Internet Appendix

for

Asset Price Dynamics with Limited Attention

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This Internet Appendix provides supplemental material to accompany the above titled paper.

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Internet Appendix 1

Notes on the Limited-Attention Model

Two gain economic intuition into the limited-attention framework, we begin with a two-period, two investor-type example.

Two-Period Example: 1/2 Investors are Attentive and 1/2 are Partially-Attentive

In this example, half of the investors are most attentive (frequent) investors and half are partially attentive. The most attentive individuals maximize their own final utility function of wealth and we assume CARA exponential utility function $U(W) = -e^{-\phi_i W}$. Here, ϕ_i is investor i's risk aversion parameter.[16] Let $W_{i,t}$ denote the wealth of investor i on date t, $B_{i,t}$ denote the amount of risk-free asset he holds, and $K_{i,t}$ denote the amount of the risky asset he holds. Investor i's, expected final utility is $E[-e^{-\phi_i W_{t_i+2}}]$ with:

$$
\begin{aligned}
E_{t_i}[W_{i,t_i+2}] &= r^2 W_{i,t_i} + rK_{i,t_i}E_{t_i}[(S_{t_i+1} + X_{t_i+1} - rS_{t_i}]) + \frac{\phi^2}{\phi_i} Z_0^2 \sigma_x^2 \\
Var_{t_i}[W_{i,t_i+2}] &= r^2 K_{i,t_i}^2 \sigma_x^2 + \frac{\phi^2}{\phi_i^2} Z_0^2 \sigma_x^2
\end{aligned}
$$

Therefore, solve the F.O.C with respect to K_{i,t_i}, we have

$$
K_{i,t_i} = \frac{E_{t_i}[S_{t_i+1} + X_{t_i+2}] - rS_{t_i}}{r\phi_i \sigma_x^2}
$$

At time t_i, the absolute risk aversion coefficient is actually $r\phi_i$ in stead of ϕ_i. At this time period, there are other investors whose absolute risk aversion coefficient are ϕ_i. In aggregate, the harmonic mean of the absolute risk-aversion coefficients is the same, which is ϕ. Therefore, the total demand at time t is

$$
K_t = \frac{E_t[S_{t+1} + X_{t+1}] - rS_t}{\phi \sigma_x^2}
$$

Therefore, if there is no shock on aggregate demand and supply, i.e., the aggregate equilibrium asset holdings is Z_0, then the price $S_{t+1} = S_t = \cdots = S_0$. Hence, in the benchmark case, the equilibrium price is $S_{0,benchmark} = \frac{Z_0 \phi \sigma_x^2}{1-r}$.

The other half of the investors are partially-attentive. These investors also maximize their own

[16] This model is close to Grossman and Miller (1988), with the exception that the earlier work assumes $r = 1$ and asset values are realized on the final date.

final utility function and we assume they have CARA exponential utility functions. A given partially-attentive investor lives 2 periods and s/he can only trade once in his/her lifetime. In this example, 1/2 of the partially-attentive investors only trade at odd periods and the other half only trade at even periods.

Suppose the risk aversion coefficient is ϕ_j for partially-attentive investor j. Assume investor j arrives at the market on date t_j, and denote $W_{j,t}$ the wealth of investor j on date t, $B_{j,t}$ the amount of risk-free asset s/he holds, and $D_{j,t}$ the amount of the risky asset s/he holds. The price of the asset on date t is denoted S_t. The wealth of the investor j is:

$$\begin{aligned} W_{j,t_j} &= D_{j,t_j} S_{t_j} + B_{j,t_j} \\ W_{j,t_j+1} &= D_{j,t_j}(S_{t_j+1} + X_{t_j+1}) + rB_{j,t_j} \\ W_{j,t_j+2} &= D_{j,t_j}(S_{t_j+2} + X_{t_j+2} + rX_{t_j+1}) + r^2 B_{j,t_j} \\ &= r^2 W_{j,t_j} + (D_{j,t_j}(S_{t_j+2} + X_{t_j+2} + rX_{t_j+1} - r^2 S_{t_j}))) \end{aligned}$$

