Internet Appendix for "Infrequent Rebalancing, Return Autocorrelation, and Seasonality"

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This appendix is in eight sections. Section I provides equilibrium existence conditions. Section II performs a stability analysis. Section III studies the role of liquidity trading persistence. Section IV solves and discusses a model in which liquidity trading takes place at different frequencies. Section V solves and discusses a model with seasonality in mean liquidity trading. Section VI solves and discusses a model with multiple groups of infrequent traders. Section VII explains how to compute trading volume when 0 < q < 1. Section VIII contains additional empirical results for daily returns. More precisely, I examine bid-ask bounce, firm size, different subsamples, and institutional ownership.

I. Equilibrium Existence

This section details equilibrium existence conditions. For completeness, I first solve for the equilibrium coefficients in the frictionless economy. Spiegel (1998) and Watanabe (2008) provide similar derivations.

PROPOSITION IA1: Let q = 0 and h = 1. In a linear stationary REE, the price vector is given by

$$P_t = \bar{P} + P_\theta \theta_t + \frac{a_D}{R - a_D} D_t, \tag{IA1}$$

where P_{θ} solves a quadratic matrix equation given below.

This equation has
$$2^N$$
 solutions if $\frac{1}{4} \left(\frac{R-a_{\theta}}{\gamma_F}\right)^2 I_N - \left(\frac{R}{R-a_D}\right)^2 \Sigma_{\theta}^{\frac{1}{2}} \Sigma_D \Sigma_{\theta}^{\frac{1}{2}}$ is positive definite.

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Proof of Proposition IA1: Conjecture that $P_t = \bar{P} + P_{\theta}\theta_t + P_D D_t$. The demand of frequent traders is $X_t^F = \frac{1}{\gamma_F} \Sigma_1^{-1} \mathbb{E}_t[Q_{t+1}]$, where $\Sigma_1 \equiv \operatorname{Var}_t[Q_{t+1}] = P_{\theta} \Sigma_{\theta} P_{\theta}' + (P_D + I_N) \Sigma_D (P_D + I_N)'$ is a constant matrix under the price conjecture. The market-clearing condition is $\gamma_F \Sigma_1 \left(\theta_t + \bar{S}\right) = \mathbb{E}_t[Q_{t+1}]$. Matching terms with the price conjecture gives

$$P_D = \frac{a_D}{R - a_D} I_N,\tag{IA2}$$

$$P_{\theta}\Sigma_{\theta}P_{\theta}' + \frac{R - a_{\theta}}{\gamma_F}P_{\theta} + \left(\frac{R}{R - a_D}\right)^2 \Sigma_D = 0_N, \quad \text{and} \tag{IA3}$$

$$\bar{P} = \frac{1}{R-1} \left((R-a_{\theta}) P_{\theta} \bar{S} + (1-a_{\theta}) P_{\theta} \bar{\theta} + \frac{(1-a_D)R}{R-a_D} \bar{D} \right).$$
(IA4)

The last equation uses the fact that $\gamma_F \Sigma_1 = -(R - a_\theta) P_\theta$ from the second equation. The price impact matrix P_θ solves the quadratic matrix equation (IA3) and must be symmetric. Assuming that Σ_θ is positive definite, multiply both sides of (IA3) by $\Sigma_\theta^{\frac{1}{2}}$ (the unique positive definite square root of Σ_θ) and reorganize terms to obtain

$$\left(\Sigma_{\theta}^{\frac{1}{2}} P_{\theta} \Sigma_{\theta}^{\frac{1}{2}} + \frac{R - a_{\theta}}{2\gamma_F} I_N\right)^2 = \frac{1}{4} \left(\frac{R - a_{\theta}}{\gamma_F}\right)^2 I_N - \left(\frac{R}{R - a_D}\right)^2 \Sigma_{\theta}^{\frac{1}{2}} \Sigma_D \Sigma_{\theta}^{\frac{1}{2}}.$$
 (IA5)

If $\frac{1}{4} \left(\frac{R-a_{\theta}}{\gamma_F}\right)^2 \Sigma_{\theta}^{-2} - \left(\frac{R}{R-a_D}\right)^2 \Sigma_{\theta}^{-\frac{1}{2}} \Sigma_D \Sigma_{\theta}^{-\frac{1}{2}}$ is positive definite, then its spectral decomposition is given by $\Gamma \Lambda \Gamma'$, where Λ is a diagonal matrix of eigenvalues λ_i (i = 1, ..., N) and Γ is an orthonormal matrix with eigenvectors as columns. Thus,

$$P_{\theta} = -\frac{1}{2} \left(\frac{R - a_{\theta}}{\gamma_F} \right) \Sigma_{\theta}^{-1} + \Gamma \Lambda^{\frac{1}{2}} \Gamma'.$$
 (IA6)

Since each diagonal element of $\Lambda^{\frac{1}{2}}$ can take values $\pm \sqrt{\lambda_i}$ to satisfy (IA5), P_{θ} admits 2^N solutions.

Using the results of Corollary 1 in the main text, it can be shown in a similar way that the infrequent rebalancing economy (q = 1) admits 2^N solutions.

To gain more intuition, I follow Watanabe (2008) and make the following assumption.

ASSUMPTION IA1 (Symmetric securities): The liquidity and dividend shock volatilities (correlations) are the same for all assets, given respectively by σ_{θ} and σ_D (ρ_{θ} and ρ_D).

The next proposition provides equilibrium existence conditions.

PROPOSITION IA2: Under Assumption IA1, the frictionless economy (q = 0, h = 1) / infrequent rebalancing economy (q = 1) admits four symmetric equilibria if

$$(R - a_{\theta})^{2} - 4\gamma^{\star 2} \sigma_{\theta}^{\star 2} \sigma_{D}^{\star 2} \left(\frac{R}{R - a_{D}}\right)^{2} \max\left\{(1 + (N - 1)\rho_{\theta})(1 + (N - 1)\rho_{D}), (1 - \rho_{\theta})(1 - \rho_{D})\right\} > 0,$$
(IA7)

where $\gamma^{\star} = \gamma_{F}$, $\sigma_{\theta}^{\star 2} = \sigma_{\theta}^{2}$, and $\sigma_{D}^{\star 2} = \sigma_{D}^{2}$ when q = 0 and h = 1, and where $\gamma^{\star} = (k + 1) \frac{(R-a_{\theta})(R^{k+1}-a_{\theta}^{k})}{(R^{k+1}-1)(R^{k+1}-a_{\theta}^{k+1})} \gamma_{I}$, $\sigma_{\theta}^{\star 2} = \left(1 + \left(\frac{R^{k+1}(1-a_{\theta}^{k})}{R^{k+1}-a_{\theta}^{k}}\right)^{2}\right) \sigma_{\theta}^{2}$, and $\sigma_{D}^{\star 2} = \left(1 + \sum_{i=1}^{k} R^{2i}\right) \sigma_{D}^{2}$ when q = 1.

