of 2018. We plot estimated coefficients $\beta_{1,\tau}$ with $\tau = -3, -2, \cdots, 3$, as well as their 95% confidence bands, in panel B of Figure OA.8.

We find that the treatment effect emerges only after the announcement of a possible US-China trade war (see panel B of Figure OA.8). 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.[17]

Because common fund flows are strongly related to economic uncertainty fluctuations, we expect that the sensitivity of China-related stocks to common fund flows (i.e., flow betas) should also increase after the first announcement of a possible US-China trade war. We again use the DID approach to examine the changes of flow betas of China-related stocks relative. As shown in panel B of Table OA.22, the flow beta of China-related stocks indeed increase significantly relative to those of China-unrelated stocks after the onset of the trade war. Importantly, similar to the relative increase in the uncertainty betas of China-related stocks, the relative increase in the flow beta of China-related stocks is also persistent (see panel C of Figure OA.8).

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.[18] 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

[17]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).

[18]See Table OA.24 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 OA.23: Mutual funds' rebalancing of the China-unrelated stocks following the unexpected announcement of a possible US-China trade war.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Changes in portfolio weights after the unexpected trade war announcement								
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)		$\Delta(w_{i,f}-w_i^M)$ (%)	
$\beta^{flow}_{i,Dec2016}$	−0.031***	−0.042**	−0.031***	−0.045**	−0.041***	−0.043**	−0.037**	−0.047***
	[−2.711]	[−2.298]	[−3.196]	[−2.463]	[−2.648]	[−2.472]	[−2.403]	[−2.592]
$\beta^{M}_{i,Dec2016}$	−0.054**	−0.074***	−0.057**	−0.076***	−0.057***	−0.048***	−0.061***	−0.051***
	[−2.166]	[−3.712]	[−2.339]	[−3.926]	[−3.411]	[−2.681]	[−3.937]	[−2.871]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	110563	110063	110563	110063	156051	155156	156051	155156
R-squared	0.04	0.04	0.04	0.04	0.02	0.03	0.02	0.03
Panel B: Changes in portfolio weights assuming no price changes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M)$ (%)	
$\beta^{flow}_{i,Dec2016}$	−0.027**	−0.051***	−0.029***	−0.059***	−0.030*	−0.033**	−0.033**	−0.043**
	[−2.280]	[−2.590]	[−2.866]	[−2.986]	[−1.918]	[−1.978]	[−2.071]	[−2.375]
$\beta^{M}_{i,Dec2016}$	−0.003	−0.042**	−0.006	−0.045**	−0.016	−0.044**	−0.020	−0.046**
	[−0.126]	[−2.117]	[−0.237]	[−2.312]	[−0.986]	[−2.352]	[−1.289]	[−2.487]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114054	113552	114054	113552	160608	159712	160608	159712
R-squared	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04

Note: This table shows how active mutual funds rebalance their China-unrelated portfolios after the unexpected announcement of a possible US-China trade war. In panel A, the dependent variable is the changes of portfolio weights in mutual funds after the unexpected trade war announcement in excess of the changes in the portfolio weights in the market portfolio. $\Delta(w_{i,f}-w_i^M) \equiv (w_{i,f,Dec2018}-w^M_{i,Dec2018})-(w_{i,f,Dec2017}-w^M_{i,Dec2017})$. 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 $w^M_{i,Dec2017}$ and $w^M_{i,Dec2018}$ represent the weight of stock i in the market portfolio in December 2017 and 2018, respectively. $\beta^{flow}_{i,Dec2016}$ is the standardized flow beta for stock i in December 2016 with a mean of 0 and a standard deviation of 1. We intentionally choose to use the flow beta in 2016 so that the cross-sectional variation in the flow beta is not related to the unexpected trade war announcement in March 2018. $\beta^{M}_{i,Dec2016}$ 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. $\Delta(\tilde{w}_{i,f}-\tilde{w}_i^M) \equiv (\tilde{w}_{i,f,Dec2018}-w^M_{i,Dec2017})-(w_{i,f,Dec2017}-w^M_{i,Dec2017})$ 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.