The maximization problem for a partially-attentive investor j is:

$$Max_{D_{j,t_j}} E_{t_j}[-e^{-W_{t_j+2}}]$$

where

$$E_{t_j}[W_{t_j+2}] = r^2 W_{j,t_j} + (D_{t_j}(E_{t_j}[S_{t_j+2} + X_{t_j+2} + rX_{t_j+1}] - r^2 S_{t_j}))) \tag{IA.1}$$

$$Var_{t_j+1}[W_{t_j+2}] = D^2_{j,t_j} \sigma_x^2 (1 + r^2) \tag{IA.2}$$

Therefore, solving the F.O.C with respect to D_{j,t_j}, we have:

$$D_{j,t_j} = \frac{E_{t_j}[S_{t_j+2} + X_{t_j+2} + rX_{t_j+1}] - r^2 S_{t_j}}{\phi_j \sigma_x^2 (1 + r^2)} \tag{IA.3}$$

Since the risky asset's total supply is constant, in the stationary state the price S_t is also constant,i.e., $S_t = S_0$, $\forall\ t$. Therefore, the aggregate demand of limited attention investors is $D_t = \frac{(1-r^2)S_0}{\phi\sigma_x^2(1+r^2)}$. Since mass $\frac{1}{2}$ of the investors have limited attention, the market clear condition at time t

is:

$$\frac{1}{2}K_t + \frac{1}{2}D_t = Z_0$$

Substitute the solutions of K_t and D_t into the market clearing condition, we have

$$\frac{1}{2}\frac{(1-r)S_0}{\phi\sigma_x^2} + \frac{1}{2}\frac{(1-r^2)S_0}{\phi\sigma_x^2(1+r^2)} = Z_0$$

If $\phi = 1$, then we get the equilibrium price $S_0 = \frac{Z_0\sigma_x^2}{1-r}\frac{2(1+r^2)}{(1+r^2)+1+r}$. The price, S_0, is lower than it would be if all investors were fully attentive.

Summary of the Two-Period Example

From the example presented above, we find that:

1. The demand functions have the same form at one period before the final period. However, the absolute risk aversion is changing (so is the demand) from period to period for each investor individually. Investors are able to adjust their asset holdings at each period. Aggregately, the demand function is unchanged. Each period, there exists not only the transfer from 'old' investors to 'new-born' investors, but also the trade between 'mid-age' investors and 'new-born' investors.

2. In the case with infrequent investors in the market, they require higher return because they are not able to adjust their asset holdings in the intermediary period. Therefore, the equilibrium price with infrequent investors in the market is lower than the benchmark price where all the investors are frequent investors.

Demand Functions in a General Model

We solve for a stationary solution to the model described in Section 2. The date t demands of the "least-attentive," "partially-attentive," and "most-attentive" individuals are denoted $D_{1,t}$, $D_{2,t}$, and $D_{3,t}$. The demands of the institutions and market makers are $K_{1,t}$ and $K_{2,t}$ respectively. Below, $E_t(\cdot)$ and $V_t(\cdot)$ denote the conditional mean and variance. S_t is the equilibrium price of the risky asset, while R_{t+k_1} and R_{t+k_2} are described in Section 2.

