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

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Contents

1 Proofs

1.1 Proof for Proposition 2.1

According to (2.3), the log-linearization approximation leads to the following representation:

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

Plugging (2.1) and (2.4) into the equation above, we can obtain

$$r_{t+1} = L(\zeta + \zeta_h(h_{t+1} - \bar{h})) - (\zeta + \zeta_h(h_t - \bar{h})) + \mu + \sqrt{h_t}Bu_{t+1} + \sqrt{h_t}\varepsilon_{t+1} + \ell. \tag{OA.2}$$

Further, if we plug (2.2) into the relation above, we can obtain

$$r_{t+1} = L(\zeta + \zeta_h(\rho(h_t - \bar{h}) + \sqrt{h_t}\sigma u_{t+1})) - (\zeta + \zeta_h(h_t - \bar{h})) + \mu + \sqrt{h_t}Bu_{t+1} + \sqrt{h_t}\varepsilon_{t+1} + \ell. \tag{OA.3}$$

Rearranging terms further leads to

$$r_{t+1} = \mu_t + \sqrt{h_t}Ku_{t+1} + \sqrt{h_t}\varepsilon_{t+1}, \tag{OA.4}$$

where

$$\mu_t = \mu + \ell + (L - I_n)\zeta + (\rho L - I_n)\zeta_h(h_t - \bar{h}) \ \text{ and } \ K = L\zeta_h\sigma + B. \tag{OA.5}$$

1.2 Proof for Proposition 2.2

According to (2.6) and (2.9), it holds that

$$\mu_t - r_f \approx (\rho L - I_n)\zeta_h h_t. \tag{OA.6}$$

1.3 Proof for Proposition 2.3

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:

$$C_{d,t} = (1-\beta)(W_{d,t} - \overline{\alpha} Q_t). \tag{OA.7}$$

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

$$r_{t+1}(\phi_{d,t}) \approx r_f + \phi_{d,t}^T (r_{t+1} - r_f \mathbf{1}) + \frac{1}{2} \phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t} \right) \tag{OA.8}$$

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

$$\max_{\phi_{d,t}} (1-\gamma)^{-1} \ln \mathbb{E}_t \left\{ e^{(1-\gamma)\left[r_f + \phi_{d,t}^T (r_{t+1} - r_f \mathbf{1}) + \frac{1}{2} \phi_{d,t}^T \left(v_t - \Sigma_t \phi_{d,t} \right) \right]} \right\} \tag{OA.9}$$

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

$$\max_{\phi_{d,t}} \phi_{d,t}^T (\mu_t - r_f \mathbf{1} + \frac{1}{2} \nu_t) - \frac{\gamma}{2} \phi_{d,t}^T \Sigma_t \phi_{d,t}. \tag{OA.10}$$

The first-order condition leads to

$$\phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t). \tag{OA.11}$$

1.4 Proof for Proposition 2.4

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

$$\max_{\phi_{c,t}, C_{c,t}} (1-\beta)\ln(C_{c,t}) + \beta\ln(W_{c,t} - C_{c,t}) \tag{OA.12}$$
$$+ \beta(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right]^{1-\gamma}\right\},$$

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

$$C_{c,t} = (1-\beta)W_{c,t} \tag{OA.13}$$
$$= (1-\beta)\lambda W_t. \tag{OA.14}$$

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

$$r_{\alpha,t+1}(\phi_{d,t}) \approx \ln\left[R_{t+1}(\phi_{d,t}) + \alpha_t + \omega\right] \tag{OA.15}$$
$$\approx \alpha_t + \omega + r_f + \phi_{d,t}^T(r_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\phi_{d,t}^T\left(v_t - \Sigma_t\phi_{d,t}\right), \tag{OA.16}$$

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:

$$\ln\left[R_f + \phi_{c,t}\left(R_{t+1}(\phi_{d,t}) + \alpha_t + \omega - R_f\right)\right] \\ \approx r_f + \phi_{c,t}\left[r_{\alpha,t+1}(\phi_{d,t}) - r_f\right] + \frac{1}{2}\phi_{c,t}(1-\phi_{c,t})\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.17)}$$

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:

$$\max_{\phi_{c,t}}\phi_{c,t}(\alpha_t+\omega) + \phi_{c,t}\phi_{d,t}^T\left(\mu_t - r_f + \frac{1}{2}v_t\right) - \frac{1}{2}\gamma\phi_{c,t}^2\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.18)}$$

The first-order condition is

$$0 = \alpha_t + \omega + \phi_{d,t}^T\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right) - \gamma\phi_{c,t}\phi_{d,t}^T\Sigma_t\phi_{d,t}. \quad \text{(OA.19)}$$

Thus, according to Proposition 2.3, the optimal delegation $\phi_{c,t}$ is

$$\phi_{c,t} = \frac{1}{\gamma}\frac{1}{\phi_{d,t}^T\Sigma_t\phi_{d,t}}\left(\alpha_t + \omega + \gamma\phi_{d,t}^T\Sigma_t\phi_{d,t}\right) = 1 + \frac{\omega+\alpha_t}{\gamma_t}, \quad \text{(OA.20)}$$

where the effective risk aversion is

$$\gamma_t \equiv S_t/\gamma, \ \text{ with } S_t \equiv \left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right)^T\Sigma_t^{-1}\left(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t\right). \quad \text{(OA.21)}$$

According to Proposition 2.2 and Equation (2.7), it holds that

$$\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t = \left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]h_t \ \text{ and } \ \Sigma_t = \Sigma h_t. \quad \text{(OA.22)}$$

Therefore, by plugging (OA.22) into (OA.20), it follows that

$$\phi_{c,t} = 1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}, \tag{OA.23}$$

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

And hence, it holds that

$$q_t = \phi_{c,t} \frac{W_{c,t} - C_{c,t}}{W_t} \tag{OA.24}$$

$$= \beta\lambda \left(1 + \frac{\omega + \alpha_t}{\overline{\gamma} h_t}\right). \tag{OA.25}$$

Finally, after rearranging terms, it follows that

$$U_c(W_{c,t}) - U_d(W_{c,t}) = \beta\phi_c(\alpha_t + \omega) - \ln\left(1 - \frac{\overline{\alpha}}{\lambda} q_t\right) \tag{OA.26}$$

$$= \beta\phi_c(\omega - \theta^{-1} q_t + \overline{\alpha} - f) - \ln\left(1 - \frac{\overline{\alpha}}{\lambda} q_t\right) \tag{OA.27}$$

$$\geq \beta\phi_c(\omega - \theta^{-1} q_t + \overline{\alpha} - f) \tag{OA.28}$$

$$\geq 0. \tag{OA.29}$$

When $\omega + \overline{\alpha} > f + \theta^{-1}\lambda\beta$ as assumed in the proposition, the last inequality in (OA.29) can be established by plugging in the equilibrium delegation q_t derived in Proposition 2.5.

1.5 Proof for Proposition 2.5

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:

$$q_t = \theta(\overline{\alpha} - f) - \theta\alpha_t \quad (q_t \text{ supplied by funds}), \tag{OA.30}$$

$$q_t = \beta\lambda\left[1 + (\omega + \alpha_t)/(\overline{\gamma} h_t)\right] \quad (q_t \text{ demanded by fund clients}). \tag{OA.31}$$

Plugging (OA.31) into (OA.30) leads to the results.

1.6 Proof for Proposition 2.6

By definition, the aggregate fund flow is

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

Thus, the aggregate fund flow can be rewritten as

$$\begin{aligned} flow_{t+1} &= \frac{q_{t+1}}{q_t}\left[(1-\lambda)\beta + (1-\overline{\alpha})q_t\right] R_{t+1}(\phi_{M,t}) - R_{t+1}(\phi_{m,t}) - \alpha_t && \text{(OA.32)} \\ &= e^{\Delta \ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] + r_{t+1}(\phi_{M,t})} - e^{r_{t+1}(\phi_{m,t})} - \alpha_t. && \text{(OA.33)} \end{aligned}$$

Log-linear approximation leads to

$$\begin{aligned} flow_{t+1} \approx\ & \Delta \ln(q_{t+1}) + \ln[(1-\lambda)\beta + (1-\overline{\alpha})q_t] \\ & + r_{t+1}(\phi_{M,t}) - r_{t+1}(\phi_{m,t}) - \alpha_t + \text{Jensen's term at } t. && \text{(OA.34)} \end{aligned}$$

According to Proposition 2.1, it holds that

$$\begin{aligned} flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_{M,t} - \phi_{m,t})^T K u_{t+1} + (\phi_{M,t} - \phi_{m,t})^T \varepsilon_{t+1}\right] \\ &\approx \sqrt{h_t}\left[\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + (\phi_{M,t} - \phi_{m,t})^T K u_{t+1}\right], && \text{(OA.35)} \end{aligned}$$

where the approximation in (OA.35) is based on $(\phi_{M,t} - \phi_{m,t})^T \varepsilon_{t+1} \approx 0$ as n approaches infinity.

Given the market clearing condition on assets, we have the (approximated) relation in

Theorem 2, which leads to

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

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

Thus, according to Proposition 2.1, it holds that

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

According to Theorem 1, we can further obtain that

$$flow_{t+1} - \mathbb{E}_t\left[flow_{t+1}\right] \approx \sqrt{h_t}\left\{\frac{q'(\bar{h})}{q(\bar{h})}\sigma u_{t+1} + [1-\eta(\bar{h})]AK^T\left(I_n + KK^T\right)^{-1} K u_{t+1}\right\} \tag{OA.36}$$

Therefore, the exposure coefficient is

$$A = \frac{q'(\bar{h})}{q(\bar{h})}\sigma + [1-\eta(\bar{h})]AK^T\left(I_n + KK^T\right)^{-1} K. \tag{OA.37}$$

1.7 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:

$$R_{t+1}(\phi_{m,t}) + \alpha_t + \pi_{t+1} = \tilde{R}_{t+1}(\tilde{\phi}_{m,t}) \tag{OA.38}$$

$$\equiv R_f + \tilde{\phi}_m^T(\tilde{R}_{t+1} - R_f\mathbf{1}), \tag{OA.39}$$

where

$$\tilde{\phi}_m \equiv \begin{bmatrix} 1 \\ \phi_m \end{bmatrix} \text{ and } \tilde{R}_{t+1} = \begin{bmatrix} R_f + \alpha_t + flow_{t+1} \\ R_{t+1} \end{bmatrix}. \tag{OA.40}$$