Proof of Proposition IA2: Under Assumption IA1, $\Sigma_{\theta} = \sigma_{\theta}^2 \Gamma \Lambda_{\theta} \Gamma'$ by the spectral decomposition of Σ_{θ} , where Λ_{θ} is a diagonal matrix of eigenvalues and Γ is an orthogonal matrix with eigenvectors x_i (i = 1, ..., n) as columns. More precisely, $x_1 = 1_N / \sqrt{N}$ and $x_i = [1'_{i-1} - (i-1)0'_{N-i}]'$ for i = 2, ..., N. The first eigenvalue equals $1 + (N-1)\rho_{\theta}$. All the other eigenvalues equal $1 - \rho_{\theta}$. In a similar way, $\Sigma_D = \sigma_D^2 \Gamma \Lambda_D \Gamma'$. Hence, $\Sigma_{\theta}^{\frac{1}{2}} \Sigma_D \Sigma_{\theta}^{\frac{1}{2}} = \sigma_{\theta}^2 \sigma_D^2 \Gamma \Lambda_{\theta} \Lambda_D \Gamma'$.

Frictionless economy: Recall from (IA5) that the following matrix has to be positive definite for an equilibrium to exist:

$$\frac{1}{4} \left(\frac{R-a_{\theta}}{\gamma_F}\right)^2 I_N - \left(\frac{R}{R-a_D}\right)^2 \Sigma_{\theta}^{\frac{1}{2}} \Sigma_D \Sigma_{\theta}^{\frac{1}{2}}.$$
 (IA8)

Plugging the previous result in the right part of (IA8) and rearranging terms gives

$$\Gamma\left(\frac{1}{4}\left(\frac{R-a_{\theta}}{\gamma}\right)^{2}I_{N}-\left(\frac{R}{R-a_{D}}\right)^{2}\sigma_{\theta}^{2}\sigma_{D}^{2}\Lambda_{\theta}\Lambda_{D}\right)\Gamma'.$$
(IA9)

This matrix must be positive definite for an equilibrium to exist. Since a symmetric matrix is positive definite if and only if each of its eigenvalues is positive, each of the diagonal elements in $\frac{1}{4} \left(\frac{R-a_{\theta}}{\gamma}\right)^2 I_N - \left(\frac{R}{R-a_D}\right)^2 \sigma_{\theta}^2 \sigma_D^2 \Lambda_{\theta} \Lambda_D$ must be positive. The eigenvalues are given by

$$\lambda_1 = \frac{1}{4} \left(\frac{R-a_\theta}{\gamma_F}\right)^2 - \left(\frac{R}{R-a_D}\right)^2 \sigma_\theta^2 \sigma_D^2 (1+(N-1)\rho_\theta)(1+(N-1)\rho_D), \quad \text{and} \tag{IA10}$$

$$\lambda_i = \frac{1}{4} \left(\frac{R - a_\theta}{\gamma_F}\right)^2 - \left(\frac{R}{R - a_D}\right)^2 \sigma_\theta^2 \sigma_D^2 (1 - \rho_D)(1 - \rho_D), \quad i = 2, \dots, N.$$
(IA11)

The result follows from comparing (IA10) and (IA11). The proof for the infrequent rebalancing economy is equivalent using (from Corollary 1 and the proof of Proposition IA1)

$$\frac{1}{4} \left(\frac{(R^{k+1}-1)(R^{k+1}-a_{\theta}^{k+1})}{\gamma_{I}(k+1)(R^{k+1}-a_{\theta}^{k})} \right)^{2} I_{N} - \left(\frac{R}{R-a_{D}} \right)^{2} \left(1 + \sum_{i=1}^{k} R^{2i} \right) \left(1 + \left(\frac{R^{k+1}(1-a_{\theta}^{k})}{R^{k+1}-a_{\theta}^{k}} \right)^{2} \right) \Sigma_{\theta}^{\frac{1}{2}} \Sigma_{D} \Sigma_{\theta}^{\frac{1}{2}}$$
(IA12)

instead of (IA8).

To prove that there exists four symmetric equilibria, use (IA8) again and $\Sigma_{\theta} = \sigma_{\theta}^2 \Gamma \Lambda_{\theta} \Gamma'$ (Assumption IA1) to obtain

$$P_{\theta} = \Gamma \sigma_{\theta}^{-2} \Lambda_{\theta}^{-1} \left(\frac{a_{\theta} - R}{2\gamma_F} I_N + \Lambda^{\frac{1}{2}} \right) \Gamma', \tag{IA13}$$

where $\Lambda = \frac{1}{4} \left(\frac{R-a_{\theta}}{\gamma_{F}}\right)^{2} I_{N} - \left(\frac{R}{R-a_{D}}\right)^{2} \sigma_{\theta}^{2} \sigma_{D}^{2} \Lambda_{\theta} \Lambda_{D}$. Each diagonal element of $\Lambda^{\frac{1}{2}}$ can take values $\pm \sqrt{\lambda_{i}}$. Given the eigenvector matrix Γ , it can be verified that all the eigenvalues (IA11) must have the same sign for P_{θ} to be symmetric with equal diagonal coefficients. Since (IA10) can take two values, this gives four symmetric equilibria. The proof is similar for the infrequent rebalancing economy.

As the number of assets N grows, an equilibrium becomes less likely to exist if dividend and liquidity shocks are correlated in the same direction across assets. In that case, agents cannot diversify liquidity and dividend risks and here must absorb a growing amount of correlated risks in equilibrium. In both economies, the effect of fundamental parameters is intuitive: more volatile and persistent sources of risk shrink the existence region. The only exception is the persistence of liquidity shocks a_{θ} . When q = 1, an equilibrium is always more likely to exist if liquidity trading is a random walk rather than an independent shock. But the reverse is true when q = 0. Section III provides additional details about the role of liquidity shock persistence.

II. Stability Analysis

To assess equilibrium stability, I examine whether small variation in the belief about next period's price impact results in a large deviation in the belief about the current price impact. In particular, in the one-asset case, an equilibrium is stable if

$$\left|\frac{\partial P_{\theta,t}}{\partial P_{\theta,t+1}}\right| < 1,\tag{IA14}$$

else the equilibrium is unstable. This analysis is equivalent to examining how a small deviation in the belief about next period's volatility affects current volatility (Bacchetta and Van Wincoop (2006)).