In the general model, N_t is the exogenous endowment exposure to the risk which can be hedged by trading the risky asset. Since the payoff of N_t is perfectly related to the payoff of the risky asset, the demand function in the general model is the mean-variance demand excluding the endowment exposure, which is:

$$
\begin{array}{llcll}
\text{Least-Attentive*} & D_{1,t} & = \frac{q_{11}}{k_1}\left(\frac{E_t(R_{t+k_1})-r^{k_1}S_t}{\phi V_t(R_{t+k_1})}+\frac{q_2}{q_1}N_t\right) & \equiv & a_1(c)\cdot Y_t+\frac{q_{11}q_2}{q_1k_1}N_t \\
\text{Partially-Attentive*} & D_{2,t} & = \frac{q_{12}}{k_2}\left(\frac{E_t(R_{t+k_2})-r^{k_2}S_t}{\phi V_t(R_{t+k_2})}+\frac{q_2}{q_1}N_t\right) & \equiv & a_2(c)\cdot Y_t+\frac{q_{12}q_2}{q_1k_1}N_t \\
\text{Most-Attentive*} & D_{3,t} & = q_{13}\left(\frac{E_t(S_{t+1}+X_{t+1})-rS_t}{\phi V_t(S_{t+1}+X_{t+1})}+\frac{q_2}{q_1}N_t\right) & \equiv & b_1(c)\cdot Y_t+\frac{q_{13}q_2}{q_1}N_t \\
\text{Institutions} & K_{1,t} & = q_2\left(\frac{E_t(S_{t+1}+X_{t+1})-rS_t}{\phi V_t(S_{t+1}+X_{t+1})}-N_t\right) & \equiv & b_2(c)\cdot Y_t-q_2N_t \\
\text{Market Makers} & K_{2,t} & = (1-q_1-q_2)\frac{E_t(S_{t+1}+X_{t+1})-rS_t}{\phi V_t(S_{t+1}+X_{t+1})} & \equiv & b_3(c)\cdot Y_t
\end{array}
\tag{IA.4}
$$

* *Indicates a subtype of individual investor.*

where E_t and V_t denote conditional mean and variance respectively, S_t denote the equilibrium price at time t and $R_{t+k}=S_{t+k}+\sum_{i=1}^{k}r^{k-i}X_{t+i}$ for $k=k_1,k_2$.

Denote $H_t=[D_{1,t-1},D_{1,t-2},\cdots,D_{1,t-k_1+1}]$ the vector of quantities held by the least-attentive investors who are <u>not</u> trading at date t. Denote $G_t=[D_{2,t-1},D_{2,t-2},\cdots,D_{2,t-k_2+1}]$ the vector of quantities held by the partially-attentive investors <u>not</u> trading at date t. Let $Y_t=[N_t,X_t,H_t,G_t]^T$ be the state vector. We hypothesize that the equilibrium price of the risky asset takes the form: $S_t=c^T\cdot Y_t$. The dynamics of the state vector Y_t are specified as the followings:

$$
\begin{array}{rcl}
N_{t+1} & = & N_t+\Delta N_{t+1} \\
X_{t+1} & = & x_{t+1} \\
H_{t+1,1} & = & D_{1,t}=a_1(c)\cdot Y_t+\frac{q_{11}q_2}{q_1k_1}N_t \\
H_{t+1,i} & = & H_{t,i-1},\quad \text{for } i\in[1,k_1-1] \\
G_{t+1,1} & = & D_{2,t}=a_2(c)\cdot Y_t+\frac{q_{12}q_2}{q_1k_2}N_t \\
G_{t+1,i} & = & G_{t,i-1},\quad \text{for } i\in[1,k_2-1]
\end{array}
\tag{IA.5}
$$

or equivalently,

$$Y_{t+1}=A(c)Y_t+B\epsilon_{t+1}, \tag{IA.6}$$

$$
\text{where } A(c)=\left(\begin{array}{cccccccccc}
1 & 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\
0 & 0 & 0 & 0 & \cdots & 0 & 0 & \cdots & 0 & 0 \\
 & & \text{——} & & \tilde{a}_1(c) & & & \text{——} & & \\
0 & 0 & 1 & \cdots & 0 & 0 & 0 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & 1 & 0 & 0 & \cdots & 0 & 0 \\
 & & \text{——} & & \tilde{a}_2(c) & & & \text{——} & & \\
0 & 0 & \cdots & 0 & 0 & 0 & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & \ddots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & \cdots & 0 & 0 & 0 & 0 & \cdots & 1 & 0
\end{array}\right)_{(k_1+k_2)\times(k_1+k_2)},
$$

$$
\text{and } B=\left(\begin{array}{cc}
\sigma^2_{\Delta N} & 0 \\
0 & \sigma^2_x \\
0 & 0 \\
\vdots & \vdots \\
0 & 0
\end{array}\right)_{(k_1+k_2)\times 2},
$$