Similar to Campbell and Viceira (1999, 2001), we can derive the approximation based on Proposition 2.6:

$$\ln(R_f + \alpha_t + flow_{t+1}) \approx \ln(1 + r_f + \alpha_t + flow_{t+1}) \tag{OA.41}$$

$$\approx r_f + \alpha_t + flow_{t+1} - \frac{1}{2}AA^T h_t, \tag{OA.42}$$

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

$$\tilde{r}_{t+1} = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + flow_{t+1} \\ r_{t+1} \end{bmatrix}, \tag{OA.43}$$

and the log returns are distributed as

$$\tilde{r}_{t+1} = \tilde{\mu}_t + \tilde{\Sigma}_t u_{t+1}, \tag{OA.44}$$

where

$$\tilde{\mu}_t = \begin{bmatrix} r_f + \alpha_t - \frac{1}{2}AA^T h_t + \mathbb{E}_t\left[flow_{t+1}\right] \\ \mu_t \end{bmatrix} \text{ and } \tilde{\Sigma}_t = \begin{bmatrix} AA^T & AK^T \\ KA^T & \Sigma \end{bmatrix} h_t. \tag{OA.45}$$

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

$$\tilde{r}_{t+1}(\tilde{\phi}_{m,t}) = \ln\left[\tilde{R}_{t+1}(\tilde{\phi}_{m,t})\right] \tag{OA.46}$$

$$\approx r_f + \tilde{\phi}_{m,t}^T(\tilde{r}_{t+1} - r_f\mathbf{1}) + \frac{1}{2}\tilde{\phi}_{m,t}^T(\tilde{v}_t - \tilde{\Sigma}_t\tilde{\phi}_{m,t}), \tag{OA.47}$$

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

$$\tilde{v}_t = \begin{bmatrix} AA^T h_t \\ v_t \end{bmatrix}. \tag{OA.48}$$

As a result, the augmented log returns are

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

Recall that $\mathcal{B}_t \equiv \mathcal{B}h_t$ with $\mathcal{B} = KA^T$, and it is the covariance of the stock log returns and the aggregate flow:

$$\mathcal{B}_t = \mathrm{Cov}_t\left[r_{t+1}, flow_{t+1}\right]. \tag{OA.49}$$

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

$$\max_{\phi_{m,t}}(1-\gamma)^{-1}\ln\mathbb{E}_t\left\{e^{(1-\gamma)\tilde{r}_{t+1}(\tilde{\phi}_{m,t})}\right\}. \tag{OA.50}$$

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

$$\max_{\phi_{m,t}} \phi_{m,t}^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t - \mathcal{B}_t) - \frac{\gamma}{2}\phi_{m,t}^T\Sigma_t\phi_{m,t} + (1-\gamma)\phi_{m,t}^T\mathcal{B}_t. \tag{OA.51}$$

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

$$\phi_{m,t} = \frac{1}{\gamma}\Sigma_t^{-1}\left(\mu_t - r_f + \frac{1}{2}\nu_t\right) - \Sigma_t^{-1}\mathcal{B}_t \tag{OA.52}$$

$$= \phi_{d,t} - \Sigma_t^{-1}\mathcal{B}_t. \tag{OA.53}$$

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

$$\phi_{m,t} = \phi_{d,t} - \Sigma^{-1}\mathcal{B}. \tag{OA.54}$$

1.8 Proof for Corollary 2.2

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

$$\text{Cov}\left[\mathcal{B}_t, \phi_{\tau,t}\right] = n^{-1}\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t - n^{-2}\left(\mathbf{1}^T\mathcal{B}_t\right)\left(\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t\right). \tag{OA.55}$$

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

$$n^{-1}\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathcal{B}_t = n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1/2})(\Sigma_t^{-1/2}\mathcal{B}_t) \tag{OA.56}$$

$$\leq n^{-1}(\mathcal{B}_t^T\mathbf{1}\mathbf{1}^T\Sigma_t^{-1}\mathbf{1}\mathbf{1}^T\mathcal{B}_t)^{1/2}(\mathcal{B}_t^T\Sigma_t^{-1}\mathcal{B}_t)^{1/2}. \tag{OA.57}$$

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

$$n^{-1}\mathcal{B}_t^T \mathbf{1}\mathbf{1}^T \Sigma_t^{-1} \mathbf{1}\mathbf{1}^T \mathcal{B}_t \leq n^{-1}\mathcal{B}_t^T \Sigma_t^{-1} \mathcal{B}_t. \tag{OA.58}$$

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

$$x^T H_y x \leq x^T x, \tag{OA.59}$$

where H_y is the orthogonal projection matrix, $H_y \equiv y(y^T y)^{-1} y^T$. Inequality (OA.59) is obviously true once we realize that H_y is an orthogonal projection matrix.

1.9 Proof of Theorem 2

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

$$q_t \phi_{m,t} + \left[(1-\lambda)\beta - \bar{\alpha} q_t\right] \phi_{d,t} = \left[(1-\lambda)\beta + (1-\bar{\alpha}) q_t\right] \phi_{M,t}. \tag{OA.60}$$

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

$$\phi_{m,t} = \phi_{M,t} - (1-\eta_t)\phi_{\tau,t}, \tag{OA.61}$$

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

1.10 Proof for Theorem 3

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

$$\mu_t - r_f + \frac{1}{2}\nu_t = \gamma \Sigma_t \phi_{m,t} + \gamma \mathcal{B}_t. \tag{OA.62}$$

According to the market-clearing condition of assets

$$\phi_{m,t} = \eta_t^{-1}\phi_{M,t} - (\eta_t^{-1} - 1)\phi_{d,t} \tag{OA.63}$$
$$= \eta_t^{-1}\phi_{M,t} - (\eta_t^{-1} - 1)\frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f + \frac{1}{2}v_t). \tag{OA.64}$$

Plugging (OA.64) into (OA.62) and rearranging terms leads to

$$\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t = \gamma\Sigma_t\phi_{M,t} + \eta_t\gamma\mathcal{B}_t. \tag{OA.65}$$

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}^M, and the covariance with common fund flow, denoted by $flow_{t+1}$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_{M,t})\right] + \eta_t\gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), flow_{t+1}\right]. \tag{OA.66}$$

1.11 Proof of Corollary 2.3

According to Proposition 2.5 and Theorem 2, $q_t = 0$ and thus $\eta_t = 0$ when $\lambda = 0$. Therefore, Theorem 3 implies the conditional CAPM when $\lambda = 0$:

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), r_{t+1}(\phi_{M,t})\right] \tag{OA.67}$$
$$= \gamma\mathrm{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi_{M,t})\right] \tag{OA.68}$$

with $\hat{r}_{t+1}(\phi_{M,t}) \equiv r_{t+1}(\phi_{M,t}) - \mathbb{E}_t r_{t+1}(\phi_{M,t})$.

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

$$\phi_{M,t} = \phi_{d,t} = \frac{1}{\gamma}\Sigma_t^{-1}(\mu_t - r_f\mathbf{1} + \frac{1}{2}\nu_t) \tag{OA.69}$$
$$= \frac{1}{\gamma}\Sigma^{-1}\left[(\rho L - I_n)\zeta_h + \frac{1}{2}\nu\right]. \tag{OA.70}$$

Thus, $\phi_{M,t}$ has constant portfolio weights, denoted by ϕ_M.

Further, according to (OA.68), it holds that

$$\phi^T(\mu_t - r_f\mathbf{1} + \frac{1}{2}v_t) = \gamma Var_t\left[\hat{r}_{t+1}(\phi_M)\right]\frac{\text{Cov}_t\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi_M)\right]}{Var_t\left[\hat{r}_{t+1}(\phi_M)\right]} \tag{OA.71}$$

$$= \gamma Var_t\left[\hat{r}_{t+1}(\phi_M)\right]\frac{\phi^T\Sigma\phi_M}{\phi_M^T\Sigma\phi_M}. \tag{OA.72}$$

Taking unconditional expectations on both sides leads to

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \Lambda\frac{\phi^T\Sigma\phi_M}{\phi_M^T\Sigma\phi_M} \tag{OA.73}$$

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, $\frac{\phi^T\Sigma\phi_M}{\phi_M^T\Sigma\phi_M}$ is actually the unconditional CAPM beta:

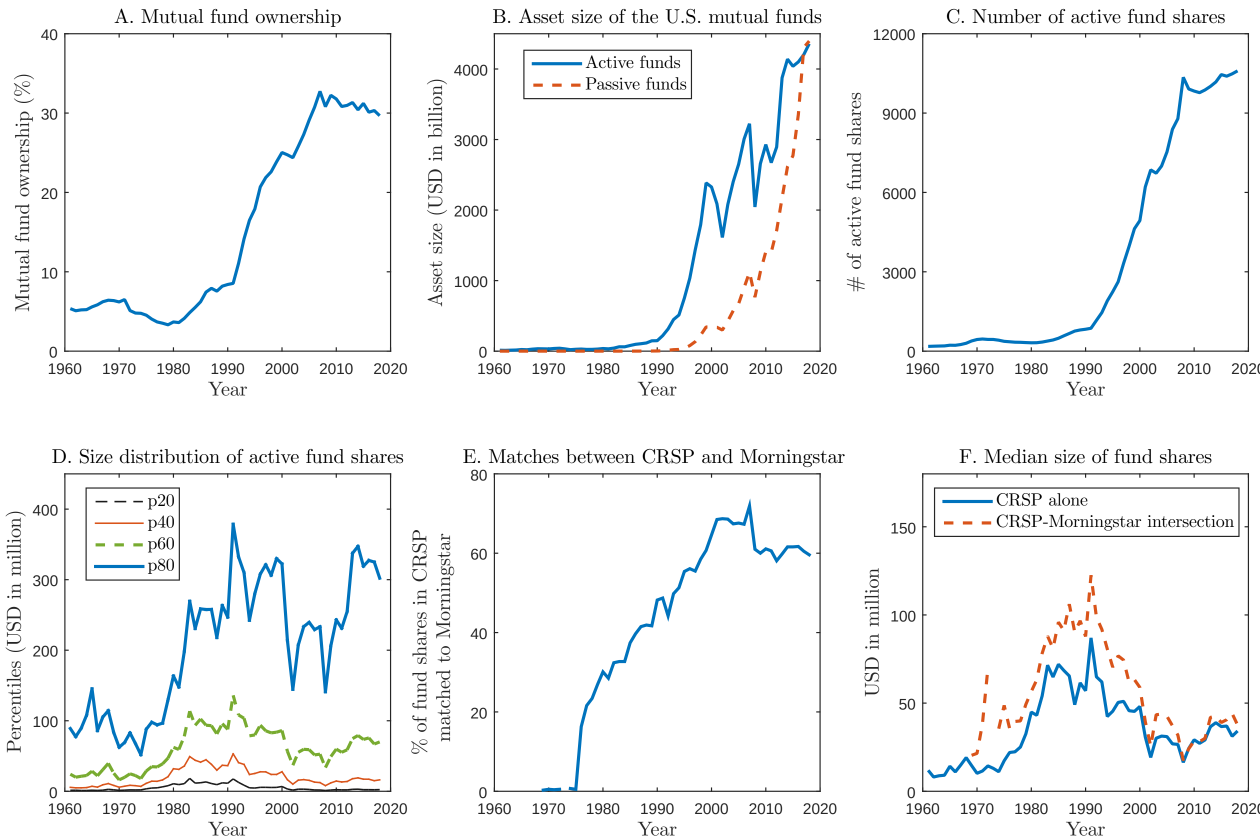
$$\frac{\phi^T\Sigma\phi_M}{\phi_M^T\Sigma\phi_M} = \beta_M(\phi) \equiv \frac{\text{Cov}\left[r_{t+1}(\phi), \hat{r}_{t+1}(\phi_M)\right]}{Var\left[\hat{r}_{t+1}(\phi_M)\right]}. \tag{OA.74}$$

Therefore, the unconditional CAPM holds:

$$\mathbb{E}\left[\phi^T r_{t+1} - r_f + \frac{1}{2}\phi^T v_t\right] = \beta_M(\phi)\Lambda. \tag{OA.75}$$

2 Supplementary Empirical Results

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 mutual fund data over time. Panel D plots the 20th, 40th, 60th, and 80th percentiles of the asset



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.

