Appendix A. Bayesian Inference

In this section, we analyze how LSN investors form beliefs about θ_t and $\overline{\omega}_t$ using Bayesian inference. By equations (8) to (10) of the main text and Theorem 12.7 of Lipster and Shiryaev (2001), we obtain

$$\begin{pmatrix} dm_{t,1} \\ dm_{t,2} \end{pmatrix} = \begin{pmatrix} \kappa\overline{\theta} - \kappa m_{t,1} \\ -(\alpha\delta+\delta)m_{t,2} \end{pmatrix} dt + \left[\begin{pmatrix} 0 \\ \delta \end{pmatrix} + \boldsymbol{\gamma}_t \begin{pmatrix} \sigma_P^{-1} \\ -\alpha \end{pmatrix} \right] [dP_t - (m_{t,1} - \sigma_P \alpha m_{t,2})dt]\sigma_P^{-1} \tag{A.1}$$

and

$$\begin{aligned} \frac{d}{dt}\boldsymbol{\gamma}_t = & -\begin{pmatrix} \kappa & 0 \\ 0 & (\alpha\delta+\delta) \end{pmatrix} \boldsymbol{\gamma}_t - \boldsymbol{\gamma}_t \begin{pmatrix} \kappa & 0 \\ 0 & (\alpha\delta+\delta) \end{pmatrix} + \begin{pmatrix} \sigma_\theta^2 & 0 \\ 0 & \delta^2 \end{pmatrix} \\ & - \left[\begin{pmatrix} 0 \\ \delta \end{pmatrix} + \boldsymbol{\gamma}_t \begin{pmatrix} \sigma_P^{-1} \\ -\alpha \end{pmatrix} \right] \left[\begin{pmatrix} 0 \\ \delta \end{pmatrix} + \boldsymbol{\gamma}_t \begin{pmatrix} \sigma_P^{-1} \\ -\alpha \end{pmatrix} \right]^T . \end{aligned} \tag{A.2}$$

To further simplify (A.1) and (A.2), we follow the literature on Kalman filtering and focus on the stationary solution of $\boldsymbol{\gamma}_t$, denoted by $\boldsymbol{\gamma}$. In this case, LSN investors' beliefs are fully specified by equations (12), (13), and (14) in the main text. Equation (A.2) implies that parameters γ_{11}, γ_{12}, and γ_{22} are the solution of

$$\begin{aligned} \begin{pmatrix} 2\kappa\gamma_{11} & (\kappa+\alpha\delta+\delta)\gamma_{12} \\ (\kappa+\alpha\delta+\delta)\gamma_{12} & 2(\alpha\delta+\delta)\gamma_{22} \end{pmatrix} = \begin{pmatrix} \sigma_\theta^2 & 0 \\ 0 & \delta^2 \end{pmatrix} \\ - \begin{pmatrix} (\sigma_P^{-1}\gamma_{11} - \alpha\gamma_{12})^2 & (\sigma_P^{-1}\gamma_{11} - \alpha\gamma_{12})(\delta + \sigma_P^{-1}\gamma_{12} - \alpha\gamma_{22}) \\ (\sigma_P^{-1}\gamma_{11} - \alpha\gamma_{12})(\delta + \sigma_P^{-1}\gamma_{12} - \alpha\gamma_{22}) & (\delta + \sigma_P^{-1}\gamma_{12} - \alpha\gamma_{22})^2 \end{pmatrix}, \end{aligned} \tag{A.3}$$

which is effectively three simultaneous equations. ■

Appendix B. Model Solution

In this section, we discuss the procedure that solves the model described in Section 3. Recall from equations (5) and (6) of the main text that both LSN investors and rational arbitrageurs have instantaneous mean-variance preferences subject to their budget constraints. Substituting (6) into (5) gives

$$N_t^i = \frac{\mathbb{E}_t^i[dP_t]/dt + D_t - rP_t}{\gamma\sigma_P^2}, \quad i \in \{l, r\}. \tag{B.1}$$

We now solve the model. We start by conjecturing that, as stated in equation (15) of the main text, the equilibrium price of the risky asset is

$$P_t = A + B \cdot m_{t,1} + C \cdot m_{t,2} + \frac{D_t}{r}. \tag{B.2}$$

We solve for the three coefficients, A, B, and C, in three steps. The first step is to solve for LSN investors' share demand. Substituting (12) and (B.2) into (B.1), we obtain

$$N_t^l = \eta_0^l + \eta_1^l m_{t,1} + \eta_2^l m_{t,2}, \tag{B.3}$$

where

$$\eta_0^l = -\frac{rA}{\gamma\sigma_P^2}, \quad \eta_1^l = \frac{1-rB}{\gamma\sigma_P^2}, \quad \eta_2^l = -\frac{\sigma_P\alpha + rC}{\gamma\sigma_P^2}. \tag{B.4}$$

The next step is to solve for rational arbitrageurs' share demand. To do so, we take the differential form of (B.2)

$$dP_t = B \cdot dm_{t,1} + C \cdot dm_{t,2} + \frac{dD_t}{r}. \tag{B.5}$$

Substituting equations (12), (13) and (14) into (B.5) yields

$$dD_t = r\begin{pmatrix} (m_{t,1} - \sigma_P\alpha m_{t,2}) - \kappa B(\overline{\theta} - m_{t,1}) \\ +C(\alpha\delta + \delta)m_{t,2} \end{pmatrix} dt + r(\sigma_P - \sigma_{m1}B - \sigma_{m2}C)d\tilde{\omega}_t^l. \tag{B.6}$$

Comparing (B.6) with (1) leads to

$$d\tilde{\omega}_t^l = d\omega_t^D + (l_0 + l_1 m_{t,1} + l_2 m_{t,2})dt \tag{B.7}$$

and

$$\sigma_P = \frac{\sigma_D}{r} + \sigma_{m1}B + \sigma_{m2}C, \tag{B.8}$$

where $l_0 \equiv \sigma_D^{-1}(g_D + r\kappa B\overline{\theta})$, $l_1 \equiv -\sigma_D^{-1}r(1+\kappa B)$, $l_2 \equiv \sigma_D^{-1}r[\sigma_P\alpha - C(\alpha\delta+\delta)]$, $\sigma_{m1} \equiv \gamma_{11}\sigma_P^{-1} - \gamma_{12}\alpha$, and $\sigma_{m2} \equiv \delta + \gamma_{12}\sigma_P^{-1} - \gamma_{22}\alpha$, as defined in Proposition 1.

Substituting (B.7) into (12) gives (16), which represents rational arbitrageurs' beliefs about the price evolution. Moreover, substituting (B.7) into (13) and (14) gives (17) and (18), which represents rational arbitrageurs' beliefs about $m_{t,1}$ and $m_{t,2}$. We combine (B.1), (16), and (B.2) for rational arbitrageurs and obtain

$$N_t^r = \eta_0^r + \eta_1^r m_{t,1} + \eta_2^r m_{t,2}, \tag{B.9}$$

where

$$\begin{aligned} \eta_0^r &= \frac{\sigma_D^{-1}\sigma_P(g_D + r\kappa B\overline{\theta}) - rA}{\gamma\sigma_P^2}, \quad \eta_1^r = \frac{\sigma_D^{-1}\sigma_P[(\sigma_D\sigma_P^{-1} - r) - r\kappa B] - rB}{\gamma\sigma_P^2}, \\ \eta_2^r &= -\frac{\sigma_D^{-1}\sigma_P[(\sigma_D\sigma_P^{-1} - r)\sigma_P\alpha + rC(\alpha\delta + \delta)] + rC}{\gamma\sigma_P^2}. \end{aligned} \tag{B.10}$$

The final step is to substitute the share demands, (B.3) and (B.9), into the market clearing condition in (7). We then obtain

$$\begin{aligned} \mu\eta_0^r + (1-\mu)\eta_0^l &= Q, \\ \mu\eta_1^r + (1-\mu)\eta_1^l &= 0, \\ \mu\eta_2^r + (1-\mu)\eta_2^l &= 0. \end{aligned} \tag{B.11}$$

Substituting (B.4), (B.8), and (B.10) into (B.11) gives three simultaneous equations for three unknowns, A, B, and C. We solve these simultaneous equations using numerical methods. Once coefficients A, B, and C are solved, σ_P is then given by (B.8). ■

Appendix C. Model Extension

In this section, we briefly describe and then solve a more generalized model, one that features three types of investors: LSN investors with $\alpha > 0$, LSN investors with $\alpha = 0$, and rational arbitrageurs. We refer to LSN investors with $\alpha = 0$ as "extrapolators," because their beliefs about the future price change depend positively on past price changes. We then refer to LSN investors with $\alpha > 0$ simply as "LSN investors."