the trade war, $\beta^{flow}_{i,Dec2016}$. Specifically, we run the following quarterly regression:

$$\Delta(w_{i,f}-w_i^M) = b_1 \times \beta^{flow}_{i,Dec2016} + b_2 \times \beta^{M}_{i,Dec2016} + \alpha_{ind} + \alpha_f + \alpha_t + \varepsilon_{i,f}, \tag{OA.192}$$

where $\Delta(w_{i,f}-w_i^M) \equiv (w_{i,f,Dec2018}-w^M_{i,Dec2018})-(w_{i,f,Dec2017}-w^M_{i,Dec2017})$, 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 $w^M_{i,Dec2017}$ and $w^M_{i,Dec2018}$ are stock i's weights in the market portfolio in December 2017 and 2018, respectively.

As we show in panel A of Table OA.23, the coefficient of the flow beta, b_1, is significantly negative, which means that the weight of the China-unrelated high-flow-beta stocks decreases significantly relative to that of the China-unrelated low-flow-beta stocks. This result remains robust after we rule out the possibility that the portfolio weight adjustment is the result of certain industries becoming less attractive in the fear of the US-China trade war (using industry fixed effects).[19]

We focus on the set of China-unrelated stocks to mitigate the concern that portfolio rebalancing responds to the change in firm fundamentals as a result of the shock, and not to the change in the funds' exposures to the common flow shocks. One potential concern is that our definition does not adequately capture the set of China-related stocks because of the spill-over effect across the supplier-customer linkage. While it is unclear how the spill-over would affect the relation between the flow betas of China-unrelated stocks (i.e., $\beta^{flow}_{i,t}$) and their portfolio weight changes (i.e., $\Delta(w_{i,f,t} - w^M_{i,t})$), 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.25 in the online appendix, our findings remain robust.

Changes of Portfolio Weights Around the Unexpected Announcement of the Possible US-China Trade War. We examine the changes of portfolio weights of China-related stocks and China-unrelated stocks in active mutual funds around the unexpected announcement of the possible US-China trade war. The summary statistics for the changes in portfolio weight are tabulated in Table OA.24. We find that active mutual funds do not significantly reduce their holdings of

[19]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 OA.23).

Table OA.24: Active mutual funds maintaining their positions in China-related stocks.

	Mean (%)	Standard error (%)	t-stat	N
$\Delta w_{i,f}$ of China-unrelated stocks	0.009	0.009	0.987	149671
$\Delta w_{i,f}$ of China-related stocks	−0.006	0.007	−0.927	220627

Note: This table shows the changes in portfolio weights around the unexpected announcement of the possible US-China trade war. $\Delta w_{i,f}$ is the weight changes of stock i of fund f from December 2017 to December 2018. 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 the bills of lading data from US Customs and Border Protection.

China-related stocks after the unexpected announcement.

Evidence Supporting the Exclusion Restriction Condition in the Trade War Setting. We focus on firms that are China-unrelated in the analysis of the trade war setting. However, one may still argue that the exclusion restriction could be violated if the China-unrelated firms are affected by the spillover effect through the supplier-customer linkage. To address this potential concern, we further drop the suppliers and customers of the China-related firms from our analysis. As shown in Table OA.25, our findings remain robust in this test.