An additional complication arises because the model features multiple assets. Assumption IA1 permits a direct extension from the one-asset case. Under this assumption, traders' asset allocation problem reduces to investing in a set of N uncorrelated funds. I can then perform the stability analysis separately for each of these funds.

Frictionless economy: The price impact of liquidity shocks is given by

$$P_{\theta} = -\frac{\gamma_F}{R - a_{\theta}} \operatorname{Var}_t [P_{t+1} + D_{t+1}].$$
(IA15)

The expression on the right-hand side is forward-looking. I can then rewrite (IA15) as follows:

$$P_{\theta,t} = -\frac{\gamma_F}{R - a_\theta} \left(P_{\theta,t+1} \Sigma_\theta P'_{\theta,t+1} + \left(\frac{R}{R - a_D}\right)^2 \Sigma_D \right), \tag{IA16}$$

where $P_{\theta,t}$ is the current price impact of liquidity shocks and $P_{\theta,t+1}$ is the price impact in the next period according to traders' beliefs. In a stationary equilibrium, $P_{\theta,t} = P_{\theta,t+1}$.

Using Assumption IA1, (IA16) can be rewritten as

$$\Lambda_{P_{\theta},t} = -\frac{\gamma_F}{R - a_{\theta}} \left(\Lambda_{P_{\theta},t+1}^2 \sigma_{\theta}^2 \Lambda_{\theta} + \left(\frac{R}{R - a_D} \right)^2 \sigma_D^2 \Lambda_D \right), \tag{IA17}$$

where $\Lambda_{P_{\theta},t}$ is the eigenvalue matrix from the spectral decomposition of P_{θ} . Let $\lambda_X(j)$ denote the j^{th} eigenvalue of Λ_X . Taking the partial derivative of the current price impact eigenvalue with respect to next period's eigenvalue gives

$$\frac{\partial \lambda_{P_{\theta},t}(j)}{\partial \lambda_{P_{\theta},t+1}(j)} = -\frac{\gamma_F}{R - a_{\theta}} 2\lambda_{P_{\theta},t+1}(j)\sigma_{\theta}^2 \lambda_{\theta}(j).$$
(IA18)

In the stationary economy, (IA17) shows that each eigenvalue $\lambda_{P_{\theta}}(j)$ has two roots given by

$$\left(2\frac{\gamma_F}{R-a_\theta}\sigma_\theta^2\lambda_\theta(j)\right)^{-1}\left(-1\pm\sqrt{1-4\left(\frac{\gamma_F}{R-a_\theta}\right)^2\sigma_\theta^2\lambda_\theta(j)\left(\frac{R}{R-a_D}\right)^2\sigma_D^2\lambda_D(j)}\right).$$
 (IA19)

Thus,

$$\frac{\partial \lambda_{P_{\theta},t}(j)}{\partial \lambda_{P_{\theta},t+1}(j)} = -1 \pm \sqrt{1 - 4\left(\frac{\gamma_F}{R - a_{\theta}}\right)^2 \sigma_{\theta}^2 \lambda_{\theta}(j) \left(\frac{R}{R - a_D}\right)^2 \sigma_D^2 \lambda_D(j)}.$$
 (IA20)

Only the positive root of (IA19) is stable according to the stability criterion (IA14). Therefore, the only stable equilibrium consists of the tuple $(\lambda_{\phi_{P_{\theta}}}(1)_{+}, \lambda_{\phi_{P_{\theta}}}(2)_{+}, \dots, \lambda_{\phi_{P_{\theta}}}(N)_{+})$. This is the low volatility equilibrium (i.e., the equilibrium with the lowest price impact).

Infrequent rebalancing economy: The price impact of liquidity shocks is given by

$$P_{\theta} = -\frac{\gamma_I(k+1)(R^{k+1} - a_{\theta}^k)}{(R^{k+1} - 1)(R^{k+1} - a_{\theta}^{k+1})} \operatorname{Var}_t \left[P_{t+k+1} + \sum_{i=1}^{k+1} R^{k+1-i} D_{t+i} \right].$$
(IA21)

Since agents trade only every k+1 periods, the stability analysis relates the price impact of liquidity shocks today to the belief about the price impact in k+1 periods. Using the results of Corollary 1 from the main text in (IA21) gives

$$P_{\theta,t} = -\frac{\gamma_I(k+1)(R^{k+1} - a_{\theta}^k)}{(R^{k+1} - 1)(R^{k+1} - a_{\theta}^{k+1})} \\ \left(\left(1 + \left(\frac{R^{k+1}(1 - a_{\theta}^k)}{R^{k+1} - a_{\theta}^k} \right)^2 \right) P_{\theta,t+1} \Sigma_{\theta} P_{\theta,t+1}' + \left(\frac{R}{R - a_D} \right)^2 \left(\sum_{i=0}^k R^{2i} \right) \Sigma_D \right).$$
(IA22)

The stability analysis is then identical to the analysis for the frictionless economy.

III. The Role of Liquidity Trading Persistence

This appendix contrasts the role of a_{θ} when q = 0 and q = 1. In the frictionless economy, frequent traders are more willing to accommodate liquidity shocks when noisy supplies reverse rapidly, since they can unwind their trades more easily in the next period. Cespa and Vives (2012) detail a similar effect in a dynamic nonstationary setup. When a_{θ} is low, traders provide more liquidity, which lowers the price impact of liquidity shocks. As a result, increasing a_{θ} increases the price impact of liquidity shocks when q = 0.

In the infrequent rebalancing economy, the role of a_{θ} is more complex. Infrequent traders absorb at each rebalancing date the following vector of adjusted supplies:

$$\tilde{\theta}_t \equiv (k+1)\theta_t - \sum_{i=1}^k X_{t-i}^I.$$
(IA23)

In equilibrium, $X_t^I = \tilde{\theta}_t$. Market-clearing implies that

$$\tilde{\theta}_{t+k+1} = (k+1)\left(\theta_{t+k+1} - \theta_{t+k}\right) + \tilde{\theta}_t, \qquad (IA24)$$

where $\tilde{\theta}_{t+k+1}$ is the vector of adjusted supplies at the next rebalancing date. The infrequent traders who rebalance today only care about the change in noisy supplies between t + k + 1 and t + k since all the previous changes in noisy supplies are out of the market (absorbed by other infrequent traders). It follows that

$$\mathbb{E}_t \Big[\tilde{\theta}_{t+k+1} \Big] = \tilde{\theta}_t - (k+1)a_{\theta}^k (1-a_{\theta})\theta_t.$$
 (IA25)

Equation (IA25) implies that when $a_{\theta} = 0$ or $a_{\theta} = 1$, there is no predictable variation in θ_{t+k+1} relative to its value at date t. Focusing only on this factor, the price impact of liquidity shocks is therefore the same regardless of whether $a_{\theta} = 0$ or $a_{\theta} = 1$. In fact, price impact is highest when $a_{\theta} = 0$ or $a_{\theta} = 1$ (focusing only on this factor). Since $\tilde{\theta}_t$ and θ_t are equal on average and $1 > a_{\theta}^k (1 - a_{\theta}) \ge 0$, $\tilde{\theta}_{t+k+1}$ reverses predictably when $0 < a_{\theta} < 1$. This makes infrequent traders at date t more willing to provide liquidity.