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.

Flow Volatility and Return Volatility. 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. 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 25% and 20% of the average return volatility for fund portfolios sorted on asset size and age, respectively. This finding shows 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

Table OA.1: Flow volatility and return volatility.

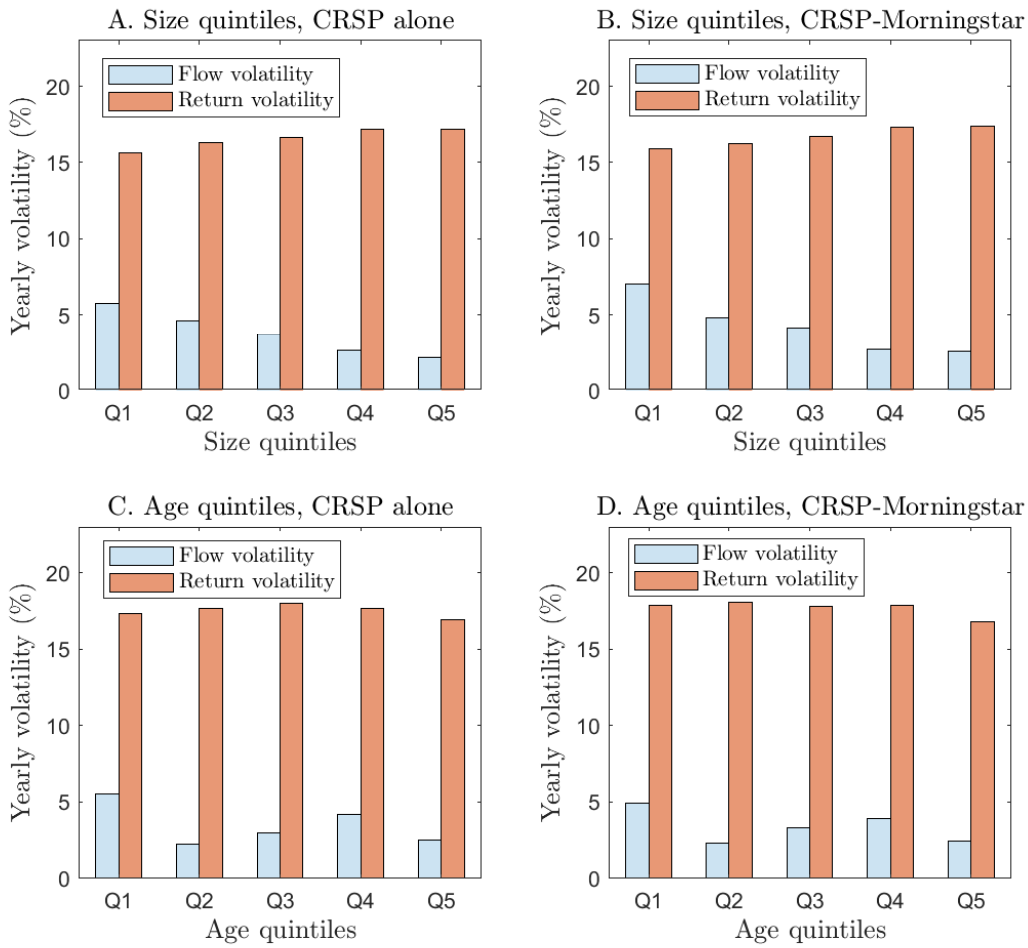
	Panel A: Yearly flow volatility and return volatility across fund portfolios sorted on asset size			
	CRSP mutual funds alone		CRSP-Morningstar intersection	
Asset size quintiles	Flow volatility	Return volatility	Flow volatility	Return volatility
Q1	0.057	0.156	0.070	0.159
Q2	0.046	0.163	0.048	0.163
Q3	0.038	0.167	0.042	0.167
Q4	0.027	0.172	0.027	0.173
Q5	0.022	0.172	0.026	0.174
Average	0.038	0.166	0.043	0.167
Avg flow vol/avg return vol	22.9%		25.5%	
	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	0.055	0.174	0.049	0.179
Q2	0.023	0.177	0.023	0.181
Q3	0.030	0.180	0.033	0.178
Q4	0.042	0.177	0.039	0.179
Q5	0.025	0.169	0.024	0.168
Average	0.035	0.175	0.034	0.177
Avg flow vol/avg return vol	19.9%		19.1%	

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.

should indeed care about fund flows.

Common Fund Flows Constructed Based on Other Fund Characteristics. Besides asset size and age, we also construct common fund flows based on other fund characteristics. Figures OA.3 and OA.4 plot fund flow shocks across fund quintiles sorted on industry concentration (Kacperczyk, Sialm and Zheng, 2005), and portfolio liquidity (Pástor, Stambaugh and Taylor, 2019), 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.2 for details).

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



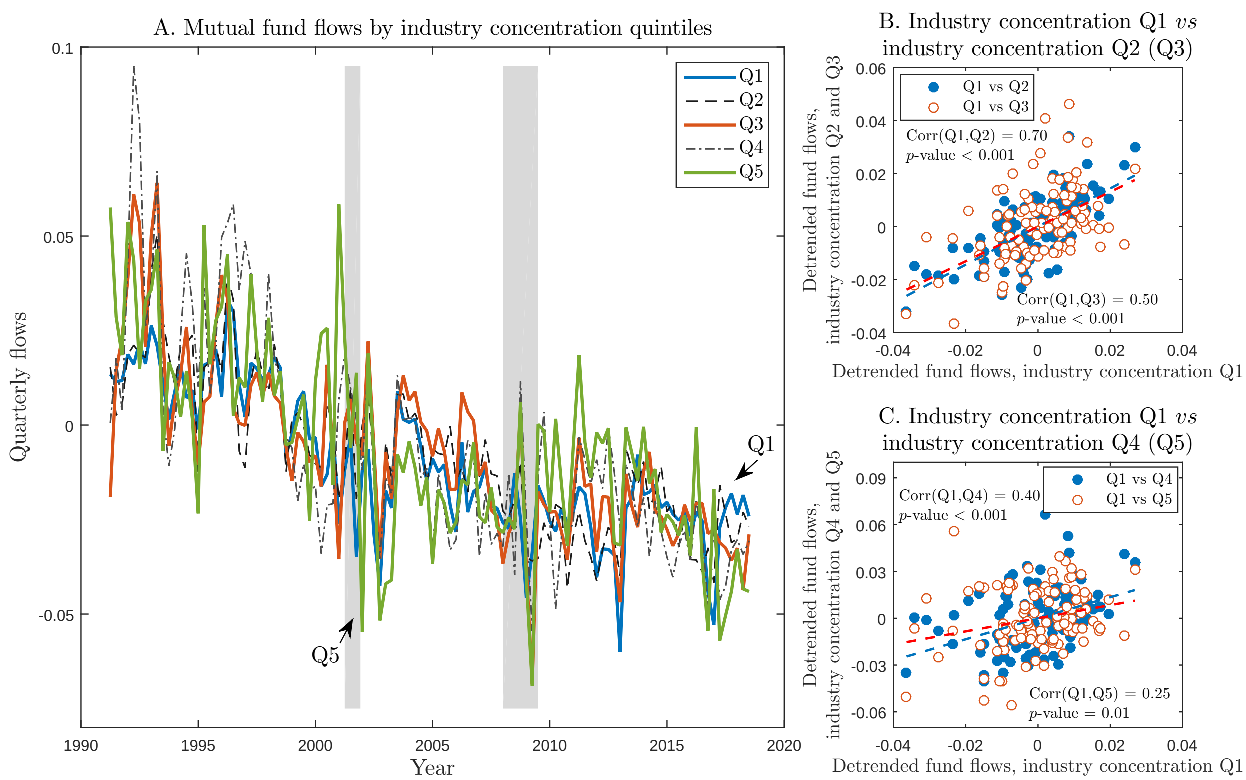
Note: Panels A and B plot the yearly flow volatility and return volatility for fund portfolios sorted on asset size. Panels C and D plot the yearly flow volatility and return volatility for fund portfolios sorted on age. Flow volatility and return volatility are computed based on the CRSP mutual fund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

using the dividend-to-price ratio and the smoothed earnings-price ratio (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.3, 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

Table OA.2: Correlation among the common fund flows constructed based on various fund share characteristics.