C.1. Model setup

Asset space. As in the baseline model, we consider two assets: a riskless asset with a constant interest rate r, and a risky asset. The risky asset has a fixed per-capita supply of Q, and its dividend payment evolves according to equation (1) in the main text. The price of the risky asset P_t is endogenously determined in equilibrium.

Investor beliefs. Rational arbitrageurs make up a fraction μ_r of the total population; extrapolators make up a fraction μ_e of the total popultion; and LSN investors make up the remaining fraction of $1 - \mu_r - \mu_e$.

LSN investors' perceived price processes are specified by equations (2) to (4). Extrapolators represent a special case of LSN investors. They believe

$$dP_t = \theta_t^e dt + \sigma_P d\tilde{\omega}_t^{P,e}, \tag{C.1}$$

where

$$d\theta_t^e = \kappa^e(\overline{\theta}^e - \theta_t^e)dt + \sigma_\theta^e d\tilde{\omega}_t^{\theta,e}, \tag{C.2}$$

and both $d\tilde{\omega}_t^{P,e}$ and $d\tilde{\omega}_t^{\theta,e}$ are perceived by extrapolators to be i.i.d. shocks that are independent of each other. Rational arbitrageurs hold fully rational beliefs: they understand the dividend process in equation (1); they observe parameters μ_r and μ_e and hence know the population fractions of LSN investors and the extrapolators; and they are aware of the belief structure of LSN investors and the belief structure of the extrapolators. Given this information set, rational arbitrageurs form correct beliefs about the evolution of the risky asset price.

Investor preferences. We assume that all three types of investors have instantaneous mean-variance preferences specified by

$$\max_{N_t^i} \left(\mathbb{E}_t^i[dW_t^i] - \frac{\gamma}{2} \mathbb{V}\text{ar}_t^i[dW_t^i] \right), \tag{C.3}$$

subject to the budget constraint on their wealth W_t^i

$$dW_t^i = rW_t^i dt - rN_t^i P_t dt + N_t^i dP_t + N_t^i D_t dt, \tag{C.4}$$

where N_t^i represents the per-capita share demand on the risky asset from investor i. Here, $i \in \{l, e, r\}$, where superscripts "l," "e," and "r" represent LSN investors, extrapolators, and rational arbitrageurs, respectively.

Market clearing. The share demands from LSN investors, extrapolators, and rational arbitrageurs satisfy the following market clearing condition

$$\mu_r N_t^r + \mu_e N_t^e + (1 - \mu_r - \mu_e) N_t^l = Q \tag{C.5}$$

at each point in time t.

C.2. Model solution

As in the baseline model, applying Kalman filters to equations (2) to (4) yields equations (12) to (14), which specifies the way in which LSN investors update their beliefs based on past prices. For the extrapolators, denote the conditional mean and variance of θ_t^e as

$$S_t = \mathbb{E}^e[\theta_t^e | \mathcal{F}_t^P], \qquad \zeta_t = \mathbb{E}^e[(\theta_t^e - S_t)^2 | \mathcal{F}_t^P]. \tag{C.6}$$

Then we apply Kalman filters (Theorem 12.7 from Lipster and Shiryaev, 2001) to (C.1) and (C.2) and obtain

$$dP_t = S_t dt + \sigma_P d\tilde{\omega}_t^e, \tag{C.7}$$

and

$$dS_t = \kappa^e(\overline{\theta}^e - S_t)dt + (\zeta \sigma_P^{-1}) d\tilde{\omega}_t^e, \tag{C.8}$$

where $d\tilde{\omega}_t^e$ is a Brownian shock perceived by extrapolators, and

$$\zeta = -\kappa^e \sigma_P^2 + \sqrt{(\kappa^e \sigma_P^2)^2 + (\sigma_\theta^e)^2 \sigma_P^2} \tag{C.9}$$

is the stationary solution for ζ_t in (C.8).

To solve the model, we first substitute (C.4) into (C.3) and obtain

$$N_t^i = \frac{\mathbb{E}_t^i[dP_t]/dt + D_t - rP_t}{\gamma \sigma_P^2}, \qquad i \in \{l, e, r\}. \tag{C.10}$$

We conjecture that the equilibrium price of the risky asset is

$$P_t = A + B_1 \cdot m_{t,1} + B_2 \cdot m_{t,2} + C \cdot S_t + \frac{D_t}{r}. \tag{C.11}$$

Substituting (12) and (C.11) into (C.10) for LSN investors, we obtain

$$N_t^l = \eta_0^l + \eta_1^l m_{t,1} + \eta_2^l m_{t,2} + \eta_3^l S_t, \tag{C.12}$$

where

$$\eta_0^l = -\frac{rA}{\gamma\sigma_P^2}, \quad \eta_1^l = \frac{1 - rB_1}{\gamma\sigma_P^2}, \quad \eta_2^l = -\frac{\sigma_P\alpha + rB_2}{\gamma\sigma_P^2}, \quad \eta_3^l = -\frac{rC}{\gamma\sigma_P^2}. \tag{C.13}$$

We then substitute (C.7) and (C.11) into (C.10) for extrapolators and obtain

$$N_t^e = \eta_0^e + \eta_1^e m_{t,1} + \eta_2^e m_{t,2} + \eta_3^e S_t, \tag{C.14}$$

where

$$\eta_0^e = -\frac{rA}{\gamma\sigma_P^2}, \quad \eta_1^e = -\frac{rB_1}{\gamma\sigma_P^2}, \quad \eta_2^e = -\frac{rB_2}{\gamma\sigma_P^2}, \quad \eta_3^e = \frac{1 - rC}{\gamma\sigma_P^2}. \tag{C.15}$$

Finally, we examine the share demand of rational arbitrageurs. We take the differential form of (C.11)

$$dP_t = B_1 \cdot dm_{t,1} + B_2 \cdot dm_{t,2} + C \cdot dS_t + \frac{dD_t}{r}. \tag{C.16}$$

Note that $dS_t = \kappa^e(\overline{\theta}^e - S_t)dt + (\zeta\sigma_P^{-2})(dP_t - S_t dt)$. Substituting this equation and equations (12) to (14) into (C.11), we get

$$\begin{aligned} dD_t = \;& r\begin{pmatrix} [1 - C \cdot (\zeta\sigma_P^{-2})](m_{t,1} - \sigma_P\alpha m_{t,2}) - \kappa B_1(\overline{\theta} - m_{t,1}) \\ +B_2(\alpha\delta + \delta)m_{t,2} - C\kappa^e\overline{\theta}^e + C[\kappa^e + (\zeta\sigma_P^{-2})]S_t \end{pmatrix} dt \\ & +r\left([1 - C \cdot (\zeta\sigma_P^{-2})]\sigma_P - B_1\sigma_{m1} - B_2\sigma_{m2}\right) d\tilde{\omega}_t^l. \end{aligned} \tag{C.17}$$

Comparing (C.17) with (1) gives

$$d\tilde{\omega}_t^l = d\omega_t^D + \sigma_D^{-1} r \begin{pmatrix} r^{-1}g_D - [1 - C \cdot (\zeta\sigma_P^{-2})](m_{t,1} - \sigma_P\alpha m_{t,2}) \\ +\kappa B_1(\overline{\theta} - m_{t,1}) - B_2(\alpha\delta + \delta)m_{t,2} \\ +C\kappa^e\overline{\theta}^e - C[\kappa^e + (\zeta\sigma_P^{-2})]S_t \end{pmatrix} dt \tag{C.18}$$

and

$$\sigma_P = \frac{1}{1 - C \cdot (\zeta\sigma_P^{-2})}\left(\frac{\sigma_D}{r} + B_1\sigma_{m1} + B_2\sigma_{m2}\right). \tag{C.19}$$

Substituting (C.18) into (12), we have

$$dP_t = \sigma_P\sigma_D^{-1} r \begin{pmatrix} r^{-1}g_D - [1 - C \cdot (\zeta\sigma_P^{-2})](m_{t,1} - \sigma_P\alpha m_{t,2}) \\ +\kappa B_1(\overline{\theta} - m_{t,1}) - B_2(\alpha\delta + \delta)m_{t,2} \\ +C\kappa^e\overline{\theta}^e - C[\kappa^e + (\zeta\sigma_P^{-2})]S_t \\ +r^{-1}\sigma_D\sigma_P^{-1}(m_{t,1} - \sigma_P\alpha m_{t,2}) \end{pmatrix} dt + \sigma_P d\omega_t^D. \tag{C.20}$$