Liquidity trading persistence increases the price impact of liquidity shocks unambiguously when q = 0. This is not the case when q = 1 since the first-difference of an autoregressive process is more volatile when the process reverses rapidly (i.e., the elements of $\operatorname{Var}_t[\theta_{t+k+1} - \theta_{t+k}]$ decrease with a_{θ}). The next proposition formalizes this difference between the frictionless and infrequent rebalancing economies.

PROPOSITION IA3: Consider the low volatility equilibrium of a single-asset economy. When q = 0,

the price impact of liquidity shocks is always larger in absolute value when $a_{\theta} = 1$ than when $a_{\theta} = 0$. When q = 1, the price impact of liquidity shocks is always larger in absolute value when $a_{\theta} = 0$ than when $a_{\theta} = 1$.

The predictability factor is the same regardless of whether $a_{\theta} = 0$ or $a_{\theta} = 1$ (equation (IA25)), but when $a_{\theta} = 0$ the volatility of adjusted noisy supplies is larger than when $a_{\theta} = 1$ (equation (IA24)). Proposition IA3 explains why varying a_{θ} has an ambiguous effect on price impact when 0 < q < 1. To prove the proposition, I use the following lemma.

LEMMA IA1: In the low volatility equilibrium of the frictionless economy with a single asset, (a) $\frac{\partial P_{\theta}}{\partial a_{\theta}} < 0$, and (b) $\frac{\partial P_{\theta}}{\partial \sigma_{\theta}^2} < 0$.

Proof of Lemma: IA1: In the one-asset economy, price impact when q = 0 is given by

$$P_{\theta} = \frac{1}{2\sigma_{\theta}^2} \left(-\frac{R-a_{\theta}}{\gamma_F} + \sqrt{\left(\frac{R-a_{\theta}}{\gamma_F}\right)^2 - 4\sigma_{\theta}^2 \sigma_D^2 \left(\frac{R}{R-a_D}\right)^2} \right).$$
(IA26)

Part (a) follows immediately from taking the partial derivative. Consider now the variance of liquidity shocks. Let $C \equiv \frac{R-a_{\theta}}{\gamma_F}$ and $D \equiv \sigma_D \frac{R}{R-a_D}$ to simplify notation. The partial derivative is given by

$$\frac{\partial P_{\theta}}{\partial \sigma_{\theta}^2} = \frac{1}{2\sigma_{\theta}^4} \left(C - \frac{C^2}{\sqrt{C^2 - 4D^2 \sigma_{\theta}^2}} + \frac{2D^2 \sigma_{\theta}^2}{\sqrt{C^2 - 4D^2 \sigma_{\theta}^2}} \right).$$
(IA27)

Therefore, $\frac{\partial P_{\theta}}{\partial \sigma_{\theta}^2} < 0$ if $C^2 - C\sqrt{C^2 - 4D^2\sigma_{\theta}^2} - 2D^2\sigma_{\theta}^2 > 0$. This is indeed the case since $C^2 - C\sqrt{C^2 - 4D^2\sigma_{\theta}^2} - 2D^2\sigma_{\theta}^2 = \frac{1}{2}\left(C - \sqrt{C^2 - 4D^2\sigma_{\theta}^2}\right)^2$.

Proof of Proposition IA3: The statement for q = 0 follows from Part (a) of Lemma IA1. When q = 1, the proof of Corollary 1 in the main text shows that price impact is given by

$$P_{\theta} = \frac{1}{2\sigma_{\theta}^{2}} \left(-\frac{R^{k+1}-1}{\gamma_{I}(k+1)} + \sqrt{\left(\frac{R^{k+1}-1}{\gamma_{I}(k+1)}\right)^{2} - 4\sigma_{\theta}^{2}\sigma_{D}^{2}\left(\frac{R}{R-a_{D}}\right)^{2}} \right), \quad \text{for } a_{\theta} = 0, \qquad (\text{IA28})$$

$$P_{\theta} = \frac{1}{4\sigma_{\theta}^2} \left(-\frac{R^{k+1} - 1}{\gamma_I(k+1)} + \sqrt{\left(\frac{R^{k+1} - 1}{\gamma_I(k+1)}\right)^2 - 8\sigma_{\theta}^2 \sigma_D^2 \left(\frac{R}{R-a_D}\right)^2} \right), \quad \text{for } a_{\theta} = 1.$$
(IA29)

The result follows by applying Part (b) of Lemma IA1.■

IV. A Model with Different Liquidity Trading Frequencies

This section examines a model in which liquidity trading occurs at different frequencies.

A. Model

I use a simplified setup to focus on the key result. Time is discrete and goes to infinity. An asset pays iid dividends $\epsilon_t^D \sim \mathcal{N}(0, \sigma_D^2)$ each period. A risk-free asset in perfectly elastic supply with gross return R > 1 is also available. Liquidity shocks occur at different frequencies: high frequency (H) and low frequency (L). Consider the simple case in which low frequency shocks take place every two periods:

$$\theta_{H,t} = a_H \theta_{H,t-1} + \epsilon_{H,t}^{\theta}, \tag{IA30}$$

$$\theta_{L,t} = a_L \theta_{L,t-2} + \epsilon_{L,t}^{\theta}, \tag{IA31}$$

where $\epsilon_{i,t}^{\theta} \sim \mathcal{N}(0, \sigma_{\theta}^2), i \in (L, H)$. For simplicity, the two liquidity shocks are uncorrelated. I consider a stationary setting in which the mass of liquidity traders is constant every period. Therefore, half the mass of low frequency liquidity traders is present in the market at each date. The total mass of liquidity traders equals one, and the mass of low frequency traders equals q. As in the main model, an agent trades every period and maximizes his exponential utility over next period's wealth. Let $x_{F,t}$ denote his asset demand. The market-clearing condition is then given by

$$x_{F,t} = (1-q)\theta_{H,t} + \frac{q}{2}\theta_{L,t} + \underbrace{\frac{q}{2}\theta_{L,t-1}}_{\text{lagged}}.$$
 (IA32)

The last term is the lagged supply from low frequency liquidity traders.

