Commonality in Noise Trading and a Transient Factor in Returns

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Abstract

We investigate theoretical and empirical implications of commonality in noise trading. Using an asset pricing model under asymmetric information we show that (1) commonality in noise trading across assets introduces a transient factor in returns in addition to the fundamental factor induced by a common value component, and (2) only a model with both fundamental and transient return factors can generate positive and negative signs for return cross-autocorrelations. Empirically, we show that negative signs are frequently observed in the cross-autocorrelations of daily returns. We use cross-autocovariance moment conditions to estimate an extended version of our model, and recover permanent and transient return factors. Our two-factor model fits daily portfolio returns very well, and the transient factor significantly helps in explaining dynamics of short term returns. We estimate “information frictions” (delays in price response to factor shocks) and show that fundamental friction is increasing, while transient friction is decreasing, in firm size. For the fundamental friction, we find an annual premium in the range of 1.7% to 4.1%. Within the subset of small firms, fundamental and transient friction premia are more pronounced and statistically significant.

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1 Introduction

“The effects of noise on the world, and on our views of the world, are profound. Noise in the sense of a large number of small events is often a causal factor much more powerful than a small number of large events can be. Noise makes trading in financial markets possible, and thus allows us to observe prices for financial assets. Noise causes markets to be somewhat inefficient, but often prevents us from taking advantage of inefficiencies.” Black (1986)

This paper examines the asset pricing implications of commonality in noise trading. Noise trading plays a critical role in financial markets, particularly in information transmission via prices. Grossman and Stiglitz (1980) observe that in a fully efficient market agents do not spend resources on gathering the information that ultimately must be reflected in prices and that a random source of trade, “noise trading” or “liquidity trading”, is necessary for a “relevant”, partially-revealing, equilibrium to exist. Recent studies provide evidence consistent with the possibility of co-movements in noise trading across securities and markets. We investigate how such commonality in noise trading affects the dynamics of stock returns. Moreover, in the presence of noise trading the information incorporation into prices becomes gradual so that new information can impact prices over several periods. Hence, we use our framework to examine how “information frictions” (delays in price response to common shocks) relate to firm characteristics and affect the cross-section of expected returns.

We offer an asset pricing model in which heterogeneity in agents’ information about a common component in noise trading induces a transient common factor (with temporary effect on prices), in addition to the fundamental common factor (with permanent effect on prices) induced by the commonality in asset fundamental values. The model indicates that a transient factor is needed to generate both negative and positive signs for return cross-autocorrelations. Empirically, we show that negative cross-autocorrelations prevail in daily returns. We estimate an extended version of our model, recover transient and fundamental return factors, and show the factors’ significant role in

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1 We use the two terms, “liquidity trading” and “noise trading”, synonymously in this paper.

2 See, for example, Chordia and Swaminathan (2000), Hasbrouck and Seppi (2001), Chordia, Sarkar and Subrahmanyam (2005).
explaining the dynamics of daily returns. In contrast to purely statistical factors, our fundamental and transient factors show economic distinction. This paper also contributes to our understanding of information frictions and their premia in the cross-section of stock returns. We estimate information frictions for our fundamental and transient factors, and find a statistically and economically significant premium for fundamental friction and a smaller and statistically insignificant premium for transient friction. For small firms, however, both fundamental and transient friction premia are more pronounced and the latter becomes statistically significant.

Our asset pricing model has two main features, (1) a common component in noise trades in addition to a common component in fundamental values, and (2) private information about both fundamental values and noise trades. As a result, equilibrium returns in our model are driven by a fundamental factor (corresponding to common shocks to fundamental values) and a transient factor (corresponding to common noise trading shocks). The transient return factor generates “excess co-movement” in returns beyond what is justified by fundamentals (c.f., Barberis, Shleifer and Wurgler (2005) and Veldkamp (2006)).

A transient return factor allows for negative and positive cross-autocorrelation signs, whereas a fundamental factor alone can only generate positive signs. Intuitively, the transient nature of noise trading shocks induces mean reversion in prices. A positive noise trading shock, for example, increases an asset’s price initially but the price returns to the asset fundamental value. If transient shocks affect prices of many stocks then, in the absence of fundamental shocks, each asset’s positive return this period predicts negative returns for other assets in the next period. Ultimately, cross-autocorrelation signs depend on the relative importance of the fundamental and transient factors. Extant literature on cross-autocorrelations in stock returns mainly focuses on their asymmetry.