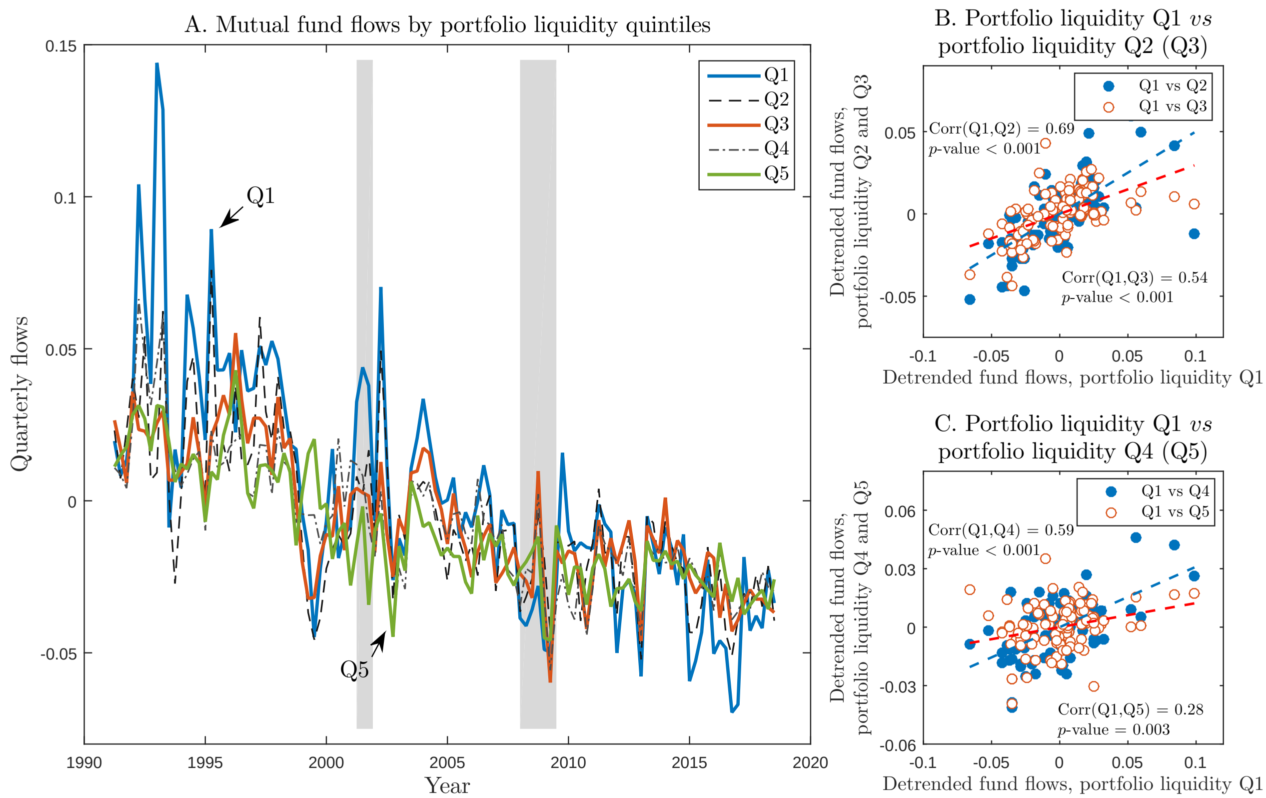
Panel A: Correlation in the CRSP mutual funds data				
Fund characteristics	Asset size	Age	Industry concentration	Portfolio liquidity
Asset size	1			
Age	0.87	1		
Industry concentration	0.88	0.95	1	
Portfolio liquidity	0.91	0.90	0.94	1
Panel B: Correlation in the CRSP-Morningstar intersection data				
Fund characteristics	Asset size	Age	Industry concentration	Portfolio liquidity
Asset size	1			
Age	0.91	1		
Industry concentration	0.91	0.96	1	
Portfolio liquidity	0.93	0.92	0.95	1



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.3: Mutual fund flows by industry concentration after removing relative performance.

results for common fund flows constructed from the CRSP-Morningstar intersection data.



Note: Panel A plots active mutual fund flows by quintiles sorted on the portfolio liquidity of fund (Pástor, Stambaugh and Taylor, 2019) 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.4: Mutual fund flows by portfolio liquidity after removing relative performance.

Table OA.3: 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	-0.249^{***}			-0.294^{***}		
	[−3.982]			[−4.503]		
$SmoothEP\_shock_t$		-0.253^{***}			-0.304^{***}	
		[−4.041]			[−4.561]	
$Sentiment\_shock_t$			0.079			0.018
			[1.230]			[0.286]
$Common\_flows_{t-1}$	0.170^{***}	0.164^{***}	0.191^{***}	0.295^{***}	0.288^{***}	0.317^{***}
	[2.998]	[2.913]	[3.357]	[5.403]	[5.310]	[5.839]
Observations	334	334	334	334	334	334
R-squared	0.093	0.096	0.042	0.180	0.186	0.099

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. 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.

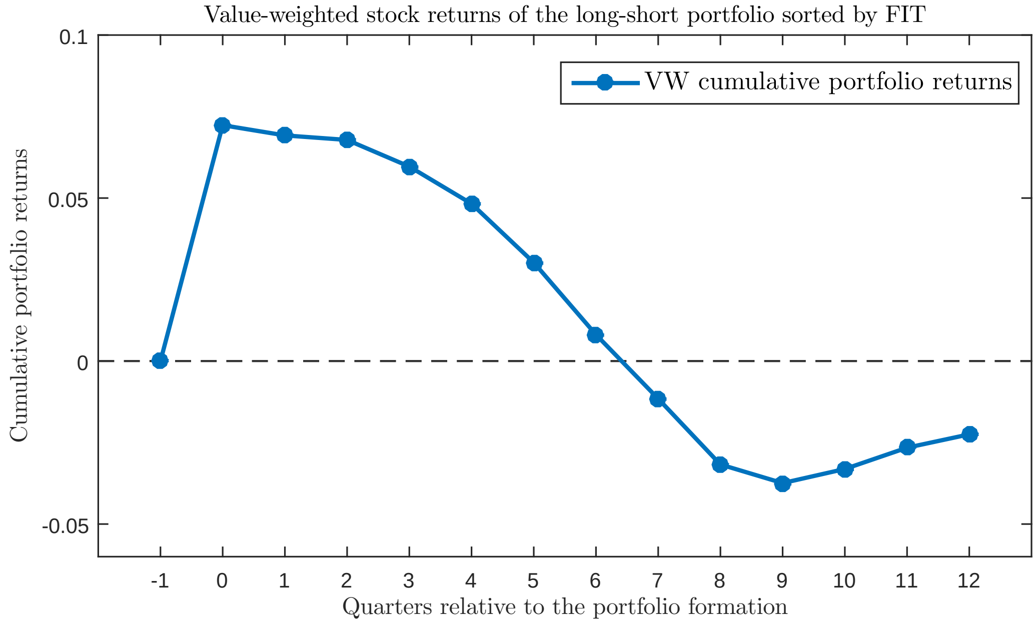
Relation Between Flow Betas and the Flow-Induced Trading Pressure. In Table 3 of the main text, we show that stocks with high flow betas are associated with higher average excess returns and higher CAPM alphas. One potential concern is that this empirical pattern could simply be driven by the flow-induced 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; 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:

$$FIT_{i,t} = \frac{\sum_j shares_{i,j,t-1} \times flow_{j,t} \times PSF_{j,t-1}}{\sum_j shares_{i,j,t-1}}, \tag{OA.76}$$

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 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.5 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.



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

Next, we examine the cross-sectional relation between flow betas and FIT using panel regressions with quarter 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.4, flow betas have insignificant correlation with the contemporaneous FIT, lagged FIT, and FIT accumulated across different time horizons. In Panel C of Table 4 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.

Relation Between Flow Betas and Price Impact. Next, we study the relation between flow betas and the price impact of each stock across different types of investors (e.g., mutual funds, households, investor advisors, and pension funds). It is possible that high flow beta

Table OA.4: 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					CRSP-Morningstar intersection				
	$\beta^{flow}_{i,t}$					$\beta^{flow}_{i,t}$				
$FIT_{i,t}$	−0.001 [−0.109]					−0.002 [−0.184]				
$FIT_{i,t-1}$		−0.005 [−0.496]					−0.003 [−0.334]			
$FIT_{i,t-2}$			−0.007 [−0.681]					−0.004 [−0.566]		
$FIT_{i,t-3}$				−0.009 [−1.012]					−0.004 [−0.620]	
$FIT_{i,t-4}$					−0.008 [−1.176]					−0.003 [−0.540]
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	0.167	0.168	0.170	0.172	0.173	0.188	0.190	0.192	0.194	0.196
Panel B: Flow betas and FIT cummulated across different time horizons										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CRSP mutual funds alone					CRSP-Morningstar intersection				
	$\beta^{flow}_{i,t}$					$\beta^{flow}_{i,t}$				
$FIT_{i,t}$	−0.001 [−0.109]					−0.002 [−0.184]				
$\sum_{k=0}^{1} FIT_{i,t-k}$		−0.004 [−0.350]					−0.003 [−0.297]			
$\sum_{k=0}^{3} FIT_{i,t-k}$			−0.010 [−0.824]					−0.006 [−0.647]		
$\sum_{k=0}^{7} FIT_{i,t-k}$				−0.015 [−1.635]					−0.004 [−0.513]	
$\sum_{k=0}^{11} FIT_{i,t-k}$					−0.013 [−1.470]					0.006 [0.701]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	351835	342890	327881	303235	280873	351835	342890	327881	303235	280873
R-squared	0.167	0.168	0.171	0.177	0.184	0.188	0.190	0.194	0.202	0.209

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. $\beta^{flow}_{i,t}$ 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.

stocks are held by investors with higher price impact, so a systematic flow shock causes larger price movement.

We obtain the price impact measures from Koijen and Yogo (2019), who estimate the price impact based on an asset pricing model with flexible heterogeneity in asset demand across investors. We examine the cross-sectional relation between flow betas and price impact using panel regressions with quarter fixed effects. Table OA.5 shows that flow

Table OA.5: Relation between flow betas and price impact measures.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. CRSP mutual funds alone				Panel B. CRSP-Morningstar intersection			
	$\beta_{i,t}^{flow}$				$\beta_{i,t}^{flow}$			
$Price\_impact\_mutual\_funds_{i,t}$	0.003				0.011**			
	[0.529]				[2.222]			
$Price\_impact\_households_{i,t}$		0.063***				0.080***		
		[4.813]				[6.485]		
$Price\_impact\_investment\_advisors_{i,t}$			0.010*				0.023***	
			[1.721]				[3.929]	
$Price\_impact\_pension\_funds_{i,t}$				0.006				0.028***
				[0.847]				[3.714]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	387986	398573	375027	297126	387986	398573	375027	297126
R-squared	0.151	0.145	0.154	0.177	0.162	0.156	0.166	0.192

Note: This table shows the relation between common flow betas and the price impact measures. The analysis is performed at the quarterly frequency. $\beta_{i,t}^{flow}$ is the common flow beta for stock i in quarter t. The price impact measures are obtained from Koijen and Yogo (2019). 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.

betas are in general positively correlated with the price impact measures. The results are especially robust for the price impact of household and investment advisors, which include many hedge funds. These investors are the direct investors in our model. The positive relation between flow betas and price impact is relatively weaker for the price impact of mutual funds and pension funds, likely because Koijen and Yogo (2019) include both active funds and passive funds in their sample of mutual funds and pension funds.

We then examine the asset pricing implications of flow betas by double sorting on price impact. As shown in Panel D of Table 4 in the main text and Table OA.6, the flow betas remain positively priced in the cross section of stocks after controlling for price impact of different types of investors, suggesting that the asset pricing implications of flow betas cannot be entirely explained by price impact.

Common Flows of Index 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 quintiles based on asset size and then compute the value-weighted flow of each quintile. 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

Table OA.6: Double-sort analysis for additional price impact measures.