In a linear stationary equilibrium, the asset price is given by

$$p_t = p_{\theta,H}\theta_{H,t} + p_{\theta,L1}\theta_{L,t} + p_{\theta,L2}\theta_{L,t-1}.$$
(IA33)

The three state variables are the supply of high frequency liquidity traders, the current supply of low

frequency liquidity traders, and the lagged supply of low frequency liquidity traders. This conjecture is verified in what follows. Since prices are normally distributed, the agent's optimal demand takes the standard form $x_t = \frac{1}{\gamma \sigma_q^2} \mathbb{E}_t[q_{t+1}]$, where $q_{t+1} \equiv p_{t+1} + d_{t+1} - Rp_t$ and $\sigma_q^2 \equiv \operatorname{Var}_t[q_{t+1}]$ is a constant matrix in equilibrium.

Using the price conjecture (IA33) and the dynamics of liquidity trading yields

$$\mathbb{E}_{t}[q_{t+1}] = (a_{H} - R)p_{\theta,H}\theta_{H,t} + (a_{L}p_{\theta,L1} - Rp_{\theta,L2})\theta_{L,t-1} + (p_{\theta,L2} - Rp_{\theta,L1})\theta_{L,t}, \quad \text{and} \quad (IA34)$$

$$\sigma_q^2 = (p_{\theta,H}^2 + p_{\theta,L}^2)\sigma_\theta^2 + \sigma_D^2. \tag{IA35}$$

Matching the coefficients with the market-clearing condition gives the following three conditions:

$$\frac{1}{\gamma \sigma_q^2} (a_H - R) p_{\theta,H} = 1 - q, \qquad (IA36)$$

$$\frac{1}{\gamma \sigma_q^2} (a_L p_{\theta,L1} - R p_{\theta,L2}) = \frac{q}{2}, \quad \text{and}$$
(IA37)

$$\frac{1}{\gamma \sigma_q^2} (p_{\theta,L2} - Rp_{\theta,L1}) = \frac{q}{2}.$$
(IA38)

If a solution exists, the price conjecture (IA33) is verified. Using (IA37) and (IA38),

$$p_{\theta,L2} = \underbrace{\frac{a_L + R}{1 + R}}_{\equiv \alpha} p_{\theta,L1}.$$
 (IA39)

Since $\frac{1}{2} < \alpha \leq 1$, $|p_{\theta,L2}| < |p_{\theta,L1}|$. Combining (IA38), (IA36), and (IA39) gives

$$p_{\theta,L1} = \frac{q/2}{1-q} \underbrace{\left(\frac{a_H - R}{\alpha - R}\right)}_{\equiv \beta} p_{\theta,H}.$$
 (IA40)

Since $\beta > 0$, $p_{\theta,L1}$ and $p_{\theta,H}$ have the same sign. Equations (IA36) and (IA40) can be used to obtain a quadratic equation for $p_{\theta,H}$:

$$\left(\left(\frac{q/2}{1-q}\beta\right)^2 + 1\right)\sigma_\theta^2 p_{\theta,H}^2 - \frac{a_H - R}{(1-q)\gamma}p_{\theta,H} + \sigma_D^2 = 0.$$
 (IA41)

When q = 0, the equation reduces to the standard equation for price impact as in the model of

Spiegel (1998) with one asset. Let $\beta_q \equiv \frac{q/2}{1-q}\beta$. The price impact of high frequency shocks is then given by

$$p_{\theta,H} = \frac{1}{2\left(\beta_q^2 + 1\right)\sigma_{\theta}^2} \left(\frac{a_H - R}{(1 - q)\gamma} \pm \sqrt{\left(\frac{a_H - R}{(1 - q)\gamma}\right)^2 - 4\left(\beta_q^2 + 1\right)\sigma_{\theta}^2\sigma_D^2}\right).$$
 (IA42)

Note that $p_{\theta,H} < 0$, which implies $p_{\theta,L1} < 0$ and $p_{\theta,L2} < 0$. The coefficient on the lagged liquidity shock is negative. Intuitively, a large lagged liquidity shock increases the asset supply, which lowers the price (for the agent to absorb the supply in equilibrium). This is similar to the infrequent rebalancing economy, in which the lagged *demand* coefficients are positive. The existence condition follows from (IA42).

B. Return Autocorrelation

This section investigates return autocorrelation in a model with high and low frequency liquidity trading. Note that $\text{Cov}[\theta_{L,t}, \theta_{L,t-1}] = 0$ since the shocks are uncorrelated. The first-order autocovariance of excess returns is given by

$$\operatorname{Cov}[q_{t+1}, q_t] = (1 - Ra_H) \frac{a_H - R}{1 - a_H^2} p_{\theta, H}^2 \sigma_{\theta}^2 + (1 - R\alpha)(1 + a_L) \frac{\alpha - R}{1 - a_L^2} \beta_q^2 p_{\theta, H}^2 \sigma_{\theta}^2.$$
(IA43)

The first component is standard: positive autocovariance requires highly persistent liquidity trading. The second component comes from the low frequency shocks ($\beta_q = 0$ when q = 0). This component is negative unless $R\alpha > 1$, which is equivalent to $a_L > 1/R - (R-1)$. This condition is only slightly less restrictive than $a_H > 1/R$, which is the necessary condition for the first component to be positive.

The second-order autocovariance of excess returns is given by

$$\operatorname{Cov}[q_{t+2}, q_t] = a_H (1 - Ra_H) \frac{a_H - R}{1 - a_H^2} p_{\theta, H}^2 \sigma_{\theta}^2 + \left(1 + (\alpha - R)^2 - (R\alpha)^2\right) \frac{\alpha - R}{1 - a_L^2} \beta_q^2 p_{\theta, H}^2 \sigma_{\theta}^2.$$
(IA44)

To obtain (IA44), use the fact that $a_L - R\alpha = \alpha - R$. Again, the first component is standard and the second component comes from low frequency shocks. The parameter condition for the second component to be positive is more stringent than for the first-order autocovariance since $R\alpha > 1$ is only a necessary condition. The following proposition states this result.

PROPOSITION IA4: If $a_H < 1/R$ and $a_L < 1/R - (R-1)$, the first- and second-order autocovariances are negative.

I expect this result to hold for all lags. The mechanism that generates positive autocorrelation in this economy differs significantly from the infrequent rebalancing mechanism. In particular, it requires a highly persistent supply of liquidity traders. This is therefore similar to the economy without infrequent traders discussed in the paper. Furthermore, a negative first-order autocorrelation implies a negative second-order autocorrelation.