3 For example, a brokerage house may have private information about the liquidity trades of its customers. “Non-fundamental speculators” in Madrigal (1996) use information about liquidity trading. Also related is the concept of “dual-trading” in Bernhardt and Taub (2007).

4 Interestingly, Hasbrouck and Seppi (2001) find that for 30 Dow stocks commonality in the order flows explains about two-thirds of the commonality in returns.
metry in characteristics such as firm size (Lo and MacKinlay (1988)), trade volume (Chordia and Swaminathan (2000)), analyst coverage (Brennan, Jegadeesh and Swaminathan (1993)), and institutional ownership (Badrinath, Kale and Noe (1995), Sias and Starks (1997)). More recently, Lewellen (2002) shows that monthly returns on industry, size, and BM portfolios feature negative autocorrelation and negative cross-autocorrelation. In contrast, we provide evidence that negative and positive signs are present in daily return cross-autocorrelations, confirming the presence of a transient common factor in daily returns.

We generalize the return-generating process implied by our structural model into a more flexible time-series model and derive analytical expressions for return cross-autocovariances. Our time-series model is related to the literature that decomposes observed prices into two unobservable components, an efficient price and a deviation term (e.g., Dimson (1979) and Cohen, Hawawini, Maier, Schwartz and Whitcomb (1980)), and also to statistical models in the price discovery literature (e.g., Hasbrouck (1995)) that contain common factors in the asset fundamental values. More recently, Brennan and Wang (2007) examine how mis-pricing errors affect realized returns. Their work differs from ours in that they do not focus on commonalities in mis-pricing. Eraker (2007) estimates a two-latent-factor time-series model from long-horizon returns. The common factors in his work have an “auto-regressive” (AR) structure. We use a combination of AR and “moving-average” (MA) structures, and our common shocks affect stock returns with different degrees of persistence. This specification allows us to capture cross-sectional differences in the speed of information processing.

We estimate the model parameters with cross-autocovariance moment conditions in a GMM framework, and use the estimates to recover unobservable factors, both from daily returns on three “size” portfolios. Adding a transient factor significantly improves our model’s ability to capture the dynamics of short-term returns. Among 25 size×BM portfolios, the model explains more than 65% of the time-series variations in a portfolio’s daily returns, with up to 43% of the variations captured by the transient factor. We find a declining pattern in loadings on the fundamental factor, and an inverted U-shaped pattern in loadings on the transient factor, with firm “size”. In our economic
model, a stock’s transient factor beta incorporates two effects, (1) the sensitivity of the stock’s liquidity trading to the common liquidity trading component, and (2) the sensitivity of the stock’s price to its order flow (Kyle lambda—a measure of illiquidity). The first effect will be stronger for larger firms if their stocks feature more correlated liquidity trading by institutional investors (e.g., portfolio rebalancing by funds due to cash in- and outflows). The second effect is weaker for larger firms as their stocks are more liquid than stocks of smaller firms. The concave pattern in the transient factor beta with size suggests that for smaller firms the first effect dominates and for larger firms the second effect.

Our econometric specification provides direct estimates of information frictions for fundamental and transient factors. We find that fundamental friction is decreasing in firm “size”, and surprisingly, transient friction is increasing in firm “size”.

The key to understanding the difference in these patterns is that fundamental friction measures the length of time fundamental shocks require to be incorporated in a stock’s price, whereas transient friction measures the length of time transient shocks require to be filtered out. Ex-ante, the two shocks are not distinguishable and effects that reduce fundamental frictions may increase transient frictions. For example, if momentum trading is more prevalent in stocks of larger firms then recovering from liquidity trading shocks becomes slower for these stocks. This process also facilitates the incorporation of fundamental shocks into stock prices of larger firms, which is consistent with their smaller fundamental frictions. Our investigation of trade volume autocorrelation provides initial confirmation for this hypothesis. Moreover, transient frictions tend to exceed fundamental frictions, indicating that it takes longer for prices to recover from transient factor shocks than to absorb fundamental factor shocks. Consistently, the frequency of negative cross-autocorrelation signs is generally increasing with the lag length.