Then, further substituting (C.20) and (C.11) into (C.10) for rational arbitrageurs, we get

$$N_t^r = \eta_0^r + \eta_1^r m_{t,1} + \eta_2^r m_{t,2} + \eta_3^r S_t, \tag{C.21}$$

where

$$\begin{aligned}
\eta_0^r &= \frac{\sigma_P \sigma_D^{-1}(g_D + r\kappa B_1 \overline{\theta} + r\kappa^e C \overline{\theta}^e) - rA}{\gamma \sigma_P^2}, \\
\eta_1^r &= \frac{\sigma_P \sigma_D^{-1}[\sigma_D \sigma_P^{-1} - r(1 - C \cdot (\zeta \sigma_P^{-2})) - r\kappa B_1] - rB_1}{\gamma \sigma_P^2}, \\
\eta_2^r &= -\frac{\sigma_P \sigma_D^{-1}[(\sigma_D \sigma_P^{-1} - r(1 - C \cdot (\zeta \sigma_P^{-2})))\sigma_P \alpha + rB_2(\alpha\delta + \delta)] + rB_2}{\gamma \sigma_P^2}, \\
\eta_3^r &= -\frac{\sigma_P \sigma_D^{-1} rC[\kappa^e + (\zeta \sigma_P^{-2})] + rC}{\gamma \sigma_P^2}.
\end{aligned} \tag{C.22}$$

The final step is to substitute the share demands, (C.12), (C.14), and (C.21), into the market clearing condition in (C.5). We obtain

$$\begin{aligned}
\mu_r \eta_0^r + \mu_e \eta_0^e + (1 - \mu_r - \mu_e)\eta_0^l &= Q, \\
\mu_r \eta_1^r + \mu_e \eta_1^e + (1 - \mu_r - \mu_e)\eta_1^l &= 0, \\
\mu_r \eta_2^r + \mu_e \eta_2^e + (1 - \mu_r - \mu_e)\eta_2^l &= 0, \\
\mu_r \eta_3^r + \mu_e \eta_3^e + (1 - \mu_r - \mu_e)\eta_3^l &= 0.
\end{aligned} \tag{C.23}$$

Substituting (C.13), (C.15), (C.19), and (C.22) into (C.23) gives four simultaneous equations for four unknowns, A, B_1, B_2, and C. We solve these simultaneous equations using numerical methods. Once coefficients A, B_1, B_2, and C are solved, σ_P is then given by (C.19). ■

Appendix D. Model-implied co-existence of the disposition effect and excess volatility

D.1. The baseline model

Our baseline model described in Section 3.1, under the specified default parameter values, generates *both* the disposition effect on the part of LSN investors and excess volatility of instantaneous price changes; see the discussions in Sections 3.4 and 3.5.

To understand how the model produces both the disposition effect and excess volatility, Fig. D1 plots the model's impulse responses. Specifically, we discretize the baseline continuous-time model at the monthly frequency and set it to the steady state at time 1. We then impose a positive Brownian shock $d\omega_t^D$ of size 1 on the risky asset's dividend at time 2. Given this impulse, we plot the fundamental component of price movement $(D_t - D_{t-1})/r$, the cumulative price movement $P_t - P_0$, LSN investors' inferred mean of θ_t, namely $m_{t,1}$, LSN investors' inferred mean of $\overline{\omega}_t$, namely $m_{t,2}$, LSN investors' beliefs $m_{t,1} - \sigma_P \alpha m_{t,2}$, and LSN investors' share demand N_t^l; here, time t goes from 1 to 40. Note that for the "cumulative price movement" panel (the upper right panel), the red dashed line plots the cumulative movement of the risky asset price's fundamental component, namely $(D_t - D_0)/r$.

[Place Fig. D1 about here]

Fig. D1 shows that, upon a good fundamental shock, LSN investors hold contrarian beliefs in the short run. Their share demand goes down, and they exhibit the disposition effect. At the same time, the risky asset price immediately exhibits overreaction: in the upper right panel, the blue solid line goes above the red dashed line at $t = 2$. Therefore, in our baseline model, the excess volatility of instantaneous price changes directly results from the trading of rational arbitrageurs: while LSN investors become contrarian at $t = 2$, rational arbitrageurs, being forward-looking, correctly anticipate that LSN investors will contribute to the subsequent momentum. Rational arbitrageurs become more extrapolative, and their aggressive buying of the risky asset directly contributes to its overpricing.

D.2. An alternative model with LSN investors and fundamental traders

The discussion above suggests an interesting implication of our baseline model: while the model's asset pricing dynamics are mainly driven by LSN investors' incorrect beliefs, the excess volatility of short-term price changes is caused by rational arbitrageurs responding to LSN investors' beliefs. In this section, we briefly describe an alternative model, one in which we replace rational arbitrageurs by boundedly-rational fundamental traders who simply lean against the wind, buying the risky asset when it is undervalued and selling when it is overvalued. As we discuss later, this alternative model allows LSN investors' beliefs to drive *all* asset pricing dynamics, including the volatility of short-term price changes.

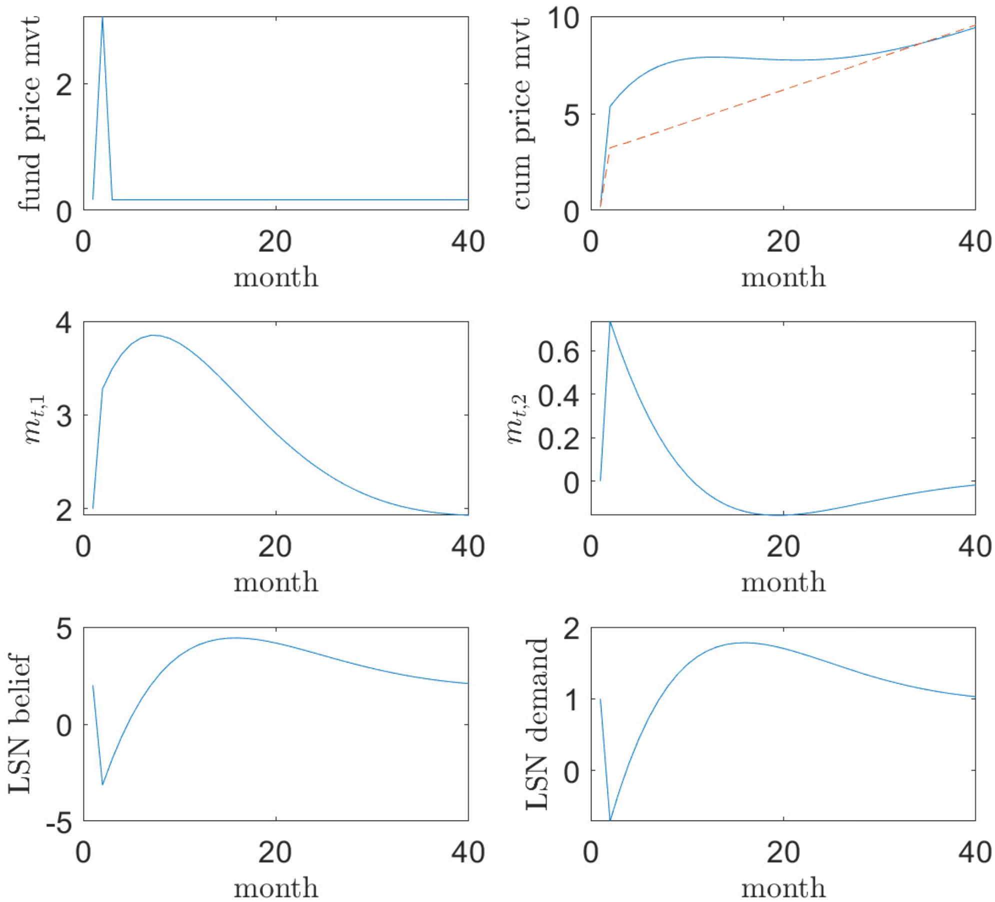


Fig. D1. Impulse responses of the baseline model.

We discretize the baseline continuous-time model described in Section 3.1 at the monthly frequency and set it to the steady state at time 1. We then impose a positive Brownian shock $d\omega_t^D$ of 1 on the risky asset's dividend at time 2. The figure plots, for time t where t goes from 1 to 40, the fundamental component of price movement $(D_t - D_{t-1})/r$, the cumulative price movement $P_t - P_0$, LSN investors' inferred mean of θ_t, namely $m_{t,1}$, LSN investors' inferred mean of $\overline{\omega}_t$, namely $m_{t,2}$, LSN investors' beliefs $m_{t,1} - \sigma_P \alpha m_{t,2}$, and LSN investors' share demand N_t^l. For the "cumulative price movement" panel (the upper right panel), the red dashed line plots the cumulative movement of the risky asset price's fundamental component, namely $(D_t - D_0)/r$. The parameter values are: $g_D = 0.05$, $\sigma_D = 0.25$, $r = 0.025$, $Q = 1$, $\kappa = 0.05$, $\sigma_\theta = 5$, $\alpha = 0.5$, $\delta = 2.77$, $\overline{\theta} = 2$, $\gamma = 0.01$, and $\mu = 0.5$.