Price impact measures	Panel A: Households				Panel B: Investor advisors				Panel C: Pension funds			
	CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar		CRSP alone		CRSP-Morningstar	
β_i^{flow} quintiles	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α	Excess returns	CAPM α
Q1	5.10	−5.72***	5.23	−4.42**	5.21	−5.57***	5.00	−4.19**	5.27	−5.53***	5.99	−3.45**
	[1.20]	[−2.73]	[1.39]	[−2.48]	[1.23]	[−2.73]	[1.41]	[−2.54]	[1.23]	[−2.60]	[1.64]	[−2.06]
Q2	6.46**	−1.66	6.62**	−0.68	7.09**	−0.68	7.35***	0.06	6.68**	−1.32	7.38***	−0.08
	[2.11]	[−1.34]	[2.38]	[−0.57]	[2.43]	[−0.58]	[2.67]	[0.06]	[2.23]	[−1.12]	[2.65]	[−0.08]
Q3	7.85***	−0.03	8.52***	0.66	8.50***	0.76	7.81***	0.11	8.19***	0.25	7.94***	0.30
	[2.64]	[−0.02]	[3.01]	[0.79]	[2.98]	[0.74]	[2.80]	[0.12]	[2.77]	[0.22]	[2.86]	[0.33]
Q4	9.90***	1.92**	10.21***	1.57	9.93***	2.13**	11.66***	3.09**	10.00***	2.32**	9.98***	1.30
	[3.42]	[2.09]	[3.20]	[1.34]	[3.48]	[2.21]	[3.65]	[2.49]	[3.56]	[2.42]	[3.12]	[1.13]
Q5	11.24***	2.11	12.81***	1.82	10.95***	1.71	11.46***	0.53	10.83***	1.25	12.95***	1.99
	[3.18]	[1.30]	[2.97]	[0.87]	[3.00]	[0.94]	[2.63]	[0.24]	[2.89]	[0.70]	[2.99]	[0.92]
Q5 − Q1	6.14**	7.83***	7.58**	6.24**	5.75**	7.27**	6.46**	4.71*	5.56**	6.78**	6.96**	5.44**
	[2.07]	[2.66]	[2.59]	[2.13]	[2.23]	[2.45]	[2.19]	[1.81]	[2.26]	[2.25]	[2.40]	[2.18]

Note: This table shows the results from the double-sort analysis. In each June, we first sort stocks into five groups based on the price impact of households (panel A), the price impact of investor advisors (panel B), and the price impact of pension funds (panel C). Next, we sort stocks within each liquidity group into quintiles based on their average common flow betas from January of year t to June of year t. We then pool the firms in the same flow beta quintiles together across the liquidity groups. 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 obtain the price impact measures from Koijen and Yogo (2019). 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.

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.7, the long-short portfolios sorted on the betas to the common flows of index funds have insignificant average excess returns and CAPM alphas.

Stock Characteristics Across Portfolios Sorted on Common Flow Betas. In Table OA.8, 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 ratio, higher historical liquidity betas, and higher Amihud illiquidity measure.

Predicted Common Flow Betas. Table 6 in the main text shows that common flow betas are closely associated with stock characteristics. Because of this feature, we further strengthen our results by predicting flow betas using stock characteristics, following previous studies

Table OA.7: 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	9.33***	1.10	8.82***	1.52
	[2.93]	[0.75]	[3.02]	[1.01]
Q2	8.37***	1.27	9.15***	2.75***
	[3.23]	[1.48]	[3.82]	[2.88]
Q3	9.28***	1.91**	8.74***	0.52
	[3.46]	[2.19]	[2.96]	[0.62]
Q4	10.96**	1.25	10.12**	−0.56
	[2.99]	[0.82]	[2.47]	[−0.30]
Q5	9.71**	−2.49	9.75*	−3.46
	[1.99]	[−1.00]	[1.81]	[−1.18]
Q5 − Q1	0.38	−3.59	0.93	−4.98
	[0.12]	[−1.19]	[0.23]	[−1.38]

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.

(e.g., Pástor and Stambaugh, 2003; Kogan and Papanikolaou, 2013).

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

$$\beta_{i,t-1}^{flow} = a_{0,i} + a_{1,i}^T Z_{i,t-1}. \quad \text{(OA.77)}$$

Vector $Z_{i,t-1}$ contains five characteristics: lagged firm size, lagged book-to-market ratio, lagged historical liquidity betas, lagged Amihud illiquidity measure, and lagged common flow betas estimated by equation (4.4) using all data available from month $t-36$ through $t-1$. Substituting the right side of equation (OA.77) for β_i^{flow} in equation (4.4), we obtain:

$$ret_{i,t} = a + a_{0,i} \times \text{common flow}_t + a_{1,i}^T Z_{i,t-1} \times \text{common flow}_t + \varepsilon_{i,t}. \quad \text{(OA.78)}$$

The above regression for stock i contains six independent variables, five 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

Table OA.8: Stock characteristics across portfolios sorted on common flow betas.

	Panel A: Summary statistics of the stock characteristics				
	Mean	Median	Standard deviation	p25	p75
$Lnsize_t$	5.33	5.23	2.10	3.86	6.70
$Lnsize_t - Lnsize_t^{median}$	0.10	0	2.01	−1.29	1.41
$LnBEME_t$	−0.40	−0.41	1.19	−1.00	0.10
$Liqbeta_t$	16.48	13.85	54.86	−8.04	41.36
AIM_t	3.05	0.04	11.38	0.01	0.63

	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
$Lnsize_t$	5.20	5.67	5.78	5.77	5.00	5.24	5.75	5.79	5.71	4.94
$Lnsize_t - Lnsize_t^{median}$	−0.01	−0.02	−0.02	−0.01	0.03	−0.02	−0.02	−0.02	0.00	0.04
$LnBEME_t$	−0.53	−0.32	−0.30	−0.33	−0.39	−0.50	−0.32	−0.30	−0.33	−0.42
$Liqbeta_t$	7.65	11.04	13.48	18.04	32.64	5.71	9.84	13.76	19.27	34.18
AIM_t	3.55	1.98	1.81	2.42	5.47	3.38	1.88	1.92	2.52	5.51

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.

based on the estimated coefficients:

$$Predicted\_\beta_{i,t-1}^{flow} = \hat{a}_{0,i} + \hat{a}_{1,i}^T Z_{i,t-1}. \quad \text{(OA.79)}$$

The predicted common flow betas exhibit many properties that are similar to those of the common flow betas. First, Table OA.9 shows that the predicted common flow betas are negatively correlated with stock size and positively correlated with book-to-market ratio, historical liquidity betas, and Amihud illiquidity measure. This result is consistent with the relation between common flow betas and stock characteristics shown in Table 6 in the main text. Next, in panel A of Table OA.10, we perform Fama-MacBeth regressions of stock returns on the predicted common flow betas. 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.10, 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.9: Predicted common flow betas and stock characteristics.

Panel A: Relation between predicted common flow betas and stock characteristics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	CRSP mutual funds alone					CRSP-Morningstar intersection				
	$Predicted\_\beta_{i,t}^{flow}$					$Predicted\_\beta_{i,t}^{flow}$				
$Lnsize_{i,t-1}$	-0.39^{***}				-0.30^{***}	-0.41^{***}				-0.37^{***}
	[−7.46]				[−5.50]	[−8.49]				[−8.18]
$LnBEME_{i,t-1}$		0.30^{***}			0.23^{***}		0.16^{***}			0.06^{**}
		[8.94]			[5.36]		[7.40]			[2.43]
$Liqbeta_{i,t-1}$			0.09^{***}		0.06			0.23^{***}		0.20^{***}
			[2.76]		[1.54]			[4.84]		[3.84]
$AIM_{i,t-1}$				0.40^{***}	0.13^{***}				0.31^{***}	0.06^{*}
				[5.49]	[3.73]				[8.60]	[1.87]
Constant	−0.01	0.01	−0.03	0.04	−0.03	−0.02	−0.01	−0.04	0.02	−0.06
	[−0.09]	[0.05]	[−0.27]	[0.35]	[−0.19]	[−0.11]	[−0.04]	[−0.21]	[0.13]	[−0.28]
Average obs./month	2886	2810	2679	2858	2607	2886	2810	2679	2858	2607
Average R-squared	0.339	0.219	0.034	0.113	0.545	0.388	0.064	0.110	0.110	0.537

Panel B: Stock characteristics across portfolios sorted on the predicted common flow betas

	CRSP mutual funds alone					CRSP-Morningstar intersection				
$Predicted\_\beta_{i,t}^{flow}$ quintiles	Q1	Q2	Q3	Q4	Q5	Q1	Q2	Q3	Q4	Q5
$Lnsize_t$	7.27	6.41	5.67	4.88	3.88	7.58	6.43	5.58	4.77	3.73
$Lnsize_t - Lnsize_t^{median}$	2.04	1.18	0.44	−0.35	−1.35	2.36	1.20	0.35	−0.45	−1.50
$LnBEME_t$	−1.14	−0.60	−0.37	−0.20	0.48	−0.82	−0.53	−0.36	−0.16	0.05
$Liqbeta_t$	9.21	13.33	16.73	21.70	29.44	−4.41	7.60	14.80	24.69	47.71
AIM_t	0.89	0.85	1.27	2.51	9.56	0.53	0.63	1.23	2.72	9.99

Note: Panel A shows the slope coefficients and test statistics in brackets from Fama-MacBeth regressions that regress predicted common flow betas on stock characteristics. $Predicted\_\beta_{i,t}^{flow}$ is the predicted common flow beta for stock i in month t. The independent variables are explained in Table 6 in the main text. All variables are standardized to have means of 0 and standard deviations of 1. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Panel B shows the stock characteristics across stock portfolios sorted on the predicted common flow betas. The characteristics in panel B are raw values before standardization. Sample period spans from 1992 to 2018.

Portfolio Tilts with Rescaled Weights. In Table 7 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.11, 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 panel A of Table OA.11, 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 panel B of Table OA.11, we further require the stocks

Table OA.10: Portfolio holdings of active mutual funds and predicted common flow betas.

	Panel A: Fama-MacBeth regressions			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone $Ret_{i,t}$ (%)		CRSP-Morningstar intersection $Ret_{i,t}$ (%)	
$Predicted\_\beta^{flow}_{i,t-1}$	0.337**	0.345**	0.385**	0.389***
	[2.356]	[2.334]	[2.557]	[2.600]
$\beta^M_{i,t-1}$		0.065		0.005
		[0.510]		[0.037]
Constant	1.313***	1.322***	1.269***	1.244***
	[3.790]	[3.748]	[3.621]	[3.365]
Average obs./month	2842	2842	2842	2842
Average R-squared	0.007	0.017	0.007	0.016

	Panel B: Active mutual funds tilt their holdings away from stocks with high predicted common flow betas			
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone $w^{MF}_{i,t} - w^M_{i,t}$		CRSP-Morningstar intersection $w^{MF}_{i,t} - w^M_{i,t}$	
$Predicted\_\beta^{flow}_{i,t-1}$	−0.205***	−0.286***	−0.217***	−0.357***
	[−9.375]	[−11.575]	[−13.012]	[−15.183]
$\beta^M_{i,t-1}$	0.055***	0.050***	0.093***	0.106***
	[6.716]	[5.669]	[10.926]	[10.906]
Quarter FE	No	Yes	No	Yes
Observations	369899	369899	369899	369899
R-squared	0.038	0.053	0.040	0.061

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. FE is fixed effects. The analysis is performed at quarterly frequency. Sample period spans from 1992 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.

in our analysis to be part of the self-disclosed benchmark portfolios. Our results remain robust to the usage of the rescaled portfolio weights.