Above, $\tilde{a}_1(c) = a_1(c) + [\frac{q_{11}q_2}{q_1k_1}, 0, \cdots, 0]$, $\tilde{a}_2(c) = a_2(c) + [\frac{q_{12}q_2}{q_1k_2}, 0, \cdots, 0]$ and ϵ_t is a 2-by-1 vector of i.i.d. standard normal random variables. Market clearing dictates that the sum of the current aggregate excess demands of each investor type equals the available supply:

$$\begin{aligned} D_{1,t} + D_{2,t} + D_{3,t} + K_{1,t} + K_{2,t} &= -D_{1,t-1} - \cdots - D_{1,t-k_1+1} - D_{2,t-1} - \cdots - D_{2,t-k_2+1} \\ &= -\mathbf{1} \cdot [H_t, G_t]^T \end{aligned}$$

Equivalently,

$$\begin{aligned} & a_1(c) \cdot Y_t + \frac{q_{11}q_2}{q_1k_1}N_t + a_2(c) \cdot Y_t + \frac{q_{12}q_2}{q_1k_2}N_t \\ + \quad & b_1(c) \cdot Y_t + \frac{q_{13}q_2}{q_1}N_t + b_2(c) \cdot Y_t - q_2N_t + b_3(c) \cdot Y_t = -\mathbf{1} \cdot [H_t, G_t]^T \end{aligned} \tag{IA.7}$$

or

$$\begin{aligned} (a_1(c) + a_2(c) + b_1(c) + b_2(c) + b_3(c)) \cdot Y_t &= \left(q_2 - \frac{q_{13}q_2}{q_1} - \frac{q_{11}q_2}{q_1k_1} - \frac{q_{12}q_2}{q_1k_2}\right)N_t - \mathbf{1} \cdot [H_t, G_t]^T \\ &= [q_2 - \frac{q_{13}q_2}{q_1} - \frac{q_{11}q_2}{q_1k_1} - \frac{q_{12}q_2}{q_1k_2}, 0, -\mathbf{1}] \cdot Y_t \\ &\equiv g \cdot Y_t \end{aligned} \tag{IA.8}$$

i.e.

$$a_1(c) + a_2(c) + b_1(c) + b_2(c) + b_3(c) = g \tag{IA.9}$$

Therefore, we can find a solution vector c such that Eq.IA.9 is satisfied.

Internet Appendix 2

Notes on the Calibration Exercise

In our model, the stock price of a company that reinvests its dividends can be written as the sum of three terms. The first term is the sum of all dividends paid since t=0 with each dividend compounding from the time it was paid until date t. The compounding rate is the company's required rate of return r. The second component is the present value of all future dividends which is zero in our model. The third term is the transitory component (S_t) which may be greater than, less than, or equal to zero in our model. We can define M_t to be the sum of the first two terms so that: $M_t \equiv \sum_{k=0}^{t} r^{t-k} X_k$. In the previous expression, X_k is the dividend from time k. The company's stock price can now be written as:

$$\begin{aligned} P_t &= M_t + S_t \\ M_t &= rM_{t-1} + X_t \end{aligned}$$

With some algebra, we can then write the company's stock return as:

$$\frac{P_{t+1}}{P_t} = \frac{M_{t+1} + S_{t+1}}{M_t + S_t} = 1 + \frac{(r-1)M_t}{P_t} + \frac{X_{t+1}}{P_t} + \frac{S_{t+1} - S_t}{P_t}$$

With a first-order Taylor approximation we have:

$$ln\left(\frac{P_{t+1}}{P_t}\right) \approx \frac{(r-1)M_t}{P_t} + \frac{X_{t+1}}{P_t} + \frac{S_{t+1} - S_t}{P_t}$$

In our empirical data, $p_{i,t}$ is the natural log of stock i's mid-quote price at the end of date t.