5.3 2014 OPEC Announcement

On November 28, 2014, OPEC announced the outcome of its 166th meeting. The organization unexpectedly decided that member countries would not cut their oil supply despite the increased supply from non-OPEC sources and falling oil prices. On the announcement day, oil prices dropped by more than 10%. After the OPEC announcement, oil price volatility increased significantly and maintained at a high level for the next year (see panel A of Figure OA.9). Facing a much more volatile oil price, the returns of oil-related stocks become more sensitive to the uncertainty of oil prices. As shown by panel B of Figure OA.9 and panel A of Table OA.26, the sensitivity of the stock returns to uncertainty of the oil-related stocks increases significantly relative to the oil-unrelated stocks following the 2014 OPEC announcement. We use two methods to construct the oil-related dummy. In the first method, oil-related firms are defined as firms that produce oil or firms in industries that heavily rely on oil products as inputs (5% or larger) according to the 2012 National Income and Product Accounts (NIPA) input-output table. In the second method,

Table OA.25: Exclusion of suppliers and customers of China-related firms.

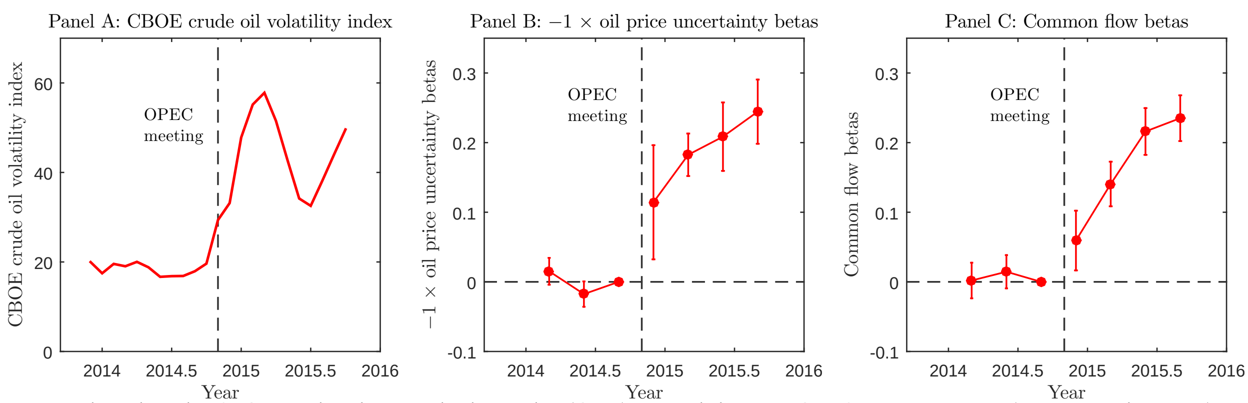
	Panel A: Changes in portfolio weights after the unexpected trade war announcement							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)	
$\beta^{flow}_{i,Dec2016}$	-0.037^{***}	-0.042^{**}	-0.037^{***}	-0.048^{**}	-0.042^{***}	-0.032^{**}	-0.040^{**}	-0.038^{***}
	[−2.894]	[−2.103]	[−3.225]	[−2.318]	[−2.718]	[−2.551]	[−2.464]	[−2.872]
$\beta^{M}_{i,Dec2016}$	-0.057^{**}	-0.082^{***}	-0.060^{***}	-0.084^{***}	-0.056^{***}	-0.047^{***}	-0.060^{***}	-0.049^{***}
	[−2.396]	[−4.338]	[−2.606]	[−4.509]	[−3.481]	[−2.707]	[−4.083]	[−2.857]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	98440	97979	98440	97979	137520	136761	137520	136761
R-squared	0.04	0.04	0.04	0.04	0.03	0.03	0.03	0.03

	Panel B: Changes in portfolio weights assuming no price changes							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
China-related measure:	Export and import				Offshore activities			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
	$\Delta(\tilde{w}_{i,f} - \tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f} - \tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f} - \tilde{w}_i^M)$ (%)		$\Delta(\tilde{w}_{i,f} - \tilde{w}_i^M)$ (%)	
$\beta^{flow}_{i,Dec2016}$	-0.034^{**}	-0.049^{**}	-0.035^{***}	-0.061^{***}	-0.031^{**}	-0.020^{*}	-0.035^{**}	-0.031^{**}
	[−2.540]	[−2.349]	[−2.977]	[−2.822]	[−1.980]	[−1.841]	[−2.092]	[−2.183]
$\beta^{M}_{i,Dec2016}$	−0.003	-0.047^{**}	−0.006	-0.049^{***}	−0.010	-0.033^{*}	−0.013	-0.035^{*}
	[−0.129]	[−2.496]	[−0.255]	[−2.633]	[−0.598]	[−1.877]	[−0.907]	[−1.961]
SIC-4 industry FE	No	Yes	No	Yes	No	Yes	No	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	101462	101001	101462	101001	141502	140743	141502	140743
R-squared	0.05	0.05	0.05	0.05	0.04	0.04	0.04	0.04