Infrequent traders provide liquidity. Thus, when they liquidate their abnormal positions, they trade in the same direction as the initial liquidity shock that they absorbed. The same is not true for low frequency liquidity shocks because they revert over time. When a trader absorbs a low frequency shock today, he requires a price discount to absorb the shock (unless the shock is highly persistent). Price reversal compensates the risk-averse trader for the liquidity he provides. Therefore, return autocorrelation is negative in this case. In fact, the effect goes in the other direction and adds a negative component to the benchmark autocorrelation. For instance, it may be the case that $\text{Cov}[q_{t+2}, q_t] < \text{Cov}[q_{t+1}, q_t]$ even when $a_L = a_H$.

V. Seasonality in Mean Liquidity Trading

Variation in the mean level of liquidity trading can generate significant cross-sectional variation in mean returns across calendar periods. In the economy without infrequent rebalancing, assume that mean liquidity trading varies with the calendar period and is given by the vector $\bar{\theta}_{c(t)}$. Thus, the vector of supplies from liquidity traders at time t equals $\theta_t + \bar{\theta}_{c(t)}$. The equilibrium price vector is given by

$$P_t = P_\theta \theta_t + \frac{a_D}{R - a_D} D_t + \bar{P}_{c(t)}.$$
 (IA45)

In this direct extension of the frictionless model, the price coefficients solve (with h = 1)

$$P_{\theta}\Sigma_{\theta}P_{\theta}' + \frac{R - a_{\theta}}{\gamma_F}P_{\theta} + \frac{R}{R - a_D}\Sigma_D = 0_{N \times N}, \quad \text{and} \tag{IA46}$$

$$\bar{P}_{c(j+1)} - R\bar{P}_{c(j)} + (R - a_{\theta})P_{\theta}\left(\bar{S} + \bar{\theta}_{c(j)}\right) = 0_{N \times 1}, \quad j = 1, \dots, C,$$
(IA47)

where C is the number of calendar periods. The seasonality in mean liquidity trading does not affect the price impact coefficients. Therefore, a model can simultaneously incorporate an autocorrelation effect from infrequent rebalancing and a seasonality effect from mean liquidity trading.

Assume that a subset of assets exhibit seasonality in mean liquidity trading. For example, with assets *i* and *j*, let $\bar{\theta}_{i,c(t)} = \bar{\theta}_{j,c(t)}$ for $c(t) = 2, \ldots, C$ and $\bar{\theta}_{i,c(t)} \neq \bar{\theta}_{j,c(t)}, i \neq j$, for c(t) = 1. Since the expected excess return in calendar period c(t) is given by $\mathbb{E}[Q_{t+1}|c(t)] = -(R - a_{\theta})P_{\theta}\bar{\theta}_{c(t)}$, the cross-sectional variance in mean return is zero in all but one period in this example. To apply this result, I simulate returns from two groups of assets in an economy with 13 calendar periods and persistent liquidity shocks. The mean supply of liquidity traders $\bar{\theta}_{c(t)}$ is constant in the first group. In the second group, $\bar{\theta}_{c(t)}$ is the same in all calendar periods but the last one. Figure IA1 shows that this seasonality in mean liquidity trading generates a persistent seasonality pattern in the cross-sectional regression coefficients. A persistent seasonality pattern arises because the price of risk is not constant across calendar periods.



Figure IA1. Seasonality in mean liquidity trading. The figure shows cross-sectional regression estimates from $Q_{i,t} = \alpha_{l,t} + \gamma_{l,t}Q_{i,t-l} + u_{i,t}$ based on averages of 1000 simulations from a T = 500 periods economy. The calibration assumes M = 13, R = 1.01, $\sigma_{\theta} = 0.4$, $a_D = 0$, $\sigma_D = 0.2$, $a_{\theta} = 0.6$, $\gamma = 1$, $\bar{\theta}_{1,j} = 1 \forall j$, $\bar{\theta}_{2,j} = 1$ for $j = 1, \ldots, 12$, and $\bar{\theta}_{2,13} = 4$.

VI. Multiple Groups of Infrequent Traders

This section extends the benchmark model to allow for infrequent traders with heterogeneous rebalancing horizons. More precisely, I consider an economy with two groups of infrequent traders (in addition to frequent traders). Group *i* has a mass q_i and an inattention period k_i . While analytical solutions are again not available, the rebalancing mechanism seems robust to having multiple groups of infrequent traders. In particular, the autocorrelation pattern is subject to shifts at *both* rebalancing horizons (lags $k_1 + 1$ and $k_2 + 1$): both autocorrelations can switch sign. This suggests that the model can simultaneously explain seasonalities at different frequencies. I provide a numerical example at the end of the section.

A. Solution

The market-clearing condition is

$$\frac{q_1}{k_1+1}X_t^{I_1} + \frac{q_2}{k_2+1}X_t^{I_2} + \frac{1-q_1-q_2}{h}\sum_{j=0}^{h-1}X_{j,t}^F = \bar{S} + \theta_t - \frac{q_1}{k_1+1}\sum_{i=1}^{k_1}X_{t-i}^{I_1} - \frac{q_2}{k_2+1}\sum_{i=1}^{k_2}X_{t-i}^{I_2}.$$
 (IA48)

The new vector of state variables is of length $(1 + (k_1 + k_2 + 2)N)$ and includes the lagged demands from the second group of infrequent traders. The matrices A_Y and B_Y in Appendix A in the main article are updated accordingly.

Define φ_{X_1} and φ_{X_2} such that $\varphi_{X_1}Y_t = X_t^{I_1}$ and $\varphi_{X_2}Y_t = X_t^{I_2}$. The system of fixed point

equations that yields the equilibrium coefficients is then given by

$$\frac{q_1/\gamma_I}{k_1+1} \Sigma_{k_1+1}^{-1} \left(\sum_{j=0}^{k_1} R^{k_1-j} A_Q A_Y^j \right) + \frac{q_2/\gamma_I}{k_2+1} \Sigma_{k_2+1}^{-1} \left(\sum_{j=0}^{k_2} R^{k_2-j} A_Q A_Y^j \right)$$
(IA49)

$$+\frac{1-q_1-q_2}{h}\left(\sum_{j=0}^{h-1}\frac{1}{\alpha_{j+1}}F_{j+1}\right) -\varphi_{\bar{S}}-\varphi_{\theta}+\frac{q_1}{k_1+1}\varphi_{X_1}+\frac{q_2}{k_2+1}\varphi_{X_2}=0,$$
 (IA50)

$$\frac{1}{\gamma_I} \Sigma_{k_1+1}^{-1} \left(\sum_{j=0}^{k_1} R^{k-j} A_Q A_Y^j \right) - B = 0, \quad \text{and}$$
(IA51)

$$\frac{1}{\gamma_I} \Sigma_{k_2+1}^{-1} \left(\sum_{j=0}^{k_2} R^{k-j} A_Q A_Y^j \right) - C = 0, \tag{IA52}$$

where C is the $N \times (1 + (k_1 + k_2 + 2)N)$ matrix of equilibrium coefficients for the demands of the second group of infrequent traders (i.e., $X_t^{I_2} = CY_t$). The other coefficients are defined in Appendix A in the main article.