For a given parameter combination, the model is solved numerically to create moving average (MA) representations of prices and quantities. Correlations are generated from the impulse response functions (IRFs) following an endowment shock at t=0. For a given parameter combination, we can also generate "data" from our model. These data can be used to check the correlations and produce the figures shown in the main text. Throughout our paper, we produce results at four frequencies (daily, weekly, biweekly, and monthly) as well as three time shifts (one period lagged, contemporaneous, and one period lead).

Internet Appendix 3

Unit Root Tests

Our model implies that market makers' inventory positions should mean revert while individuals' trading is not mean reverting. We test these predictions with a unit root test, which is also needed to verify stationarity of the trading variables that enter the state-space (statistical) model. The augmented Dickey-Fuller test is performed on a stock-by-stock basis using the regressions below. Note that while $MM_{i,t}$ and $\Delta Indv_{i,t}$ are variables found throughout this paper, $\Delta MM_{i,t}$ and $Indv_{i,t}$ are used only for the unit root tests. All variables are defined explicitly in Appendix A.

$$\begin{aligned}\Delta MM_{i,t} &= \alpha + \beta MM_{i,t-1} + \phi_1 \Delta MM_{i,t-1} + \ldots + \phi_4 \Delta MM_{i,t-4} + \varepsilon_{i,t} \\ \Delta Indv_{i,t} &= \alpha + \beta Indv_{i,t-1} + \phi_1 \Delta Indv_{i,t-1} + \ldots + \phi_4 \Delta Indv_{i,t-4} + \varepsilon_{i,t}\end{aligned}$$

The table on the following page presents the results of the augmented Dickey-Fuller tests. The table reports the cross-sectional mean of the β coefficients and the mean of the associated "t-statistics". The table also reports the p-value of a meta test statistic that counts the number of significant $t-$values under (over) the 10% (90%) critical value if the cross-sectional mean is negative (positive).[17] This meta test statistic is binomially distributed under null where the probability of "success" equals the significance level of the augmented Dickey-Fuller test performed for each stock. We use a 10% critical value.

We reject the existence of unit roots in the market makers' inventory positions at all conventional levels. 862 of the 1,019 stocks reject the null. Our results indicate that NYSE market makers behave in a manner consistent with theoretical models of market making. After building a position, market makers quickly unwind their trades and mean-revert inventories towards target levels.[18]

We fail to reject the existence of unit roots in the individual inventory positions. Cross-sectionally, we fail to reject for 968 of the 1,019 stocks at the 10%-level. Note that using the 10% threshold represents a weaker-than-normal test that still results in the vast majority of stocks failing to reject. Our results indicate that individuals do not seem to mean revert their holdings.

[17] The 10% critical value of an augmented Dickey-Fuller test is -2.57—see Cheung and Lai (1995).

[18] For related examples, see Ho and Stoll (1981), Hasbrouck (1993), Madhavan and Smidt (1993), and Grossman and Miller (1988).

NYSE market makers' inventory levels are stationary, while the levels for individuals are not stationary. These results provide support for using the *level* of NYSE market makers' inventories ($MM_{i,t}$) and the *change in levels*, or net trades, of individuals' holdings ($\Delta Indv_{i,t}$) throughout the paper.