Note: This table shows how active mutual funds rebalance their China-unrelated portfolios after the unexpected announcement of the possible US-China trade war. We exclude from the sample (i.e., China-unrelated firms) the suppliers and customers of the China-related firms. The variables are explained in Table OA.23 in the main text. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

oil-related firms are defined as firms in industries that have positive oil risk premium according to the estimates of Chiang, Hughen and Sagi (2015).

More importantly, we find that the common flow betas of the oil-related stocks also increase significantly (see panel C of Figure OA.9 and panel B of Table OA.26). Therefore, similar to the US-China trade war setting, the 2014 OPEC announcement allows us to examine whether active mutual funds adjust their holdings to hedge against the increased common flow risk. Table OA.27 examines how active mutual funds rebalance their holdings in response to the increased common flow risk after the 2014 OPEC announcement. Consistent with the prediction of our model, we find that active mutual funds tilt their holdings of oil-unrelated stocks further toward low-flow-beta stocks.



Note: Panel A plots the CBOE crude oil ETF volatility index (OVX) around the 2014 OPEC announcement (i.e., November 2014). Panel B plots the oil price uncertainty betas (i.e., betas to the OVX index) around the 2014 OPEC announcement for oil-related stocks relative to oil-unrelated stocks. Because stock prices tend to react negatively to increases in economic uncertainty, we multiply the oil price uncertainty betas with -1 so that higher values in the y-axis of panel B represent higher sensitivity of stock returns to uncertainty. Oil-related firms are firms that produce oil or firms in industries that heavily rely on oil products as inputs (5% or more) according to the 2012 NIPA input-output table. Panel C plots the common flow betas around the 2014 OPEC announcement for oil-related stocks relative to oil-unrelated stocks. Oil price uncertainty betas and common flow betas are standardized to have means of 0 and standard deviations of 1.

Figure OA.9: Uncertainty betas and flow betas around the 2014 OPEC announcement.

Table OA.26: Changes in uncertainty betas and flow betas following the 2014 OPEC announcement.

	Panel A: Changes in oil price uncertainty betas			
	(1)	(2)	(3)	(4)
Oil-related measure:	Input-output tables		Oil risk premium	
	$-1 \times \beta_{i,t}^{uncertainty}$		$-1 \times \beta_{i,t}^{uncertainty}$	
$Oil\_related_i \times \mathbf{1}_{\{t>November\_2014\}}$	0.188***	0.188***	0.248***	0.249***
	[7.131]	[7.135]	[9.102]	[9.105]
$Oil\_related_i$	0.020	0.020	0.055**	0.054**
	[0.735]	[0.732]	[2.079]	[2.071]
$\mathbf{1}_{\{t>November\_2014\}}$	−0.005		−0.008	
	[−0.518]		[−0.666]	
Month FE	No	Yes	No	Yes
Observations	134952	134952	135576	135576
R-squared	0.01	0.01	0.02	0.02