In this model, fundamental traders are assumed to make up a fraction μ of the total population. They maximize instantaneous mean-variance preferences

$$\max_{N_t^f} \left(\mathbb{E}_t^f[dW_t^f] - \frac{\gamma}{2} \mathbb{V}\mathrm{ar}_t^f[dW_t^f] \right), \tag{D.1}$$

subject to the budget constraint on their wealth W_t^f

$$dW_t^f = rW_t^f dt - rN_t^f P_t dt + N_t^f dP_t + N_t^f D_t dt, \tag{D.2}$$

where N_t^f represents the per-capita share demand on the risky asset from fundamental traders. Given equations (D.1) and (D.2), the fundamental traders' optimal share demand is

$$N_t^f = \frac{\mathbb{E}_t^f[dP_t]/dt + D_t - rP_t}{\gamma \mathbb{V}\mathrm{ar}_t^f[dP_t]/dt}. \tag{D.3}$$

Recall that the price equation in equilibrium is

$$P_t = A + B \cdot m_{t,1} + C \cdot m_{t,2} + \frac{D_t}{r}. \tag{D.4}$$

We specify fundamental traders' beliefs about $\mathbb{E}_t^f[dP_t]/dt$ and $\mathbb{V}\mathrm{ar}_t^f[dP_t]/dt$ as

$$\mathbb{E}_t^f[dP_t]/dt \equiv \psi[B(\overline{\theta} - m_{t,1}) + C(-m_{t,2})] + \frac{g_D}{r} \tag{D.5}$$

and

$$\mathbb{V}\mathrm{ar}_t^f[dP_t]/dt = \sigma_P^2. \tag{D.6}$$

In words, equation (D.5) says that when observing an equilibrium price of P_t, fundamental traders expect it to convert towards a "fundamental price" of

$$P_{f,t} = A + B \cdot \overline{\theta} + C \cdot 0 + \frac{D_t}{r}, \tag{D.7}$$

and the speed of such convergence is captured by parameter ψ. Equation (D.6) says that fundamental traders correctly observe price volatility; this is a natural assumption for continuous-time models.

The model described above can be solved in the same way as for the baseline model. For this alternative model, Fig. D2 plots its impulse responses. Specifically, we set the following parameter values: $g_D = 0.05$, $\sigma_D = 0.25$, $r = 0.025$, $Q = 1$, $\kappa = 0.05$, $\sigma_\theta = 5$, $\alpha = 0.5$, $\delta = 2.77$, $\overline{\theta} = 2$, $\psi = 1.5$, $\gamma = 0.01$, and $\mu = 0.5$. We discretize the model at the monthy frequency and set it to the steady state at time 1. We then impose a positive Brownian shock $d\omega_t^D$ of size 1 on the risky asset's dividend at time 2. Given this impulse, we plot the fundamental component of price movement $(D_t - D_{t-1})/r$, the cumulative price movement $P_t - P_0$, LSN investors' inferred mean of θ_t, namely $m_{t,1}$, LSN investors' inferred mean of $\overline{\omega}_t$, namely $m_{t,2}$, LSN investors' beliefs $m_{t,1} - \sigma_P \alpha m_{t,2}$, and

LSN investors' share demand N_t^l; here, time t goes from 1 to 40. Note that for the "cumulative price movement" panel (the upper right panel), the red dashed line plots the cumulative movement of the risky asset price's fundamental component, namely $(D_t - D_0)/r$.

[Place Fig. D2 about here]

Fig. D2 shows that, upon a good fundamental shock, LSN investors hold contrarian beliefs in the short run. Their share demand goes down, and they exhibit the disposition effect. The disposition effect in turn causes the risky asset price to exhibit immediate underreaction; in the upper right panel, the blue solid line is below the red dashed line at $t = 2$. In this model, fundamental traders only passively respond to the mispricing caused by LSN investors; they do not cause excess volatility. As such, the asset pricing dynamics match closely with LSN investors' beliefs: we observe initial under-volatility of short-term price changes; we then observe subsequent excess volatility of longer-term price changes. This model again generates both short-term momentum and long-term reversals.

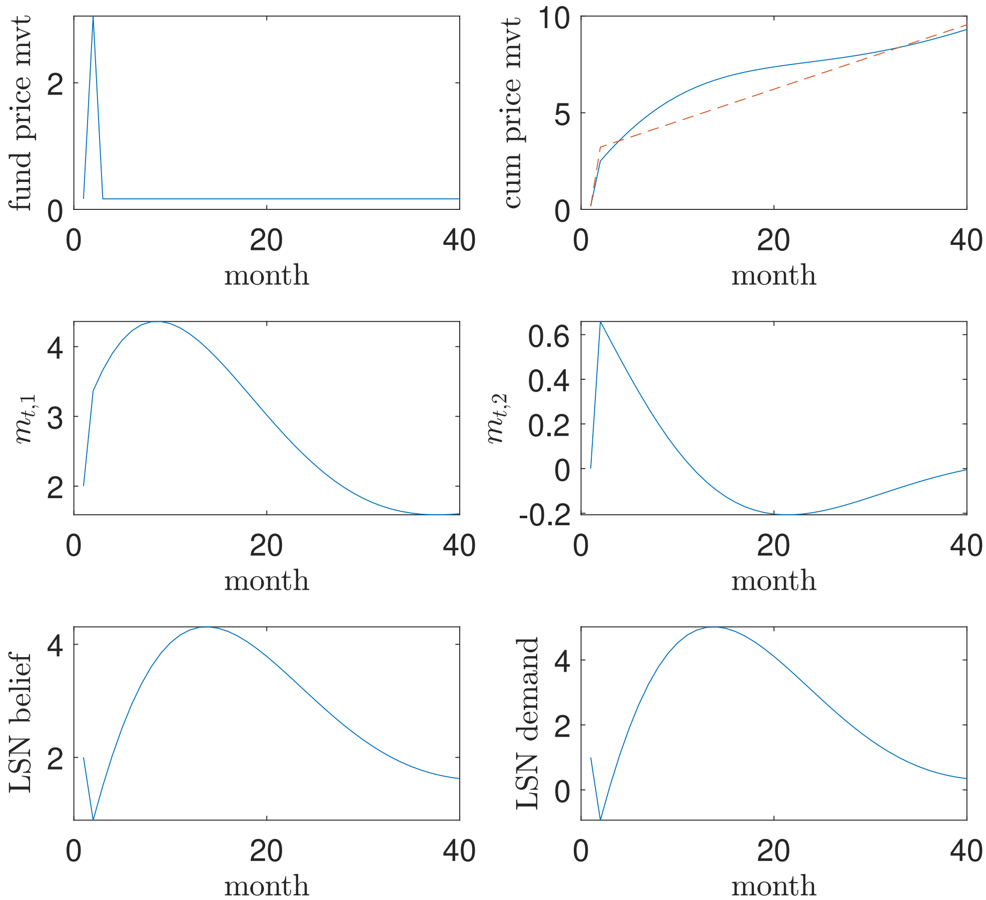


Fig. D2. Impulse responses of the alternative model with LSN investors and fundamental traders.

We discretize the alternative continuous-time model described in Section D.2 at the monthly frequency and set it to the steady state at time 1. We then impose a positive Brownian shock $d\omega_t^D$ of 1 on the risky asset's dividend at time 2. The figure plots, for time t where t goes from 1 to 40, the fundamental component of price movement $(D_t - D_{t-1})/r$, the cumulative price movement $P_t - P_0$, LSN investors' inferred mean of θ_t, namely $m_{t,1}$, LSN investors' inferred mean of $\overline{\omega}_t$, namely $m_{t,2}$, LSN investors' beliefs $m_{t,1} - \sigma_P \alpha m_{t,2}$, and LSN investors' share demand N_t^l. For the "cumulative price movement" panel (the upper right panel), the red dashed line plots the cumulative movement of the risky asset price's fundamental component, namely $(D_t - D_0)/r$. The parameter values are: $g_D = 0.05$, $\sigma_D = 0.25$, $r = 0.025$, $Q = 1$, $\kappa = 0.05$, $\sigma_\theta = 5$, $\alpha = 0.5$, $\delta = 2.77$, $\overline{\theta} = 2$, $\psi = 1.5$, $\gamma = 0.01$, and $\mu = 0.5$.