Augmented Dickey-Fuller Tests

This table presents results of augmented Dickey-Fuller tests using daily, weekly, biweekly, and monthly data respectively starting from January 1999 to December 2005. We report the cross-sectional mean of the β coefficient. Below the coefficients, and in parentheses, we report the cross-sectional means of the associated t-statistics. We consider variables from market makers and individuals:

$$\Delta MM_{i,t} = \alpha + \beta MM_{i,t-1} + \phi_1 \Delta MM_{i,t-1} + \ldots + \phi_4 \Delta MM_{i,t-4} + \varepsilon_{i,t}$$

$$\Delta Indv_{i,t} = \alpha + \beta Indv_{i,t-1} + \phi_1 \Delta Indv_{i,t-1} + \ldots + \phi_4 \Delta Indv_{i,t-4} + \varepsilon_{i,t}$$

The p-values, reported in square brackets, are based on a test statistic that counts the number of significant augmented Dickey-Fuller test statistics across all stock-estimates in the bin. The test statistic is binomial distributed under the null (we use the 0.10 or 0.90 critical values from the DF-test). The number of observations is given in Appendix A.3.

		Market Makers	Individuals
Daily	β-Avg	-0.303	-0.000
	T-Avg	(-10.95)	(-0.57)
	P-value	[0.00]	[1.00]
Weekly	β-Avg	-0.510	-0.004
	T-Avg	(-6.25)	(-0.89)
	P-value	[0.00]	[1.00]
Biweekly	β-Avg	-0.619	-0.009
	T-Avg	(-4.81)	(-1.02)
	P-value	[0.00]	[1.00]
Monthly	β-Avg	-0.782	-0.019
	T-Avg	(-3.52)	(-0.82)
	P-value	[0.00]	[1.00]

Internet Appendix 4

Notes on the Number of Unique Correlations

Step	Number of Correlations	Description	Additional Notes
#1	108	Total correlations	3 series × 3 series × 3 lead/lags × 4 frequencies The 3 series consist of the holdings/trades of 2 investor types + 1 return series
#2	36	Above the main diagonals (symmetry)	These corrs are not shown in Tables 3 & 4
	12	"Ones" on the comtemp main diags	Shown in Tables 3 & 4 for clarity only
	60	On or below the main diagonals*	Correlations of interest
	—-	————————————	———————
	108	Total correlations	From Step 1
#3	12	"Repeats" across time	Example of a repeat: Corr(r_{t-1},r_t) = Corr(r_t,r_{t+1})
	48	**Unique correlations**	**We focus on these 48 unique correlations**
	—-	————————————	———————
	60	On or below the main diagonals*	From Step 2

* Excludes "ones" on the contemporaneous main diagonals.

Internet Appendix 5

ARIMA Model

In the state space model, we have

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \delta_{i,t} + \beta_i f_t + w_{i,t} \\ w_{i,t} &= \kappa_i^{MM} \tilde{M}M_{i,t} + \kappa_i^{indv} \Delta \tilde{I}ndv_{i,t} + u_{i,t} \\ s_{i,t} &= \alpha_i^{MM} MM_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \epsilon_{i,t} \end{aligned}$$

The corresponding ARIMA model is

$$\begin{aligned} r_{i,t}^{idio} &= (\kappa_i^{MM} + \alpha_i^{MM}) MM_{i,t} - \alpha_i^{MM} MM_{i,t-1} + (\kappa_i^{indv} + \alpha_i^{indv}) \Delta Indv_{i,t} - \alpha_i^{indv} \Delta Indv_{i,t-1} \\ &\quad + u_{i,t} + \epsilon_{i,t} - \epsilon_{i,t-1} \end{aligned}$$

or

$$\begin{aligned} r_{i,t}^{idio} &= \zeta_{i0}^{MM} MM_{i,t} + \zeta_{i1}^{MM} MM_{i,t-1} + \zeta_{i0}^{indv} \Delta Indv_{i,t} + \zeta_{i1}^{indv} \Delta Indv_{i,t-1} \\ &\quad + \eta_{i,t} + \theta \eta_{i,t-1} \end{aligned} \tag{IA.10}$$