Model-Implied Portfolio Tilt. In equilibrium, the portfolio tilt is equal to

$$\Sigma_t^{-1}\mathcal{B}_t = \left(v^2 I_n + KK^T\right)^{-1}\mathcal{B} \quad \text{(OA.80)}$$

$$= v^{-2}\left[I_n - K\left(v^2 I_k + K^T K\right)^{-1} K^T\right]\mathcal{B}. \quad \text{(OA.81)}$$

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

Table OA.11: Active mutual funds tilt their holdings away from stocks with high flow betas: analysis with rescaled portfolio weights.

Panel A: Using the market portfolio as the benchmark portfolio

	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$rescaled\_w^{MF}_{i,t} - rescaled\_w^{M}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{M}_{i,t}$	
$\beta^{flow}_{i,t-1}$	-0.020^{***}	-0.027^{***}	-0.013^{***}	-0.023^{***}
	[−4.850]	[−5.666]	[−3.506]	[−5.219]
$\beta^{M}_{i,t-1}$	0.071^{***}	0.073^{***}	0.071^{***}	0.075^{***}
	[10.649]	[10.552]	[10.790]	[10.866]
Quarter FE	No	Yes	No	Yes
Observations	413321	413321	413321	413321
R-squared	0.004	0.005	0.004	0.005

Panel B: Using the self-declared benchmarks as the benchmark portfolio

	(1)	(2)	(3)	(4)	(5)	(6)
Benchmarks	S&P 500 TR		Russell 1000 Growth TR		Russell 2000 TR	
	CRSP	CRSP-MS	CRSP	CRSP-MS	CRSP	CRSP-MS
	$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$		$rescaled\_w^{MF}_{i,t} - rescaled\_w^{Benchmark}_{i,t}$	
$\beta^{flow}_{i,t-1}$	-0.061^{***}	-0.040^{**}	-0.053^{***}	-0.048^{***}	-0.018^{**}	-0.023^{***}
	[−3.281]	[−2.159]	[−3.809]	[−3.544]	[−2.477]	[−3.057]
$\beta^{M}_{i,t-1}$	0.105^{***}	0.106^{***}	0.079^{***}	0.085^{***}	−0.012	−0.009
	[3.206]	[3.112]	[4.142]	[4.260]	[−1.166]	[−0.822]
Observations	26208	26208	30780	30780	88017	88017
R-squared	0.009	0.007	0.008	0.008	0.001	0.001

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 7 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 panel A, 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 panel B, we further require that the stocks in our analysis to be part of the self-disclosed benchmark portfolios. FE is fixed effects. We include t-statistics in brackets. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

identity.

We empirically estimate Σ_t^{-1} using equation (OA.81). 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.12, 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

Table OA.12: Relation between mutual fund weight deviation and theoretical tilt.

	(1)	(2)	(3)	(4)
Panel A: Without controlling for market betas				
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$w^{MF}_{i,t} - w^{M}_{i,t}$		$w^{MF}_{i,t} - w^{M}_{i,t}$	
$\Sigma^{-1}_{t-1}\beta^{flow}_{i,t-1}$	-0.017^{***}	-0.016^{***}	-0.014^{***}	-0.013^{***}
	[−3.516]	[−3.182]	[−3.234]	[−2.981]
Quarter FE	No	Yes	No	Yes
Observations	408054	408054	408054	408054
R-squared	0.001	0.006	0.001	0.006
Panel B: Controlling for market betas				
	(1)	(2)	(3)	(4)
	CRSP mutual funds alone		CRSP-Morningstar intersection	
	$w^{MF}_{i,t} - w^{M}_{i,t}$		$w^{MF}_{i,t} - w^{M}_{i,t}$	
$\Sigma^{-1}_{t-1}\beta^{flow}_{i,t-1}$	-0.017^{***}	-0.016^{***}	-0.014^{***}	-0.013^{***}
	[−3.513]	[−3.181]	[−3.232]	[−2.981]
$\Sigma^{-1}_{t-1}\beta^{M}_{i,t-1}$	0.001	0.000	0.001	0.001
	[0.563]	[0.255]	[0.640]	[0.320]
Quarter FE	No	Yes	No	Yes
Observations	408054	408054	408054	408054
R-squared	0.001	0.006	0.001	0.006

Note: This table studies the relation between the theoretical portfolio tilt and active mutual funds' weight deviation from the market. Variable $w^{MF}_{i,t}$ is the weight for stock i in the aggregate active mutual fund holdings in quarter t; and $w^{M}_{i,t}$ is the weight for stock i in the equity market portfolio. $w^{MF}_{i,t} - w^{M}_{i,t}$ represents the weight deviation of the aggregate active mutual fund portfolio from the equity market portfolio. Independent variable $\Sigma^{-1}_{t-1}\beta^{flow}_{i,t-1}$ represents the lagged theoretical 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. $\Sigma^{-1}_{t-1}\beta^{flow}_{i,t-1}$, $\Sigma^{-1}_{t-1}\beta^{M}_{i,t-1}$, and $w^{MF}_{i,t} - w^{M}_{i,t}$ are standardized to have means of 0 and standard deviations of 1. FE is fixed effects. The analysis is performed at a quarterly frequency. 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. Sample period spans from 1991 to 2018.

strong support to Theorems 1 and 2 of our model.

Portfolio Tilts of Flow Betas and Firm Characteristics. Our findings shed light on some of the puzzling patterns found by Lettau, Ludvigson and Manoel (2018), who show that active mutual funds do not systematically tilt their portfolios toward profitable return factors, such as small stocks or stocks with high book-to-market ratios (value stocks). These patterns are also suggested for a broader set of institutional investors (e.g., Gompers and Metrick, 2001; Bennett, Sias and Starks, 2003; Lewellen, 2011). In a recent paper, Blume and Keim (2017) allow for a more flexible nonlinear relation between log market cap and portfolio weights to improve estimation and find that institutional investors overweigh large-cap stocks, but have started to underweight mega-cap and overweigh small-cap stocks for the

Table OA.13: Portfolio tilts of flow betas and book-to-market ratio.

	Pane A: Aggregate mutual fund tilts					
	(1)	(2)	(3)	(4)	(5)	(6)
	$w_{i,t}^{MF} - w_{i,t}^{M}$					
$Predicted\_\beta_{i,t-1}^{flow}$	-0.284^{***}		-0.276^{***}			-0.278^{***}
	[−11.321]		[−8.553]			[−8.370]
$LnBEME_{i,t-1}$		-0.149^{***}	−0.011	-0.148^{***}	-0.146^{***}	−0.010
		[−14.300]	[−0.728]	[−14.288]	[−13.986]	[−0.630]
$Liqbeta_{i,t-1}$				-0.016^{***}		0.014
				[−2.905]		[1.540]
$AIM_{i,t-1}$					-0.033^{***}	-0.012^{**}
					[−5.807]	[−2.216]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	354891	354891	354891	354891	354891	354891
R-squared	0.051	0.022	0.051	0.023	0.023	0.051
	Pane B: Individual mutual fund tilts					
	(1)	(2)	(3)	(4)	(5)	(6)
	$w_{i,f,t} - w_{i,t}^{M}$					
$Predicted\_\beta_{i,t-1}^{flow}$	-0.210^{***}		-0.284^{***}			-0.285^{***}
	[−14.648]		[−11.032]			[−10.281]
$LnBEME_{i,t-1}$		-0.063^{***}	0.083^{***}	-0.060^{***}	-0.059^{***}	0.085^{***}
		[−7.027]	[5.086]	[−6.828]	[−6.633]	[5.064]
$Liqbeta_{i,t-1}$				-0.031^{***}		0.013^{*}
				[−5.871]		[1.983]
$AIM_{i,t-1}$					-0.041^{***}	-0.026^{***}
					[−3.931]	[−3.229]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16036661	16036661	16036661	16036661	16036661	16036661
R-squared	0.038	0.019	0.041	0.020	0.021	0.042

Note: This table examines the portfolio tilts of flow betas and book-to-market ratio. The dependent variables in panel A are the weight deviation of aggregate mutual funds from the market portfolio ($w_{i,t}^{MF} - w_{i,t}^{M}$). The dependent variables in panel B are the weight deviation of individual mutual funds from the market portfolio ($w_{i,f,t} - w_{i,t}^{M}$). All variables are standardized to have means of 0 and standard deviations of 1. FE is fixed effects. The analysis is performed at a quarterly frequency. Sample period spans from 1992 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.

last few decades. Put together, there is little evidence showing that portfolio overweighting is monotonically decreasing in market cap or increasing in book-to-market ratio.

Our results help make sense of the absence of the value tilt in the funds' portfolios. As we show above, the book-to-market ratio and the beta on common fund flows are positively correlated in the cross-section of stocks (see Table 6 in the main text). This suggests that a simple tilt based solely on the book-to-market ratio would expose funds to elevated flow risk. Yet, there is an incentive for the funds to favor value stocks with lower flow betas. In Table OA.13, column (2), we replicate the finding that active mutual funds underweight value stocks in their portfolios – both at the aggregate, and individual fund levels. Column (3) shows that this tilt becomes insignificant at the aggregate level and significantly positive at the individual fund level when we add the common flow betas to the regression. Thus, controlling for the flow betas, funds do tilt their portfolios toward value stocks. We explicitly address one alternative interpretation of these results: because high-flow-beta stocks are relatively illiquid (see Table 6 in the main text), the flow beta may be capturing effects of stock illiquidity. Columns (4) and (5) of Table OA.13 show that directly controlling for liquidity does not reverse the puzzling tilt toward growth stocks, although funds do tend to underweigh less liquid stocks, as expected. When controlling for illiquidity and liquidity risk, the effect of flow betas on portfolio weights remains virtually unchanged, and the growth tilt reverses at the fund level.[1]

Table OA.15 shows that the cross-sectional correlation between the book-to-market ratio and flow betas is not accidental, and has fundamental underpinnings. In this table, we relate the "uncertainty betas" of stocks, measured by their time-series betas on changes in the CBOE S&P 100 volatility index, to the book-to-market characteristics. Value stocks tend to have higher exposure to aggregate uncertainty shocks, according to this definition. Taking the relation between book-to-market and uncertainty as given, the logic of our model then dictates that value stocks should, on average, have higher flow betas. The above relation survives when controlling for stock illiquidity and liquidity risk. We should note here that our controls for illiquidity capture stock properties that are outside of our theoretical model, but are natural to consider in the context of portfolio choice. In future work, it would be useful to extend our equilibrium model to incorporate heterogeneous stock liquidity and endogenous firm characteristics.