Appendix E. Alternative Specification of LSN Beliefs

The baseline model described in Section 3.1 applies the LSN to the price process; beliefs of LSN investors are specified by equations (2) to (4) in the main text. In this section, we consider an alternative specification in which the LSN is applied to the dividend process. As before, this modified model contains two assets: a risk-free asset and a risky asset. The risk-free asset pays a constant interest rate of r. The stock market has a fixed per-capita supply of Q, and its dividend payment evolves according to

$$dD_t = g_D dt + \sigma_D d\omega_t^D. \tag{E.1}$$

LSN investors are now assumed to perceive the following dividend process

$$\begin{aligned} dD_t = \theta_t dt + \sigma_D d\tilde{\omega}_t^D, \qquad d\theta_t = \kappa(\bar{\theta} - \theta_t)dt + \sigma_\theta d\tilde{\omega}_t^\theta, \\ d\tilde{\omega}_t^D = d\tilde{\omega}_t - \alpha\left(\delta \int_{-\infty}^{t} e^{-\delta(t-s)} d\tilde{\omega}_s^D\right) dt. \end{aligned} \tag{E.2}$$

In words, LSN investors perceive future dividend changes as coming from two components: a persistent yet time-varying quality component, and a transitory noise component that exhibits a negative serial autocorrelation.

An equivalent specification of (E.2) is

$$\begin{aligned} dD_t &= (\theta_t - \sigma_D \alpha \overline{\omega}_t)dt + \sigma_D d\tilde{\omega}, \qquad d\theta_t = \kappa(\bar{\theta} - \theta_t)dt + \sigma_\theta d\tilde{\omega}_t^\theta, \\ d\overline{\omega}_t &= -(\alpha\delta + \delta)\overline{\omega}_t dt + \delta d\tilde{\omega}_t, \end{aligned} \tag{E.3}$$

where $\overline{\omega}_t \equiv \int_{-\infty}^{t} \delta e^{-\delta(t-s)} d\tilde{\omega}_s^D$ and $\mathbb{E}_t^l[d\tilde{\omega}_t \cdot d\tilde{\omega}_t^\theta] = 0$.

LSN investors do not observe θ_t and $\overline{\omega}_t$; they use Bayesian inference to estimate both quantities and then use these estimated quantities to guide trading decisions. Their information set at time t, $\mathcal{F}_t^D$, is defined using past dividends $\{D_s, s \leq t\}$—that is, LSN investors update their beliefs about θ_t and $\overline{\omega}_t$ using past dividends as informative signals. The conditional means and variances of $\boldsymbol{\theta}_t \equiv (\theta_t, \overline{\omega}_t)$ are defined by

$$\begin{aligned} \boldsymbol{m}_t &= (m_{t,1}, m_{t,2}) \equiv \mathbb{E}^l[(\theta_t, \overline{\omega}_t)|\mathcal{F}_t^D], \\ \boldsymbol{\gamma}_t &= \begin{pmatrix} \gamma_{t,11} & \gamma_{t,12} \\ \gamma_{t,21} & \gamma_{t,22} \end{pmatrix} \equiv \mathbb{E}^l[(\boldsymbol{\theta}_t - \boldsymbol{m}_t)^T(\boldsymbol{\theta}_t - \boldsymbol{m}_t)|\mathcal{F}_t^D]. \end{aligned} \tag{E.4}$$

We then apply Kalman filtering and obtain

$$dD_t = (m_{t,1} - \sigma_D \alpha m_{t,2})dt + \sigma_D d\tilde{\omega}_t^l \tag{E.5}$$

and

$$dm_{t,1} = \kappa(\overline{\theta} - m_{t,1})dt + \underbrace{(\gamma_{11}\sigma_D^{-1} - \gamma_{12}\alpha)}_{\sigma_{m1}} d\tilde{\omega}_t^l, \tag{E.6}$$

$$dm_{t,2} = -(\alpha\delta + \delta)m_{t,2}dt + \underbrace{(\delta + \gamma_{12}\sigma_D^{-1} - \gamma_{22}\alpha)}_{\sigma_{m2}} d\tilde{\omega}_t^l, \tag{E.7}$$

where $d\tilde{\omega}_t^l$ is a Brownian shock perceived by LSN investors, and γ_{11}, γ_{12}, and γ_{22} are the stationary solutions for $\gamma_{t,11}$, $\gamma_{t,12}$, and $\gamma_{t,22}$, respectively. In these equations, $m_{t,1}$ and $m_{t,2}$ represent the inferred quantities of θ_t and $\overline{\omega}_t$. Moreover, γ_{11}, γ_{12}, and γ_{22} are the solution of

$$\begin{pmatrix} 2\kappa\gamma_{11} & (\kappa + \alpha\delta + \delta)\gamma_{12} \\ (\kappa + \alpha\delta + \delta)\gamma_{12} & 2(\alpha\delta + \delta)\gamma_{22} \end{pmatrix} = \begin{pmatrix} \sigma_\theta^2 & 0 \\ 0 & \delta^2 \end{pmatrix}$$
$$- \begin{pmatrix} (\sigma_D^{-1}\gamma_{11} - \alpha\gamma_{12})^2 & (\sigma_D^{-1}\gamma_{11} - \alpha\gamma_{12})(\delta + \sigma_D^{-1}\gamma_{12} - \alpha\gamma_{22}) \\ (\sigma_D^{-1}\gamma_{11} - \alpha\gamma_{12})(\delta + \sigma_D^{-1}\gamma_{12} - \alpha\gamma_{22}) & (\delta + \sigma_D^{-1}\gamma_{12} - \alpha\gamma_{22})^2 \end{pmatrix}. \tag{E.8}$$

As in the baseline model, we assume there are two types of investors: LSN investors and rational arbitrageurs. Rational arbitrageurs make up μ fraction of the total population; LSN investors make up the remaining $1 - \mu$ fraction. Both LSN investors and rational arbitrageurs maximize instantaneous mean-variance preferences, specified by

$$\max_{N_t^i} \left(\mathbb{E}_t^i[dW_t^i] - \frac{\gamma}{2} \mathbb{V}\mathrm{ar}_t^i[dW_t^i] \right), \tag{E.9}$$

subject to the budget constraint on their wealth W_t^i

$$dW_t^i = rW_t^i dt - rN_t^i P_t dt + N_t^i dP_t + N_t^i D_t dt, \tag{E.10}$$

where N_t^i represents the per-capita share demand on the risky asset from investor i and $i \in \{l, r\}$. Substituting (E.10) into (E.9) gives

$$N_t^i = \frac{\mathbb{E}_t^i[dP_t]/dt + D_t - rP_t}{\gamma\sigma_P^2}. \tag{E.11}$$

The conjectured equilibrium price of the stock market is

$$P_t = A + B \cdot m_{t,1} + C \cdot m_{t,2} + \frac{D_t}{r}. \tag{E.12}$$

As before, we solve for the three unknowns, A, B, and C, in three steps. The first step is to solve for LSN investors' share demand. LSN investors differentiate both sides of (E.12) and obtain

$$dP_t = B \cdot dm_{t,1} + C \cdot dm_{t,2} + \frac{dD_t}{r}. \tag{E.13}$$

They then substitute equations (E.5) and (E.6) to the right hand side of (E.12) and obtain

$$\begin{aligned} dP_t &= B\kappa(\overline{\theta} - m_{t,1})dt + B\sigma_{m1}d\omega_t^l - C(\alpha\delta + \delta)m_{t,2}dt + C\sigma_{m2}d\omega_t^l \\ &+ r^{-1}(m_{t,1} - \sigma_D\alpha m_{t,2})dt + r^{-1}\sigma_D d\omega_t^l. \end{aligned} \tag{E.14}$$

LSN investors' expected price change is therefore

$$\mathbb{E}_t^l[dP_t]/dt = B\kappa(\overline{\theta} - m_{t,1}) - C(\alpha\delta + \delta)m_{t,2} + r^{-1}(m_{t,1} - \sigma_D\alpha m_{t,2}). \tag{E.15}$$

Substituting (E.15) and (E.12) into (E.11) gives

$$\begin{aligned} N_t^l &= \frac{B\kappa(\overline{\theta} - m_{t,1}) - C(\alpha\delta + \delta)m_{t,2} + r^{-1}(m_{t,1} - \sigma_D\alpha m_{t,2}) - rA - rB \cdot m_{t,1} - rC \cdot m_{t,2}}{\gamma\sigma_P^2} \\ &\equiv \eta_0^l + \eta_1^l m_{t,1} + \eta_2^l m_{t,2}, \end{aligned} \tag{E.16}$$

where

$$\eta_0^l = \frac{B\kappa\overline{\theta} - rA}{\gamma\sigma_P^2}, \quad \eta_1^l = \frac{r^{-1} - \kappa B - rB}{\gamma\sigma_P^2}, \quad \eta_2^l = -\frac{C(\alpha\delta + \delta) + r^{-1}\sigma_D\alpha + rC}{\gamma\sigma_P^2}. \tag{E.17}$$