Above, $r_{i,t}^{idio}$ is a stationary series following a $MA(1)$ process (plus explanatory variables.) We can use an AR(q) model to approximate the above ARIMA series and estimate it by OLS

$$\left(1 - \sum_{j=1}^{q} \varphi_{ij} L^j\right) r_{i,t}^{idio} = \sum_{j=0}^{1} \gamma_{ij}^{MM} MM_{i,t-j} + \sum_{j=0}^{1} \gamma_{ij}^{indv} \Delta Indv_{i,t-j} + \eta_{i,t} \tag{IA.11}$$

The long-run effect of market makers' inventories on price is then equal to $\frac{\sum_{j=0}^{1} \gamma_{ij}^{MM}}{1-\sum_{j=1}^{q} \varphi_{ij}}$, and the temporary effect of market makers' inventories is $\gamma_{i0}^{MM} - \frac{\sum_{j=0}^{1} \gamma_{ij}^{MM}}{1-\sum_{j=1}^{q} \varphi_{ij}}$. Similarly, the effect of individuals' net trades on efficient price is $\frac{\sum_{j=0}^{1} \gamma_{ij}^{indv}}{1-\sum_{j=1}^{q} \varphi_{ij}}$ and the effect on temporary price is $\gamma_{i0}^{indv} - \frac{\sum_{j=0}^{1} \gamma_{ij}^{indv}}{1-\sum_{j=1}^{q} \varphi_{ij}}$.

Corresponding to the coefficients in the state space model, we define

$$
\begin{aligned}
\dot{\kappa}_i^{MM} &\equiv \frac{\sum_{j=0}^{1} \gamma_{ij}^{MM}}{1 - \sum_{j=1}^{q} \varphi_{ij}} \\
\dot{\kappa}_i^{indv} &\equiv \frac{\sum_{j=0}^{1} \gamma_{ij}^{indv}}{1 - \sum_{j=1}^{q} \varphi_{ij}} \\
\dot{\alpha}_i^{MM} &\equiv \gamma_{i0}^{MM} - \frac{\sum_{j=0}^{1} \gamma_{ij}^{MM}}{1 - \sum_{j=1}^{q} \varphi_{ij}} \\
\dot{\alpha}_i^{indv} &\equiv \gamma_{i0}^{indv} - \frac{\sum_{j=0}^{1} \gamma_{ij}^{indv}}{1 - \sum_{j=1}^{q} \varphi_{ij}}
\end{aligned}
$$

We estimate the model on a stock-by-stock basis and report the cross-sectional average of the coefficients in the table on the following page. The variances of the coefficients at the individual stock level are derived by the delta method. Standard errors of the cross-sectional means are adjusted for contemporaneous correlation across stocks.

ARIMA Model Estimates

(cf. Table 6 in the main text)

This table presents estimates from an AR(8) model with market makers' inventories and individuals' net trading as explanatory variables. Below the coefficient estimates, there are t-values in parentheses. Standard errors are adjusted for contemporaneous correlations among the stocks. In these equations, $r_{i,t}$ is the idiosyncratic return of stock i over month t.

$$\left(1-\sum_{j=1}^{8}\varphi_{ij}L^{j}\right)r_{i,t}=\sum_{j=0}^{1}\gamma_{ij}^{MM}MM_{i,t-j}+\sum_{j=0}^{1}\gamma_{ij}^{indv}\Delta Indv_{i,t-j}+\eta_{i,t}$$

Coefficients related to efficient price effects ($\dot{\kappa}_i^{MM}$ and $\dot{\kappa}_i^{indv}$) as well as coefficients related to transitory price effects ($\dot{\alpha}_i^{MM}$ and $\dot{\alpha}_i^{indv}$) are defined below. Coefficients estimates are reported directly below in the table.