B. Numerical Example

Figure IA2 plots the autocorrelations in an economy with two groups of infrequent traders $(k_1 = 1 \text{ and } k_2 = 5)$. I set $a_{\theta} = 0$ to focus solely on the impact of infrequent rebalancing. The second and sixth autocorrelations are positive, as predicted by the baseline model when $a_{\theta} = 0$. The magnitude of the pattern depends on the proportion of infrequent traders in each group as well as the volatility of liquidity shocks. As can be seen by comparing Panels A and B, this extended model can generate a rich set of dynamics.

VII. Trading Volume

This section explains how to compute trading volume when 0 < q < 1. The following standard lemma is stated without proof.

LEMMA IA2: Let X and Y be jointly normal random variables with zero mean, variances σ_X^2 and σ_Y^2 , and correlation ρ . Then, $\operatorname{Cov}[|X|, |Y|] = \frac{2}{\pi} \left(\rho \operatorname{arcsin}(\rho) + \sqrt{1 - \rho^2} - 1 \right) \sigma_X \sigma_Y$.



Figure IA2. Partial autocorrelations predicted by the model with multiple groups of infrequent traders for different liquidity shocks volatility σ_{θ} . The calibration assumes $q_1 = 0.6, q_2 = 0.3, k_1 = 1, k_2 = 5, h = 20, R = 1.01, a_{\theta} = 0, a_D = 0, \sigma_D = 0.1, N = 2$, and $\rho_D = 0.3$.

Trading volume is given by

$$V_t = \frac{1}{2} \left(\frac{q}{k+1} \left| X_t^I - X_{t-k-1}^I \right| + \frac{1-q}{h} \left| \sum_{j} (X_{j,t}^F - X_{j,t-1}^F) \right| + |\theta_t - \theta_{t-1}| \right).$$
(IA53)

For simplicity, this formulation ignores the trading among frequent traders. The extra terms can be computed, but I find volume autocorrelations to be almost identical regardless of whether h = 1or h = 2 in my calibrations. The autocovariance of volume changes is given by

$$\operatorname{Cov}[\Delta V_t, \Delta V_{t+j}] = \operatorname{Cov}[V_t, V_{t+j}] - \operatorname{Cov}[V_t, V_{t+j-1}] + \operatorname{Cov}[V_{t-1}, V_{t+j-1}] - \operatorname{Cov}[V_{t-1}, V_{t+j}].$$
(IA54)

Hence, it is necessary to compute $\text{Cov}[V_t, V_{t+j}]$ $(j \ge 1)$. From (IA53), the autocovariance in volume is the (weighted) sum of the autocovariances between absolute changes in θ , X^I , and X^F .

First, define φ_{I_k} such that $X_{t-k-1}^I = \varphi_{I_k} Y_{t-1}$. Second, note that $X_t^F = B^F Y_t$, where $B^F = \frac{h}{1-q} \left(\varphi_{\bar{S}} + \varphi_{\theta} - \frac{q}{k+1} (\varphi_X + B) \right)$ from the market-clearing condition (recall that $X_t^I = BY_t$). As a

result,

$$X_{t}^{I} - X_{t-k-1}^{I} = (BA_{Y} - \varphi_{I_{k}})Y_{t-1} + BB_{Y}\epsilon_{t}, \qquad (IA55)$$

$$\theta_t - \theta_{t-1} = (\varphi_{\theta} A_Y - \varphi_{\theta}) Y_{t-1} + \varphi_{\theta} B_Y \epsilon_t, \text{ and}$$
(IA56)

$$X_{t}^{F} - X_{t-1}^{F} = \left(B^{F}A_{Y} - B^{F}\right)Y_{t-1} + B^{F}B_{Y}\epsilon_{t}.$$
(IA57)

Thus, all the previous variables can be expressed as $\Delta_t^X = M_X Y_{t-1} + K_X \epsilon_t$, where M_X and K_X are some constant parameter matrices associated with variable X.

To get an expression for $\text{Cov}\left[|\Delta_t^X|, |\Delta_t^Z|\right]$, first compute the covariance between the two variables:

$$Cov \left[\Delta_t^X, \Delta_{t+j}^Z\right] = Cov [M_X Y_{t-1} + K_X \epsilon_t, M_Z Y_{t+j-1} + K_Z \epsilon_{t+j}]$$

= $M_X V_Y (A_Y^j)' M_Z' + K_X \Sigma_Y B_Y' (A_Y^{j-1})' M_Z', \quad j \ge 1,$ (IA58)

using the fact that $Y_{t+j-1} = A_Y^j Y_{t-1} + \sum_{i=0}^{j-1} A_Y^i B_Y \epsilon_{t+j-1-i}$. Similarly, $\operatorname{Var}\left[\Delta_t^X\right] = K_X \Sigma_Y K'_X + M_X V_Y M'_X$. Hence, the correlation matrix between variables X and Z, $\operatorname{Corr}\left[\Delta_t^X, \Delta_{t+j}^Z\right]$, can be obtained easily. By joint normality, apply Lemma IA2 to compute the autocovariance between |X| and |Z| (for each asset).

Finally, the autocorrelation of volume changes for asset i is given by

$$\operatorname{Corr}\left[\Delta V_{i,t}, \Delta V_{i,t+j}\right] = \frac{\operatorname{Cov}\left[\Delta V_{i,t}, \Delta V_{i,t+j}\right]}{\operatorname{Var}\left[\Delta V_{i,t}\right]},$$

where $\operatorname{Var}[\Delta V_{i,t}] = 2 \left(\operatorname{Var}[V_{i,t}] - \operatorname{Cov}[V_{i,t}, V_{i,t+1}] \right).$

VIII. Additional Empirical Results

This section contains robustness checks and additional results for the empirical analysis on daily returns.

Midquote returns: To control for the bid-ask bounce, I perform the regressions on midquote returns over the period 1993 to 2012 (continuous series of bid and ask data are available on CRSP as of the end of 1992). As expected, using midquote returns weakens reversal at the first lag (see

Figure IA3). Surprisingly, the first coefficient is positive (but insignificant) for high turnover stocks. Hypothesis 1 cannot be rejected for the sample of all stocks but is rejected with a t-statistic of 2.27 for high turnover stocks. More generally, correcting for bid-ask bounce should reduce reversal effects, which may explain the decrease in statistical significance. Still, restricting the sample to the one-third of largest stocks by capitalization at each date and using midquote returns rejects the null at the 5% level (t-statistic of 2.08).