The next step is to solve for rational arbitrageurs' share demand. We compare (E.5) with (E.1) and obtain

$$d\omega_t^l = d\omega_t^D + \sigma_D^{-1}(g_D - m_{t,1} + \sigma_D\alpha m_{t,2})dt. \tag{E.18}$$

Substituting (E.18) into (E.14) gives

$$dP_t = \begin{pmatrix} B\kappa(\bar{\theta} - m_{t,1}) - C(\alpha\delta + \delta)m_{t,2} \\ +r^{-1}(m_{t,1} - \sigma_D\alpha m_{t,2}) \\ +\sigma_D^{-1}\sigma_P(g_D - m_{t,1} + \sigma_D\alpha m_{t,2}) \end{pmatrix} dt + \sigma_P d\omega_t^D \tag{E.19}$$

and

$$\sigma_P = \frac{\sigma_D}{r} + \sigma_{m1}B + \sigma_{m2}C. \tag{E.20}$$

Equations (E.19) and (E.20) represent rational arbitrageurs' beliefs about price evolution. We then combine (E.19), (E.11), and (E.12) to obtain

$$N_t^r \equiv \eta_0^r + \eta_1^r m_{t,1} + \eta_2^r m_{t,2}, \tag{E.21}$$

where

$$\eta_0^r = \frac{B\kappa\bar{\theta} - rA + \sigma_D^{-1}\sigma_P g_D}{\gamma\sigma_P^2}, \quad \eta_1^r = \frac{r^{-1} - \kappa B - rB - \sigma_D^{-1}\sigma_P}{\gamma\sigma_P^2},$$
$$\eta_2^r = -\frac{C(\alpha\delta + \delta) + r^{-1}\sigma_D\alpha + rC - \sigma_P\alpha}{\gamma\sigma_P^2}. \tag{E.22}$$

The final step is to substitute the share demands (E.16) and (E.21) into the market clearing condition $\mu N_t^r + (1-\mu)N_t^l = Q$. We arrive at three equations

$$\begin{aligned} \mu\eta_0^r + (1-\mu)\eta_0^l &= Q, \\ \mu\eta_1^r + (1-\mu)\eta_1^l &= 0, \\ \mu\eta_2^r + (1-\mu)\eta_2^l &= 0. \end{aligned} \tag{E.23}$$

Substituting (E.17), (E.20), and (E.22) into (E.23) gives three simultaneous equations for three unknowns, A, B, and C. We solve these equations using numerical methods. ■

Appendix F. Summary statistics

In this section, we present the summary statistics of the brokerage data. Given that we apply different filters and use a different procedure in constructing the final data set, our final sample is slightly different from the one used in Barber and Odean (2000). In Table F1 below, we directly compare the distributions of trade size and transaction price to those in Barber and Odean (2000) (Table 1). Overall, the distributions are very similar in magnitude, suggesting direct comparability.

	Mean	25th Percentile	Median	75th Percentile	Standard Deviation	N
Panel A: purchases						
Trade size ($)	10,092	2,450	4,800	9,875	31,708	850,579
Price per share	28.86	10.75	21.75	37.88	113.32	850,579
Panel B: sales						
Trade size ($)	12,807	2,875	5,875	12,975	27,416	464,713
Price per share	28.73	11.38	22.13	38.63	78.84	464,713

Table F1. Summary statistics of the brokerage data.

Appendix G. Evidence from initial buys

In this section, we present additional evidence on the return patterns of initial buys. We aggregate the lagged monthly market-adjusted return before the purchase takes place across all initial buys. The stock tends to exhibit strong positive returns from approximately 36 months prior to the purchase up until around 5 months prior, but then experiences a decline in returns, including some periods of negative returns. This decrease in return is particularly evident for the most recent month, with a median lagged one-month return of approximately -0.4%.

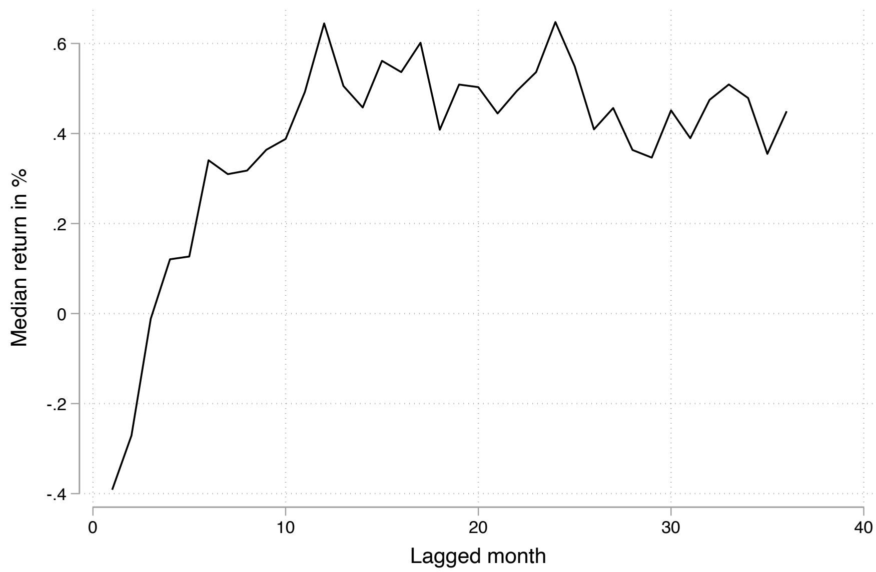


Fig. G1. Return patterns before initial buys.

This figure plots the return patterns before initial buys, using transactions observed in the brokerage data. An initial buy is defined as a purchase of a stock that is currently not in the portfolio. Detailed descriptions about the data and the filters used in constructing the data set can be found in Section 4.1. Each initial buy is considered as a separate observation, and we aggregate across all initial buys the lagged monthly market-adjusted return before the buy takes place. The line plots the median monthly return across all observations.

Appendix H. Evidence from a Chinese broker

Similar to Table 3, we regress buying and selling propensities on past returns, using data from a large Chinese brokerage firm. The main difference is that Chinese retail investors have a much shorter look-back window compared to investors in the U.S. brokerage data. For instance, in Table 3, the regression coefficient in Column (2) flips signs for the lagged return from three quarters ago; by contrast, in Table H1, the sign flips for the lagged return from about three weeks ago.

	(1)	(2)	(3)	(4)
	(Buy−Sell)/(Buy+Sell)		Buy−Sell	
Lagged return, 1W	–0.329***	–0.326***	–0.0104***	–0.0104***
	(0.0146)	(0.0146)	(0.00118)	(0.00119)
Lagged return, 2W	–0.0634***	–0.0600***	–0.00134**	–0.00134**
	(0.00969)	(0.00981)	(0.000620)	(0.000613)
Lagged return, 3W	0.00182	0.00516	–0.00152*	–0.00152*
	(0.00921)	(0.00928)	(0.000790)	(0.000800)
Lagged return, 4W	0.0333***	0.0381***	0.000957*	0.000987*
	(0.00885)	(0.00898)	(0.000531)	(0.000526)
Lagged return, 5W		0.0365***		0.000522
		(0.00857)		(0.000617)
Lagged return, 6W		0.0215**		0.000329
		(0.00844)		(0.000598)
Lagged return, 7W		0.0147*		–0.000465
		(0.00836)		(0.000548)
Lagged return, 8W		0.0288***		0.000175
		(0.00821)		(0.000484)
Lagged return, 9W		0.0282***		–0.000109
		(0.00777)		(0.000498)
Lagged return, 10W		0.0152**		–0.000144
		(0.00770)		(0.000405)
Lagged return, 11W		0.0277***		–0.000680
		(0.00793)		(0.000634)
Lagged return, 12W		0.0155**		–0.000912*
		(0.00718)		(0.000530)
Observations	2,754,207	2,754,207	2,754,207	2,754,207
R-squared	0.014	0.014	0.001	0.001

Clustered standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table H1. Stock-level regressions results, Chinese brokerage data.

On each date, we aggregate all the transactions for each stock to get the total volume (in thousand shares) of buy and sell, denoted by Buy and Sell. Stock and date fixed effects are included. Standard errors are double-clustered by stock and date.

Appendix I. Additional evidence on the V-shape

Our model makes predictions about the sensitivity of trading to *recent* returns. When the holding period is short, recent returns overlap but do not coincide exactly with *holding-period* returns. In this section, we reexamine the probability of selling and the probability of buying, each as a function of the past one-month return, and find supportive evidence for Prediction 6.

We again confirm the existence of the V-shape by first plotting, in Fig. I1, the probability of selling as a function of the past one-month return observed in daily portfolios. As before, we only consider positions with a prior holding-period of less than one month, and we require that a daily portfolio contains at least five positions. The upper left panel in Fig. I1 clearly shows a V-shape. In the other panels, we examine the pattern of selling propensity separately for the five groups described in Sections 4.4 and 4.5. We find substantial heterogeneity. For instance, in Groups 4 and 5, the sensitivity of selling to the past one-month return is close to zero in the loss region.