$$\dot{\kappa}_i^{MM}\equiv\frac{\sum_{j=0}^{1}\gamma_{ij}^{MM}}{1-\sum_{j=1}^{8}\varphi_{ij}} \qquad \dot{\alpha}_i^{MM}\equiv\gamma_{i0}^{MM}-\frac{\sum_{j=0}^{1}\gamma_{ij}^{MM}}{1-\sum_{j=1}^{8}\varphi_{ij}}$$

$$\dot{\kappa}_i^{indv}\equiv\frac{\sum_{j=0}^{1}\gamma_{ij}^{indv}}{1-\sum_{j=1}^{8}\varphi_{ij}} \qquad \dot{\alpha}_i^{indv}\equiv\gamma_{i0}^{indv}-\frac{\sum_{j=0}^{1}\gamma_{ij}^{indv}}{1-\sum_{j=1}^{8}\varphi_{ij}}$$

	Efficient Price Effects				Transitory Price Effects			
	$\dot{\kappa}_i^{MM}$	$\lvert\dot{\kappa}_i^{MM}\rvert \times \sigma(MM)$	κ_i^{indv}	$\lvert\dot{\kappa}_i^{indv}\rvert \times \sigma(\Delta Indv)$	$\dot{\alpha}_i^{MM}$	$\lvert\dot{\alpha}_i^{MM}\rvert \times \sigma(MM)$	$\dot{\alpha}_i^{indv}$	$\lvert\dot{\alpha}_i^{indv}\rvert \times \sigma(\Delta Indv)$
Daily	-0.16	36	-0.03	18	-0.56	121	-0.09	13
	(-27.6)		(-4.8)		(-18.0)		(-7.9)	
Weekly	-0.37	83	-0.04	60	-0.58	128	-0.09	44
	(-21.6)		(-3.4)		(-16.9)		(-12.0)	
Biweekly	-0.53	119	-0.03	99	-0.56	129	-0.09	89
	(-17.7)		(-1.7)		(-14.7)		(-8.0)	
Monthly	-0.67	179	-0.06	190	-0.61	169	-0.09	168
	(-12.2)		(-5.0)		(-12.8)		(-10.5)	

Internet Appendix 6

State Space Model with Model-Generated Data

The price equations in Internet Appendix 2 in log-form are:

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + \delta_{i,t} + w_{i,t} \end{aligned} \tag{IA.12}$$

The log stock price is written as the sum of an efficient (permanent) part and a transitory part. The efficient price ($m_{i,t}$) is modeled as a process of uncorrelated increments with a nonzero drift equal to the stock's required return ($\delta_{i,t}$). These increments are related to the dividend surprises and are denoted $w_{i,t}$. We use Eq.IA.12 and the approach in Internet Appendix 2 when generating data to serve as the basis for our empirical estimation in Section 4 of the main text.

This table presents estimates of a state space model from data simulated by our theoretical model. The estimated state space model is shown below. We run 1,000 simulations of the model with length $T = 1,760$ days. $p_{i,t}$ (in bps) is the model generated price along with the deviation (s_t) and random walk component (m_t). $MM_{i,t}$ is the model generated market maker's inventory positions, $\Delta Indv_{i,t}$ is the model generated individuals' net trades. Since our theoretical model does not include information-based trading, we exclude the trading variables from the efficient price equation. We report the averages of the estimates from 100 times simulations and the t-values are reported in the parentheses.

$$\begin{aligned} p_{i,t} &= m_{i,t} + s_{i,t} \\ m_{i,t} &= m_{i,t-1} + w_{i,t} \\ s_{i,t} &= \alpha_i^{MM} MM_{i,t} + \alpha_i^{indv} \Delta Indv_{i,t} + \epsilon_{i,t} \end{aligned}$$

	$\sigma(w)$	α_i^{MM}	α_i^{indv}	$\sigma(\epsilon)$
Daily	226	-2.34	-0.05	15
		(-337.9)	(-14.7)	
Weekly	500	-2.13	-0.09	44
		(-79.4)	(-7.9)	
Biweekly	698	-2.01	-0.15	82
		(-84.1)	(-24.4)	
Monthly	988	-2.42	-0.07	150
		(-54.9)	(-9.2)	