	Panel B: Changes in common flow betas							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Oil-related measure:	Input-output tables				Oil risk premium			
	CRSP		CRSP-Morningstar		CRSP		CRSP-Morningstar	
	$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$	
$Oil\_related_i \times \mathbf{1}_{\{t>November\_2014\}}$	0.178***	0.179***	0.119***	0.119***	0.269***	0.270***	0.204***	0.204***
	[6.648]	[6.669]	[5.489]	[5.498]	[8.102]	[8.159]	[7.834]	[7.854]
$Oil\_related_i$	−0.126***	−0.126***	−0.047	−0.047	−0.333***	−0.334***	−0.248***	−0.248***
	[−3.994]	[−3.999]	[−1.480]	[−1.483]	[−9.929]	[−9.941]	[−7.255]	[−7.262]
$\mathbf{1}_{\{t>November\_2014\}}$	0.256***		0.103***		0.244***		0.089***	
	[7.204]		[4.561]		[6.878]		[3.837]	
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	134952	134952	134952	134952	135573	135573	135573	135573
R-squared	0.03	0.03	0.01	0.01	0.03	0.04	0.01	0.01

Note: This table shows the changes in stocks' oil price uncertainty betas ($\beta_{i,t}^{uncertainty}$, panel A) and common flow betas ($\beta_{i,t}^{flow}$, panel B) following the 2014 OPEC announcement. Sample period spans from November 2013 to October 2015. $Oil\_related_i$ is a dummy variable that equals one for oil-related industries. $\mathbf{1}_{\{t>November\_2014\}}$ is a dummy variable that equals 1 for the time period after the OPEC announcement in November 2014. Both $\beta_{i,t}^{uncertainty}$ and $\beta_{i,t}^{flow}$ are standardized to have means of 0 and standard deviations of 1. Because stock prices tend to react negatively to increases of economic uncertainty, we multiply $\beta_{i,t}^{uncertainty}$ with -1 so that higher values of the outcome variable in panel A represent higher sensitivity of stock returns to uncertainty. FE is fixed effects. 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. We include *t*-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table OA.27: Mutual funds' rebalancing of oil-unrelated stocks after the 2014 OPEC announcement.

	(1)	(2)	(3)	(4)
Oil-related measure:	Input-output tables		Oil risk premium	
	CRSP alone	CRSP-Morningstar	CRSP alone	CRSP-Morningstar
	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)
$\beta^{flow}_{i,Dec2013}$	-0.029^{***}	-0.033^{***}	-0.017^{***}	-0.020^{***}
	[−5.592]	[−6.719]	[−3.445]	[−4.378]
$\beta^{M}_{i,Dec2013}$	-0.071^{***}	-0.070^{***}	-0.053^{***}	-0.052^{***}
	[−11.412]	[−11.340]	[−8.999]	[−9.142]
Fund FE	Yes	Yes	Yes	Yes
Observations	154430	154430	166667	166667
R-squared	0.04	0.04	0.03	0.03

Note: This table shows how active mutual funds rebalance their oil-unrelated holdings after the 2014 OPEC announcement. The dependent variable is the changes of stock weights in mutual funds around the announcement in excess of the changes in stock weights in the market portfolio. $\Delta(w_{i,f} - w_i^M) = (w_{i,f,Sep2015} - w^M_{i,Sep2015}) - (w_{i,f,Sep2014} - w^M_{i,Sep2014})$. Variable $w_{i,f,Sep2014}$ represents the weight of stock i in fund f in September 2014 (i.e., the quarter end prior to the OPEC announcement). Variable $w_{i,f,Sep2015}$ represents the weight of stock i in fund f in September 2015. Variable $w^M_{i,Sep2014}$ and $w^M_{i,Sep2015}$ represent the weight of stock i in the market portfolio in September 2014 and September 2015, respectively. $\beta^{flow}_{i,Dec2013}$ is the standardized common flow beta for stock i in December 2013 with a mean of 0 and a standard deviation of 1. We intentionally choose to use the common flow betas in 2013 so that the cross-sectional variation in the common flow betas is not related to the oil shock. $\beta^{M}_{i,Dec2013}$ is the standardized market beta for stock i in December 2013 with a mean of 0 and a standard deviation of 1. FE is fixed effects. Standard errors are clustered at the fund level. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

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