[Place Fig. I1 about here]

We repeat this analysis for buying behavior in Fig. I2. First, in the upper left panel, the probability of buying as a function of the past one-month return is V-shaped. In the other panels, we examine the pattern of buying propensity separately for the five groups. Again, we find substantial heterogeneity. The contrast across the five groups is stark. For instance, in Group 1, the buying propensity is monotonically increasing in the past one-month return in the gain region but remains flat in the loss region. In Group 5, these patterns flip: the buying propensity is monotonically decreasing in the past one-month return in the loss region but remains flat in the gain region.

[Place Fig. I2 about here]

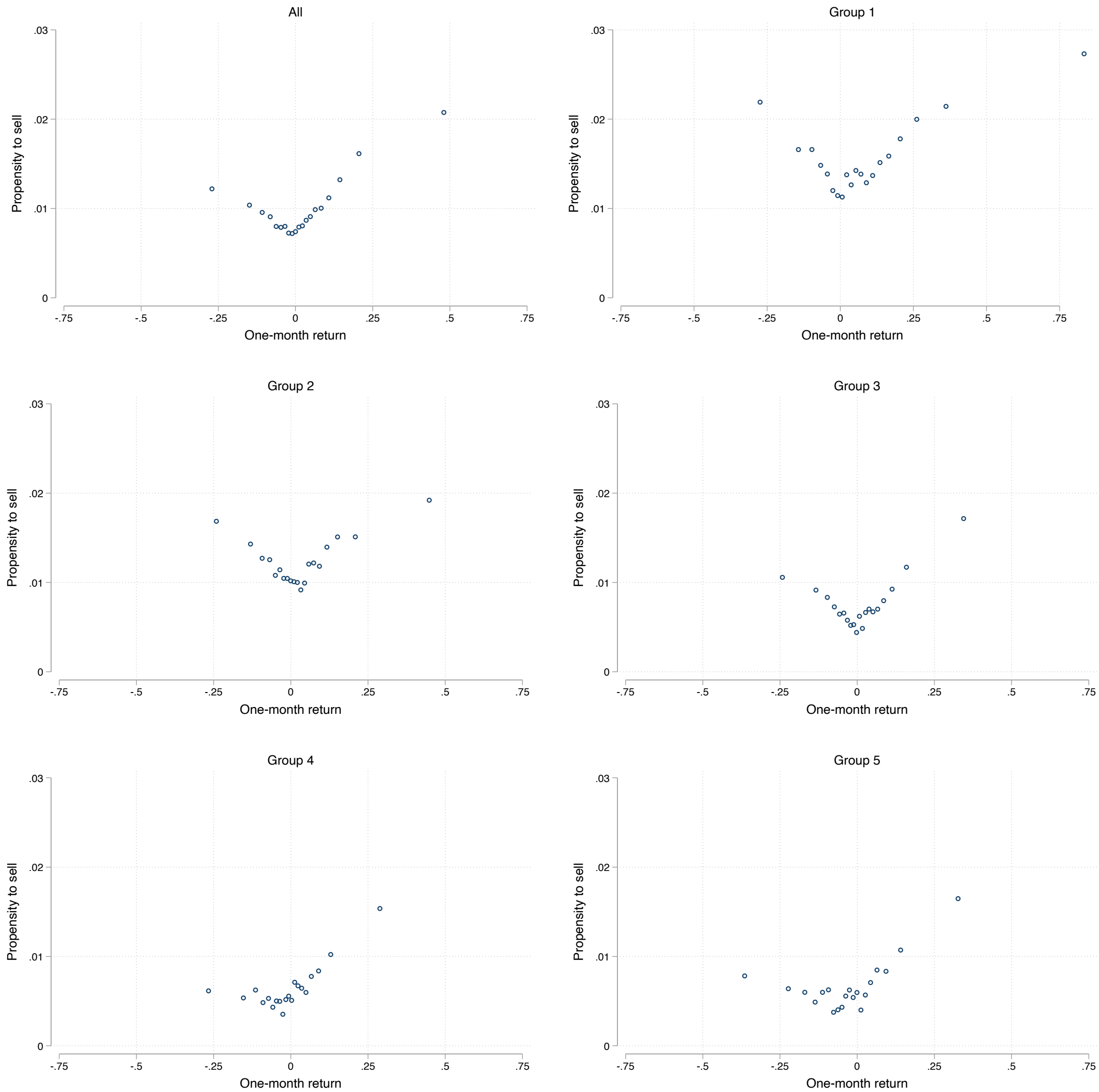


Fig. I1. V-shape selling behavior.

This figure examines the probability of selling as a function of holding-period returns, using the daily portfolios constructed from the brokerage data. Detailed descriptions about the data and the filters used in constructing the daily portfolios can be found in Section 4.1. When calculating the probability of selling, we consider only positions with a prior holding period of less than one month. In addition, we require that a daily portfolio contains at least five positions. In a given panel, each dot plots, on a random day, the probability of selling a stock conditional on the past one-month return, shown in the x-axis. The upper left panel concerns all investors. For the remaining five panels, they each concern one group of investors. All investors are first sorted into five groups based on their degree of doubling down, measured by the average stock return in most recent month across all buys. Each panel then represents one group, with Group 1 having the lowest degree of doubling down while Group 5 highest.

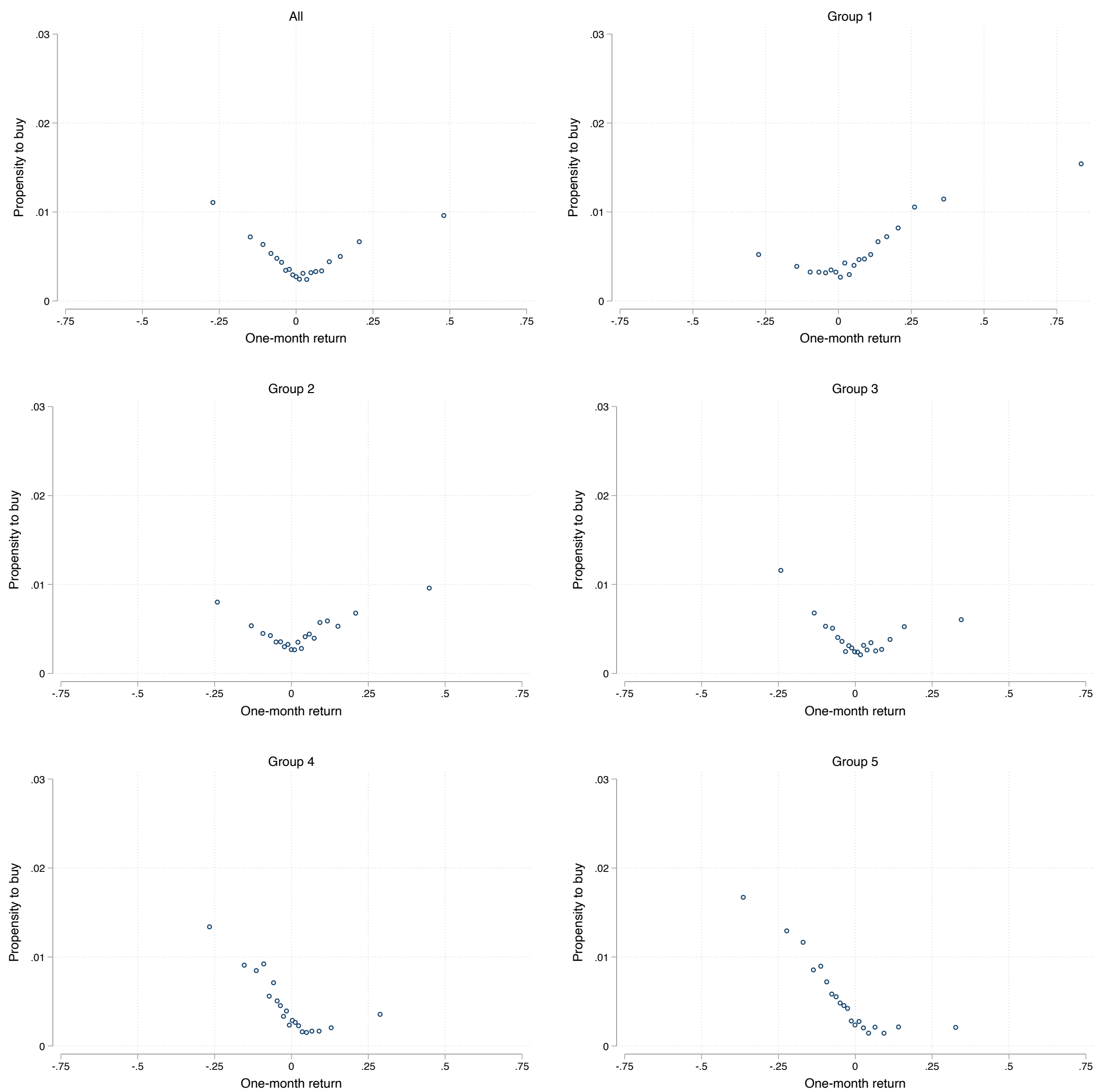


Fig. I2. V-shape buying behavior.