Firm size: The results are also robust to controlling for firm size. At each date, I sort stocks into three groups based on average market capitalization over the past year. Figure IA4 shows that the infrequent rebalancing pattern holds for all size groups. Small stocks do not drive the results.

Evolution of the pattern over time: Panel A of Figure IA5 plots estimates of the multiple regressions for the extended sample from 1963 to 1993, while Panel B plots estimates on the subsample from 1998 to 2012. Evidence of infrequent rebalancing at the fifth and tenth lags seems strong for the most recent sample but difficult to discern for the older sample. The pattern thus appears to be a recent phenomenon that holds in years that witnessed the emergence of high frequency trading. As a robustness check, I find that the pattern also holds in the subsample 1983 to 1998 but is weaker at the tenth lag. The regression coefficients for the old sample tend to be larger (in absolute value) than those for the recent one. This evidence suggests that market quality has improved over time, consistent with the analysis of Chordia, Roll, and Subrahmanyam (2011).

As documented by Chordia, Roll, and Subrahmanyam (2011) for U.S. stocks, institutional trading appears to be an important contributor to the rise in turnover observed since the early 1990s. While an increase in professional investing could have fostered market efficiency, institutional trading could have also resulted in specific predictability patterns. To evaluate whether institutional ownership can help explain the autocorrelation structure in daily returns, I obtain institutional ownership data from the Thomson-Reuters Institutional Holdings (13F) Database. Any institution with more than \$100 million in assets under discretionary management has to report its holdings to the SEC on a quarterly basis. When available, I obtain institutional ownership for each stock used in the previous analysis. This procedure leaves an average of 1,600 stocks in the data set at each date with both return and ownership data. The increase in institutional ownership in recent years is substantial: the first (second) tercile of institutional ownership rises from roughly 10% (35%) in 1983 to 50% (80%) in 2012. Stocks are then split into three groups at each date based on the level

of institutional ownership, and the multiple regression is estimated for each group. The regression estimates—plotted in Figure IA6—are consistent with the empirical results of Sias and Starks (1997): daily return autocorrelations increase with institutional ownership. There is no evidence, however, that stocks with high institutional ownership exhibit more pronounced autocorrelation patterns than medium ownership stocks. I reach a similar conclusion when jointly controlling for institutional ownership and turnover with double sorts.



Figure IA3. Cross-sectional multiple regressions of daily midquote returns. The following cross-sectional regression is estimated for each day t: $r_{i,t} = \alpha_t + \gamma_{1,t}r_{i,t-1} + \ldots + \gamma_{20,t}r_{i,t-20} + \gamma_{\mu,t}\mu_{i,t} + u_{i,t}$, where $r_{i,t}$ is the return computed from quote midpoints of stock i on day t and μ_{it} is the average same-weekday (the same weekday as day t) return on stock i over the previous year excluding the past 20 returns. The sample consists of NYSE/Amex common stock midquote returns over the period 1993 to 2012. The left-hand charts plot the time-series averages of $\gamma_{l,t}$ ($l = 1, \ldots, 20$). The right-hand charts plot t-statistics computed using a Newey-West correction with twenty lags. Black lines indicate significance bounds at the 5% level. Panel A: all stocks. Panel B: the third of stocks with the highest average turnover over the past 250 days as of date t - 20.





-10

-15

lag

Figure IA4. Cross-sectional multiple regressions of daily returns for different market capitalization groups. At each date t, stocks are allocated into three groups based on their market capitalization as of date t - 21. The following cross-sectional regression is then estimated for each group: $r_{i,t} = \alpha_t + \gamma_{1,t}r_{i,t-1} + \ldots + \gamma_{20,t}r_{i,t-20} + \gamma_{\mu,t}\mu_{i,t} + u_{i,t}$, where $r_{i,t}$ is the simple return of stock i on day t and μ_{it} is the average same-weekday (the same weekday as day t) return on stock i over the previous year excluding the past 20 returns. The sample consists of NYSE/Amex common stock returns over the period 1983 to 2012. The left-hand charts plot the time-series averages of $\gamma_{l,t}$ ($l = 1, \ldots, 20$). The right-hand charts plot t-statistics computed using a Newey-West correction with 20 lags. Black lines indicate significance bounds at the 5% level. Panel A: low market capitalization stocks. Panel B: mid market capitalization stocks. Panel C: high market capitalization stocks.

-2

lag



Figure IA5. Cross-sectional multiple regressions of daily returns for different subsamples. The following cross-sectional regression is estimated for each day t: $r_{i,t} = \alpha_t + \gamma_{1,t}r_{i,t-1} + \dots + \gamma_{20,t}r_{i,t-20} + \gamma_{\mu,t}\mu_{i,t} + u_{i,t}$, where $r_{i,t}$ is the simple return of stock i on day t and μ_{it} is the average same-weekday (the same weekday as day t) return on stock i over the previous year excluding the past 20 returns. The sample consists of NYSE/Amex common stock returns. The left-hand charts plot the time-series averages of $\gamma_{l,t}$ ($l = 1, \dots, 20$). The right-hand charts plot t-statistics computed using a Newey-West correction with 20 lags. Black lines indicate significance bounds at the 5% level. Panel A: period 1963 to 1992. Panel B: period 1998 to 2012.





Panel A. Low institutional ownership stocks

Figure IA6. Cross-sectional multiple regressions of daily returns for different institutional ownership groups. At each date t, stocks are allocated into three groups based on their institutional ownership as of date t - 21. The following cross-sectional regression is then estimated for each group: $r_{i,t} = \alpha_t + \gamma_{1,t}r_{i,t-1} + \ldots + \gamma_{20,t}r_{i,t-20} + \gamma_{\mu,t}\mu_{i,t} + u_{i,t}$, where $r_{i,t}$ is the simple return of stock i on day t and μ_{it} is the average same-weekday (the same weekday as day t) return on stock i over the previous year excluding the past 20 returns. The sample consists of NYSE/Amex common stock returns over the period 1983 to 2012. The left-hand charts plot the time-series averages of $\gamma_{l,t}$ ($l = 1, \ldots, 20$). The right-hand charts plot t-statistics computed using a Newey-West correction with 20 lags. Black lines indicate significance bounds at the 5% level. Panel A: low institutional ownership stocks. Panel B: mid institutional ownership stocks. Panel C: high institutional ownership stocks.

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