Finally, we examine the relationship between frictions and expected returns. Previous studies

\footnote{Tetlock (2007), using data from online trading in short-horizon binary outcome securities, finds that prices of illiquid securities converge more quickly toward their terminal cash flows. His interpretation is that liquidity proxies for noise trading, which can impede market efficiency.}
(e.g., Hou and Moskowitz (2005)) suggest that investors demand compensation for holding portfolios of stocks with higher frictions. We find a statistically significant annual premium of 1.7%–4.1% (depending on our control for risk) for portfolios of stocks in the tenth decile of fundamental friction relative to the first decile. Transient frictions, however, do not appear to be compensated in the cross-section of expected returns. Within the sub-sample of the first “size” quintile, the fundamental friction annual premium increases to 5.8%–13.7% and the transient friction annual premium increases to 4.2%–8.3% (depending on our control for risk), all statistically significant at the 1% level. Our framework distinguishes between the two components of friction premium, fundamental and transient premia, which is new to the literature. The separation is important because not only the two friction components show different patterns with firm characteristics (such as size), but also their premia are different. Mixing the two effects, therefore, can produce misleading empirical findings.

2 Theory

Section 2.1 offers an asset-pricing model under asymmetric information with a common noise trading component. Section 2.2 generalizes the return generating process and derives cross-autocovariances.

2.1 An Asset Pricing Model with Commonality in Noise-Trading

Consider a discrete-time framework with a finite number of assets indexed by $s = 1, \ldots, S$. Asset fundamental values evolve according to

$$V_t^s = V_{t-1}^s + \omega_s g_t^s + \beta_s m_t$$

$$g_t^s, m_t \sim N(0, 1), \quad s = 1, \ldots, S,$$  \hspace{1cm} (1)

where the innovations $g_t^s$ and $m_t$ are jointly Normal and independently distributed of each other and all past innovations. Here, $g^s$ is the component of the innovation to the value of asset $s$ that is specific to the asset, and $m$ is a market component common to all assets. The choice of a random walk for the evolution of the fundamental value $V_t$ is common for short horizon (e.g., daily) prices and returns. We assume that fundamental values become publicly known at the end of each
period (information is short-lived in our model) and that fundamental values are not observable to econometricians.

Four groups of risk-neutral traders are in the market: Informed traders with fundamental information, informed traders with noise trading information (speculators), noise traders, and market makers. Noise trading in stock $s$, $u^s_t$, is driven by common and idiosyncratic components:

$$u^s_t = \Omega_s G^s_t + B_s M_t, \quad G^s_t, M_t \sim \mathcal{N}(0, 1) \quad s = 1, \ldots, S,$$

where the idiosyncratic ($G^s_t$) and common ($M_t$) shocks are i.i.d. Normal and independently distributed of each other and all past innovations.

Some speculators observe the idiosyncratic component of liquidity trades, $G^s$, while others observe the market-wide component, $M$. Some informed agents with fundamental information observe the idiosyncratic fundamental component, $g^s$, while others observe the market-wide component, $m$. The assumption of independence means that these informed agents could be the ‘same’, i.e., agents who observe $G^s$ may also observe $M$, $g^s$, or $m$. Outcomes only depend on the numbers of agents with each type of information. There are $n_s$ ($n_m$) traders with fundamental idiosyncratic (market) information, whose orders are denoted by $x^s_t$ ($y^s_t$), and there are $N_s$ ($N_m$) speculators with noise trading idiosyncratic (market) information, whose orders are denoted by $X^s_t$ ($Y^s_t$). Market makers are competitive, setting prices, $P^s_t$, at which they fill all orders such that they earn zero expected profit given the net order flow, $Z^s_t \equiv \Omega_s G^s_t + B_s M_t + n_s x^s_t + n_m y^s_t + N_s X^s_t + N_m Y^s_t$.

In the beginning of period $t$, agents with private information receive their signals. Next, all traders submit their orders. At the end of period $t$, market makers set the prices, $\{P^s_t, s = 1, \ldots, S\}$, and all traders realize profits or losses.