This figure examines the probability of buying as a function of holding-period returns, using the daily portfolios constructed from the brokerage data. Detailed descriptions about the data and the filters used in constructing the daily portfolios can be found in Section 4.1. When calculating the probability of buying, we consider only positions with a prior holding period of less than one month. In addition, we require that a daily portfolio contains at least five positions. In a given panel, each dot plots, on a random day, the probability of selling a stock conditional on the past one-month return, shown in the x-axis. The upper left panel concerns all investors. For the remaining five panels, they each concern one group of investors. All investors are first sorted into five groups based on their degree of doubling down, measured by the average stock return in most recent month across all buys. Each panel then represents one group, with Group 1 having the lowest degree of doubling down while Group 5 highest.

Appendix J. Evidence from asset prices

J.1. Data

In this section, we test the model's prediction about asset prices. In particular, the model predicts that, in the cross-section of individual stocks, those associated with more pronounced LSN beliefs should exhibit both stronger short-term momentum *and* stronger long-term reversals. Instead of using the brokerage data, we test this prediction using quarterly holdings of mutual funds data, since the coverage is much more comprehensive and the price impacts of mutual funds are likely to be greater.

Our data cover all US equity mutual funds from 1980 to 2019. Quarterly fund holdings data are from the Thomson/Refinitiv Mutual Fund Holdings (S12) database. We follow the same procedure used in Peng and Wang (2023), which contains more details. In a nutshell, we 1) focus on funds that specialize in US equities, 2) require the reporting date and the filing date to be sufficiently close, 3) require the ratio of equity holdings to total net assets (TNAs) to be close to one, 4) require a minimum fund size of $1 million, and 5) require that the TNAs reported in the Thomson Reuters database and in the CRSP database do not differ by more than a factor of two.

J.2. Results

J.2.1. Measuring the LSN

To measure a fund's degree of LSN, we first construct two measures based on mutual fund holdings. First, we measure fund j's holding-based demand for *long-term* returns in quarter q as

$$LongRet^{fund}_{j,q} = \frac{\sum_i Dollar_{i,j,q} \times LongRet_{i,q}}{\sum_i Dollar_{i,j,q}}, \tag{J.1}$$

where $Dollar_{i,j,q}$ is the dollar amount of stock i held by fund j at the end of quarter q, and $LongRet_{i,q}$ is stock i's past five-year return by the end of quarter q. Second, we measure fund j's holding-based demand for *short-term* returns in quarter q as

$$ShortRet^{fund}_{j,q} = \frac{\sum_i Dollar_{i,j,q} \times ShortRet_{i,q}}{\sum_i Dollar_{i,j,q}}, \tag{J.2}$$

where $Dollar_{i,j,q}$ is again the dollar amount of stock i held by fund j at the end of quarter q, and $ShortRet_{i,q}$ is stock i's past quarterly return by the end of quarter q.

A fund's degree of LSN, denoted by $FundLSN$, is then constructed as

$$FundLSN_{j,q} = LongRet^{fund}_{j,q} - ShortRet^{fund}_{j,q}. \tag{J.3}$$

The idea is that funds more prone to the LSN are more likely to hold stocks with good returns over the long-run but poor returns in more recent periods.

Next, we aggregate fund-level factor demand to the stock-level in each quarter as

$$\overline{LSN}_{i,q} = \frac{\sum_i shares_{i,j,q} \times FundLSN_{j,q}}{\sum_i shares_{i,j,q}}, \tag{J.4}$$

where $shares_{i,j,q}$ is the number of stock i shares held by fund j in quarter q, and $\overline{LSN}_{i,q}$ measures the degree of LSN of the underlying invesors holding stock i in quarter q.

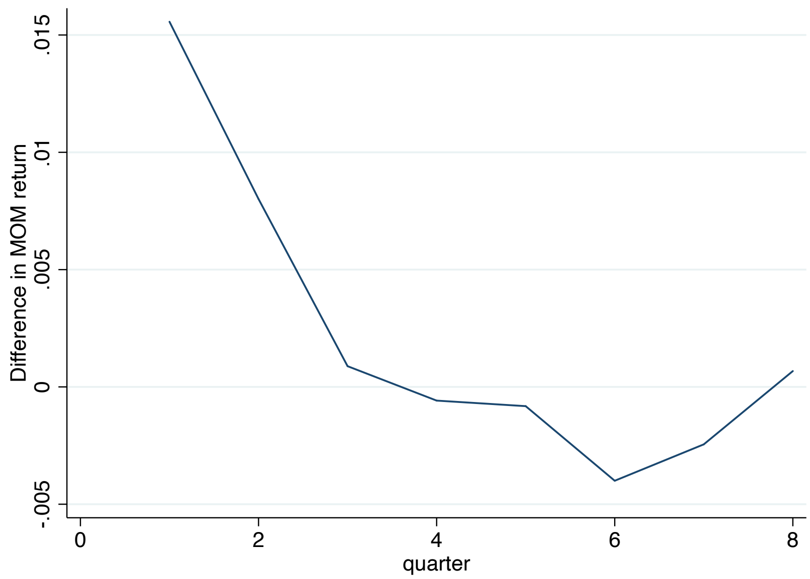
J.2.2. Cross-sectional return predictability

To test the model's predictions on cross-sectional return predictability, at the end of each quarter, all stocks are independently sorted into 25 portfolios based on their past one-year returns and $\overline{LSN}_{i,q}$. To address potential microstructure issues and focus on mutual fund behavior, we exclude stocks with a price below five dollars, total mutual fund ownership below 1%, or market capitalization in the bottom decile.

[Place Fig. J1 about here]

To illustrate the impact of LSN, we take the difference between the LSN momentum return—that is, the return of the winner-minus-loser strategy conditional on stocks in the highest decile based on $\overline{LSN}_{i,q}$—and the unconditional momentum return. Fig. J1 shows the results. Consistent with the model's prediction, we see that the LSN momentum return is stronger initially but then falls down in later quarters.

Panel A: Equal-weighted



Panel B: Value-weighted

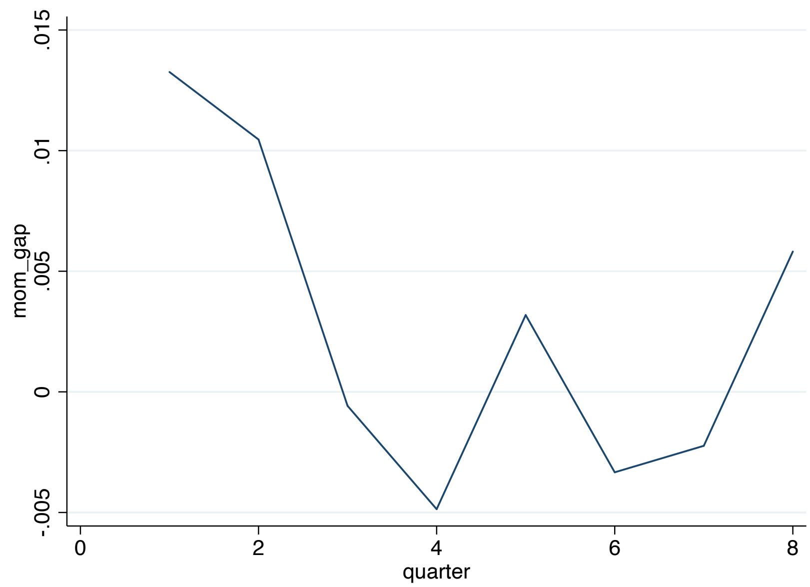


Fig. J1. Cross-sectional return predictability.

At the end of each quarter, all stocks are independently sorted into 25 portfolios based on their past one-year returns and $\overline{LSN}_{i,q}$, where $\overline{LSN}_{i,q}$ measures underlying funds' degree of LSN. To address potential microstructure issues and focus on mutual fund behavior, we exclude stocks with a price below five dollars, total mutual fund ownership below 1%, or market capitalization in the bottom decile. We then take the difference between the LSN momentum return—that is, the return of the winner-minus-loser strategy conditional on stocks in the highest decile based on $\overline{LSN}_{i,q}$—and the unconditional momentum return. Panel A presents equal-weighted momentum returns, while Panel B presents value-weighted momentum returns.