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

[1] We further examine the relation between flow betas, stock liquidity, and portfolio tilts in Table OA.14. When taken separately, funds tend to tilt away from high-beta stocks, and illiquid or high-liquidity-risk stocks. When used jointly, the coefficients on flow betas remain virtually unchanged and remain highly significant, while the relation between the portfolio tilt and market liquidity is largely subsumed by the common flow beta.

Table OA.14: Portfolio tilts of flow betas and stock liquidity.

	(1)	(2)	(3)	(4)	(5)	(6)
Pane A: Portfolio tilts of flow betas and historical liquidity betas						
	Aggregate tilt $w^{MF}_{i,t} - w^{M}_{i,t}$			Fund-level tilt $w_{i,f,t} - w^{M}_{i,t}$		
$Predicted\_\beta^{flow}_{i,t-1}$	-0.286^{***}		-0.288^{***}	-0.213^{***}		-0.215^{***}
	[−11.626]		[−11.575]	[−14.805]		[−14.467]
$Liqbeta_{i,t-1}$		-0.019^{***}	0.014		-0.034^{***}	0.008
		[−3.405]	[1.556]		[−6.127]	[1.651]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	369899	369899	369899	17028364	17028364	17028364
R-squared	0.051	0.004	0.051	0.039	0.016	0.039
Pane B: Portfolio tilts of flow betas and Amihud illiquidity measure						
	(1)	(2)	(3)	(4)	(5)	(6)
	Aggregate tilt $w^{MF}_{i,t} - w^{M}_{i,t}$			Fund-level tilt $w_{i,f,t} - w^{M}_{i,t}$		
$Predicted\_\beta^{flow}_{i,t-1}$	-0.286^{***}		-0.284^{***}	-0.213^{***}		-0.208^{***}
	[−11.626]		[−11.382]	[−14.805]		[−14.278]
$AIM_{i,t-1}$		-0.049^{***}	-0.012^{**}		-0.046^{***}	-0.026^{***}
		[−7.273]	[−2.248]		[−4.213]	[−3.052]
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	369899	369899	369899	17028364	17028364	17028364
R-squared	0.051	0.006	0.051	0.039	0.018	0.039

Note: Panel A examines the portfolio tilts of flow betas and historical liquidity betas. Panel B examines the portfolio tilts of flow betas and the Amihud illiquidity measure (panel B). The dependent variables are the weight deviation of aggregate mutual funds from the market portfolio ($w^{MF}_{i,t} - w^{M}_{i,t}$) in columns (1) to (3) , and are the weight deviation of individual mutual funds from the market portfolio ($w_{i,f,t} - w^{M}_{i,t}$) in columns (4) to (6). All variables are standardized to have means of 0 and standard deviations of 1. FE is fixed effects. The analysis is performed at a quarterly frequency. Sample period spans from 1992 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.

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

Table OA.15: Relation between uncertainty betas and stock characteristics.

	(1)	(2)	(3)	(4)
		$\beta_{i,t}^{VXO}$		
$LnBEME_{i,t-37}$	0.07**			0.06**
	[2.14]			[1.98]
$Liqbeta_{i,t-37}$		−0.09***		−0.10***
		[−3.93]		[−3.89]
$AIM_{i,t-37}$			0.12***	0.10***
			[4.76]	[3.75]
Constant	0.03	0.05	0.02	0.07
	[0.31]	[0.64]	[0.22]	[0.93]
Average obs./month	2451	2327	2701	2235
Average R-squared	0.013	0.010	0.007	0.029

Note: This table shows the slope coefficients and test statistics in brackets from Fama-MacBeth regressions that regress uncertainty betas on 3-year lagged stock characteristics. We measure uncertainty betas using $\beta_{i,t}^{VXO}$, which is the betas to the monthly changes of the CBOE S&P 100 volatility index. $Liqbeta_{i,t-37}$ is the historical liquidity betas estimated by regressing stock returns on the shocks of aggregated liquidity. $AIM_{i,t-37}$ is the Amihud illiquidity measure. All variables are standardized to have means of 0 and standard deviations of 1. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. Sample period spans from 1992 to 2018.

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 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 10 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,

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				CRSP-Morningstar intersection			
	$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	−0.017*	−0.020*	−0.022**	−0.025**	−0.020**	−0.021**	−0.026**	−0.026**
	[−1.842]	[−1.899]	[−1.982]	[−2.211]	[−2.201]	[−2.152]	[−2.194]	[−2.164]
$\beta^{flow}_{i,t-1}$	0.036***	0.059***	0.067***	0.095***	0.019**	0.040***	0.053***	0.070***
	[3.991]	[5.478]	[5.949]	[6.680]	[2.110]	[3.400]	[4.488]	[4.411]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.004	0.018*	0.013	0.023*	0.007	0.020*	0.016	0.025**
	[0.407]	[1.662]	[1.096]	[1.926]	[0.660]	[1.773]	[1.345]	[2.045]
$\beta^{M}_{i,t-1}$	0.004	−0.013*	0.043***	0.019	0.005	−0.015*	0.040***	0.016
	[0.529]	[−1.654]	[3.314]	[1.310]	[0.604]	[−1.819]	[3.023]	[1.107]
$ND_{f,t}$	−0.082***	−0.409***	−0.182***	−0.409***	−0.084***	−0.409***	−0.184***	−0.410***
	[−5.923]	[−15.445]	[−11.318]	[−15.586]	[−6.016]	[−15.420]	[−11.497]	[−15.601]
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	0.010	0.011	0.016	0.017	0.010	0.011	0.016	0.017

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 9 and 10 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.

2016) is prevalent. To address this potential concern, we further drop the suppliers and customers of the affected firms from our analysis. As 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.

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	0.046	0.046	0.029	0.029

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.

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

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

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***	−0.039***	−0.037***	−0.042***	−0.028***	−0.033***	−0.034***	−0.037***
	[−3.618]	[−3.995]	[−3.569]	[−3.879]	[−2.739]	[−3.059]	[−3.105]	[−3.284]
$\beta^{flow}_{i,t-1}$	0.028***	0.060***	0.047***	0.085***	0.014**	0.045***	0.035***	0.065***
	[4.173]	[7.742]	[5.427]	[8.092]	[2.034]	[5.427]	[3.913]	[5.834]
$\beta^M_{i,t-1} \times ND_{f,t}$	0.012	0.026**	0.016	0.027**	0.015	0.029***	0.020*	0.030**
	[1.118]	[2.367]	[1.402]	[2.295]	[1.368]	[2.620]	[1.693]	[2.526]
$\beta^M_{i,t-1}$	0.013**	−0.008	0.060***	0.034***	0.014**	−0.011*	0.059***	0.031***
	[2.037]	[−1.360]	[6.472]	[3.409]	[2.212]	[−1.731]	[6.228]	[3.035]
$ND_{f,t}$	−0.069***	−0.252***	−0.114***	−0.255***	−0.071***	−0.254***	−0.116***	−0.257***
	[−6.909]	[−13.122]	[−10.289]	[−13.054]	[−7.091]	[−13.198]	[−10.465]	[−13.142]
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	0.009	0.010	0.014	0.015	0.009	0.010	0.014	0.015

	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 $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	−0.022**	−0.027**	−0.023*	−0.026**	−0.027**	−0.030**	−0.029**	−0.032**
	[−1.969]	[−2.293]	[−1.902]	[−2.084]	[−2.233]	[−2.432]	[−2.310]	[−2.430]
$\beta^{flow}_{i,t-1}$	0.019**	0.052***	0.036***	0.071***	0.004	0.038***	0.026**	0.056***
	[2.421]	[5.567]	[3.818]	[5.944]	[0.553]	[3.786]	[2.516]	[4.209]
$\beta^M_{i,t-1} \times ND_{f,t}$	0.004	0.018	0.011	0.022	0.007	0.021*	0.015	0.026*
	[0.299]	[1.435]	[0.772]	[1.567]	[0.575]	[1.650]	[1.067]	[1.806]
$\beta^M_{i,t-1}$	0.008	−0.013*	0.051***	0.027**	0.011	−0.014*	0.051***	0.025**
	[1.115]	[−1.686]	[4.477]	[2.222]	[1.506]	[−1.849]	[4.500]	[2.075]
$ND_{f,t}$	−0.084***	−0.389***	−0.183***	−0.388***	−0.086***	−0.390***	−0.185***	−0.390***
	[−6.088]	[−12.150]	[−10.849]	[−11.994]	[−6.227]	[−12.152]	[−10.951]	[−12.022]
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	0.010	0.011	0.017	0.018	0.010	0.011	0.017	0.018

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 9 and 10 in the main text. In panel A, we map firms to natural disaster shocks based on headquarter-level information as done in Table 10. 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.

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

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 $\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-0.031^{***}	-0.032^{***}	-0.035^{***}	-0.039^{***}	-0.025^{**}	-0.025^{**}	-0.031^{***}	-0.033^{***}
	[−3.390]	[−3.328]	[−3.605]	[−3.734]	[−2.575]	[−2.411]	[−3.006]	[−2.908]
$\beta^{flow}_{i,t-1}$	0.040^{***}	0.063^{***}	0.061^{***}	0.091^{***}	0.026^{***}	0.046^{***}	0.048^{***}	0.069^{***}
	[5.692]	[7.711]	[6.783]	[8.392]	[3.836]	[5.363]	[5.452]	[5.980]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.021^{**}	0.032^{***}	0.026^{**}	0.036^{***}	0.024^{**}	0.035^{***}	0.029^{***}	0.039^{***}
	[2.202]	[3.297]	[2.479]	[3.383]	[2.350]	[3.310]	[2.650]	[3.404]
$\beta^{M}_{i,t-1}$	0.006	-0.010^{*}	0.053^{***}	0.026^{**}	0.005	-0.014^{**}	0.051^{***}	0.023^{**}
	[1.012]	[−1.754]	[5.398]	[2.427]	[0.803]	[−2.242]	[5.112]	[2.116]
$AIM_{i,t-1} \times ND_{f,t}$	−0.003	0.008	0.003	0.009	−0.003	0.008	0.003	0.009
	[−0.471]	[1.048]	[0.358]	[1.212]	[−0.414]	[1.072]	[0.426]	[1.248]
$AIM_{i,t-1}$	-0.047^{***}	0.010	-0.020^{***}	0.005	-0.047^{***}	0.010	-0.020^{***}	0.005
	[−8.907]	[1.548]	[−3.502]	[0.812]	[−8.870]	[1.535]	[−3.492]	[0.828]
$ND_{f,t}$	-0.058^{***}	-0.259^{***}	-0.094^{***}	-0.258^{***}	-0.060^{***}	-0.260^{***}	-0.096^{***}	-0.260^{***}
	[−5.794]	[−15.156]	[−8.509]	[−15.473]	[−5.983]	[−15.215]	[−8.748]	[−15.569]
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9477152	9477152	9476833	9476833	9477152	9477152	9476833	9476833
R-squared	0.007	0.007	0.011	0.012	0.007	0.007	0.011	0.011

Note: This table shows how active mutual funds rebalance their holdings unaffected by natural disasters after 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 10 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, 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 world. We find that the annualized fund returns is 49 basis points ($p < 0.001$) higher than those in the counterfactual world.

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			
	$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$				$\Delta(w_{i,f,t} - w^M_{i,t})$ $(\times 10^3)$			
$\beta^{flow}_{i,t-1} \times ND_{f,t}$	-0.027^{***}	-0.027^{***}	-0.032^{***}	-0.035^{***}	-0.024^{**}	-0.023^{**}	-0.030^{***}	-0.030^{***}
	[−3.076]	[−2.893]	[−3.408]	[−3.415]	[−2.570]	[−2.215]	[−2.965]	[−2.736]
$\beta^{flow}_{i,t-1} \times lnsize_{f,t-1}$	−0.007	−0.007	0.001	0.002	0.000	−0.006	0.005	0.000
	[−0.675]	[−0.675]	[0.136]	[0.150]	[0.031]	[−0.608]	[0.500]	[0.014]
$\beta^{flow}_{i,t-1} \times lnBEME_{f,t-1}$	-0.039^{***}	-0.036^{***}	-0.044^{***}	-0.044^{***}	-0.019^{*}	−0.018	-0.022^{*}	-0.023^{**}
	[−3.562]	[−3.287]	[−3.700]	[−3.843]	[−1.771]	[−1.620]	[−1.929]	[−2.029]
$\beta^{flow}_{i,t-1} \times liqbeta_{f,t-1}$	-0.026^{***}	-0.015^{*}	-0.023^{***}	−0.013	-0.013^{*}	−0.002	−0.010	0.001
	[−3.382]	[−1.861]	[−2.663]	[−1.426]	[−1.771]	[−0.299]	[−1.205]	[0.142]
$\beta^{flow}_{i,t-1} \times AIM_{f,t-1}$	0.019^{***}	0.015^{**}	0.020^{***}	0.018^{***}	0.013^{**}	0.012^{*}	0.014^{***}	0.014^{**}
	[3.072]	[2.335]	[3.469]	[3.010]	[2.147]	[1.833]	[2.579]	[2.528]
$\beta^{flow}_{i,t-1}$	0.045^{***}	0.062^{***}	0.068^{***}	0.093^{***}	0.031^{***}	0.047^{***}	0.053^{***}	0.071^{***}
	[5.967]	[7.395]	[7.161]	[8.363]	[3.933]	[5.127]	[5.410]	[5.933]
$\beta^{M}_{i,t-1} \times ND_{f,t}$	0.018^{*}	0.030^{***}	0.024^{**}	0.035^{***}	0.024^{**}	0.035^{***}	0.030^{***}	0.040^{***}
	[1.943]	[3.073]	[2.339]	[3.235]	[2.360]	[3.288]	[2.674]	[3.413]
$\beta^{M}_{i,t-1}$	0.009	−0.008	0.053^{***}	0.026^{**}	0.004	-0.015^{**}	0.048^{***}	0.020^{*}
	[1.434]	[−1.335]	[5.314]	[2.435]	[0.694]	[−2.357]	[4.822]	[1.837]
$ND_{f,t}$	-0.070^{***}	-0.259^{***}	-0.101^{***}	-0.258^{***}	-0.068^{***}	-0.260^{***}	-0.101^{***}	-0.261^{***}
	[−6.752]	[−14.844]	[−9.092]	[−15.147]	[−6.641]	[−14.898]	[−9.120]	[−15.247]
$Lnsize_{f,t-1}$	0.044^{***}	0.081^{*}	0.038^{***}	0.092^{**}	0.042^{***}	0.086^{*}	0.036^{**}	0.094^{**}
	[3.197]	[1.844]	[2.703]	[2.055]	[3.016]	[1.936]	[2.501]	[2.117]
$LnBEME_{f,t-1}$	0.050^{**}	−0.056	0.029	-0.056^{*}	0.049^{**}	-0.060^{*}	0.026	-0.061^{*}
	[2.514]	[−1.643]	[1.436]	[−1.651]	[2.474]	[−1.768]	[1.319]	[−1.783]
$Liqbeta_{f,t-1}$	-0.023^{**}	−0.004	-0.020^{*}	−0.008	-0.019^{**}	−0.003	−0.015	−0.006
	[−2.324]	[−0.193]	[−1.934]	[−0.402]	[−1.981]	[−0.133]	[−1.516]	[−0.320]
$AIM_{f,t-1}$	-0.046^{***}	0.007	-0.025^{***}	0.001	-0.046^{***}	0.008	-0.024^{***}	0.002
	[−6.104]	[0.870]	[−3.067]	[0.139]	[−6.001]	[0.929]	[−2.979]	[0.234]
Quarter FE	No	Yes	No	Yes	No	Yes	No	Yes
Stock FE	No	No	Yes	Yes	No	No	Yes	Yes
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9477152	9477152	9476833	9476833	9477152	9477152	9476833	9476833
R-squared	0.007	0.008	0.011	0.012	0.007	0.007	0.011	0.012

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 10 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.

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.22. We find that active mutual funds do not significantly reduce

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.

Table OA.22: 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.

their holdings of 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.23, our findings remain robust in this test.

2014 OPEC Announcement. On November 28, 2014, OPEC announced the outcome of its 166th meeting. The organization unexpectedly decided that member countries would not

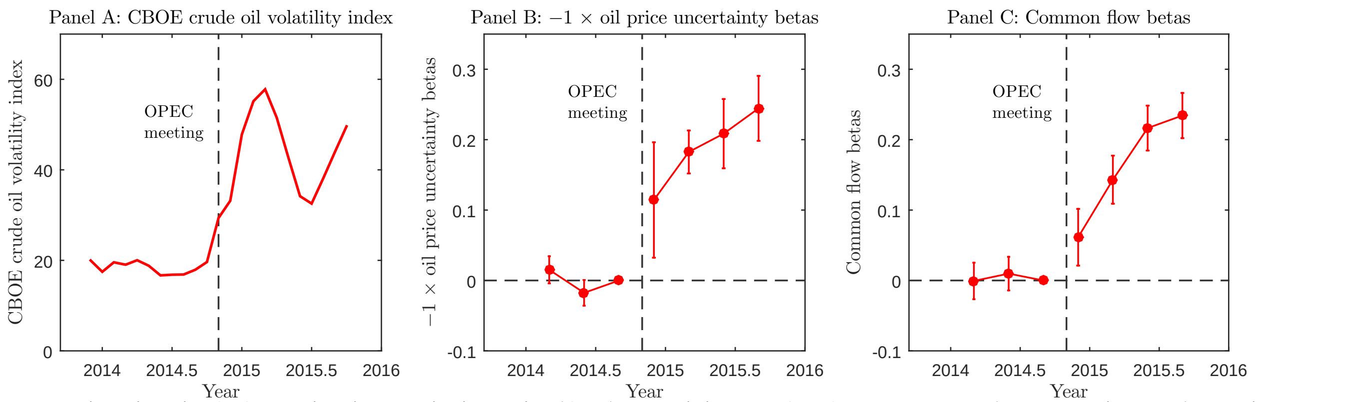
Table OA.23: Exclusion of suppliers and customers of China-related firms.

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	
	$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)		$\Delta(w_{i,f} - w_i^M)$ (%)	
$\beta^{flow}_{i,Dec2016}$	-0.035^{***}	-0.041^{**}	-0.035^{***}	-0.045^{**}	-0.041^{***}	-0.033^{**}	-0.039^{**}	-0.037^{***}
	[−2.723]	[−2.007]	[−3.079]	[−2.222]	[−2.732]	[−2.553]	[−2.547]	[−2.974]
$\beta^{M}_{i,Dec2016}$	-0.056^{**}	-0.082^{***}	-0.059^{**}	-0.083^{***}	-0.055^{***}	-0.047^{***}	-0.059^{***}	-0.048^{***}
	[−2.339]	[−4.235]	[−2.524]	[−4.366]	[−3.372]	[−2.655]	[−3.899]	[−2.799]
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	0.035	0.039	0.035	0.039	0.025	0.029	0.025	0.029

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^{**}	-0.048^{**}	-0.034^{***}	-0.059^{***}	-0.030^{**}	-0.019^{*}	-0.034^{**}	-0.028^{**}
	[−2.446]	[−2.266]	[−2.883]	[−2.736]	[−1.974]	[−1.846]	[−2.101]	[−2.093]
$\beta^{M}_{i,Dec2016}$	−0.002	-0.046^{**}	−0.005	-0.047^{**}	−0.009	-0.033^{*}	−0.012	-0.034^{*}
	[−0.095]	[−2.404]	[−0.203]	[−2.492]	[−0.548]	[−1.851]	[−0.807]	[−1.917]
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	0.049	0.052	0.049	0.052	0.041	0.044	0.041	0.044

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 12 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.

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.6). 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.6 and panel A of Table OA.24, 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



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.6: Uncertainty betas and flow betas around the 2014 OPEC announcement.

larger) according to the 2012 National Income and Product Accounts (NIPA) input-output table. In the second method, 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.6 and panel B of Table OA.24). 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.25 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.

Table OA.24: 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	0.008	0.009	0.015	0.016

	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	
	$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$		$\beta_{i,t}^{flow}$	
$Oil\_related_i \times \mathbf{1}_{\{t>November\_2014\}}$	0.182***	0.182***	0.121***	0.122***	0.273***	0.274***	0.212***	0.212***
	[6.825]	[6.846]	[5.595]	[5.606]	[8.393]	[8.453]	[8.091]	[8.115]
$Oil\_related_i$	−0.138***	−0.138***	−0.071**	−0.071**	−0.339***	−0.340***	−0.268***	−0.268***
	[−4.384]	[−4.389]	[−2.247]	[−2.250]	[−10.040]	[−10.052]	[−7.756]	[−7.764]
$\mathbf{1}_{\{t>November\_2014\}}$	0.271***		0.121***		0.259***		0.105***	
	[7.845]		[5.605]		[7.491]		[4.720]	
Month FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	134952	134952	134952	134952	135573	135573	135573	135573
R-squared	0.028	0.035	0.007	0.009	0.035	0.043	0.012	0.014

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.25: 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
	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)	$\Delta(w_{i,f} - w_i^M)$ (%)
$\beta^{flow}_{i,Dec2013}$	-0.030^{***}	-0.033^{***}	-0.017^{***}	-0.020^{***}
	[−5.605]	[−6.571]	[−3.416]	[−4.144]
$\beta^{M}_{i,Dec2013}$	-0.072^{***}	-0.071^{***}	-0.053^{***}	-0.052^{***}
	[−11.467]	[−11.437]	[−8.966]	[−9.134]
Fund FE	Yes	Yes	Yes	Yes
Observations	154430	154430	166667	166667
R-squared	0.035	0.035	0.032	0.032

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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