**Equilibrium.** We conjecture that equilibrium price is linear in the net order flow, $P^s_t = V^s_{t-1} + \lambda^s_s Z^s_t$. Given this conjecture, we solve each agent’s optimal trade problem and then verify the

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6 We could allow for a non-i.i.d. component in the liquidity trade, e.g. $u^s_t = \rho^s u^s_{t-1} + \Omega_s G^s_t + B_s M_t$, without any significant change in the results.
Proposition 1  In the unique linear equilibrium, the price for stock $s$ is given by

$$P_t^s = V_{t-1}^s + \lambda_s Z_t^s$$

where

$$\lambda_s^2 = \frac{n_s}{(n_s+1)^2} \omega_s^2 + \frac{n_m}{(n_m+1)^2} \beta_s^2$$

trades for informed agents with fundamental information are:

$$x_t^s = \frac{\omega_s}{\lambda_s(n_s+1)} g_t^s \quad ; \quad y_t^s = \frac{\beta_s}{\lambda_s(n_m+1)} m_t \quad ; \quad s = 1, \ldots, S$$

and trades for speculators with noise trading information are:

$$X_t^s = -\frac{\Omega_s}{N_s + 1} G_t^s \quad ; \quad Y_t^s = -\frac{B_s}{N_m + 1} M_t \quad ; \quad s = 1, \ldots, S$$

Proofs are in Appendix A  Equation (5) indicates that the optimal trades of speculators are independent of market maker pricing (i.e., of the $\lambda$’s), and that, speculation (on noise trading information) serves only to reduce the effective liquidity in the market.

Next lemma derives price changes and their cross-autocovariances. With a short time-horizon, price changes in our model approximate observed returns. The lemma also shows that cross-autocorrelation signs are positive in the absence of a transient factor.

Lemma 1

1.

$$\Delta_t P_t^s = \frac{n_m}{n_m + 1} \beta_s m_t + \frac{1}{n_m + 1} \beta_s m_{t-1} + \frac{\lambda_s B_s}{N_m + 1} \Delta_t M + \epsilon_t^s$$

where:

$$\epsilon_t^s = \frac{n_s}{n_s + 1} \omega_s g_t^s + \frac{1}{n_s + 1} \omega_s g_{t-1}^s + \frac{\lambda_s \Omega_s}{N_s + 1} \Delta_t G^s$$

7 We can write the model in a multiplicative form and formally derive the approximation at the cost of longer algebra.
2. 

\[ E[\Delta_{t+1}P_s \Delta_t P_{s'}] = \frac{n_m}{(n_m + 1)^2} \beta_s \beta_{s'} - \frac{\lambda_s \lambda_{s'}}{(N_m + 1)^2} B_s B_{s'} \quad \text{if} \quad s \neq s' \]

\[ = \frac{n_m}{(n_m + 1)^2} \beta_s \beta_{s'} \left( 1 - \sqrt{\frac{1 + \frac{n_s}{n_m} \left( \frac{n_m + 1}{n_s + 1} \omega_s \beta_s \right)^2}{1 + \left( \frac{n_s}{n_m} \frac{n_m + 1}{n_s + 1} \omega_s \beta_s \right)^2}} \right) \tag{8} \]

3. \( B_s = B_{s'} = 0 \quad \& \quad \beta_s \beta_{s'} \geq 0 \quad \Rightarrow \quad E[\Delta_{t+1}P_s \Delta_t P_{s'}] \geq 0 \). That is, without common liquidity trading, the cross-autocovariance of two returns is positive unless one, and only one, of the assets has a negative loading on the common fundamental factor.

The cross-autocovariance of two returns is negative when the common component of liquidity trade “matters more” for both returns than the common component of fundamental shocks. Here, “matters more” reflects the numbers of each type of informed traders as well as the magnitudes of the idiosyncratic shocks. That is, cross-autocorrelations become negative when prices contain more information about common liquidity trading than about common fundamental shocks and when there is less noise due to trade on idiosyncratic component of liquidity trading than noise due to trading on idiosyncratic component of fundamentals. For example, in symmetric settings with equal numbers of traders of each type and equal idiosyncratic shock variances, cross-autocorrelations are negative if and only if the variance of the common liquidity trading shock, \( B_s \), exceed that of the common fundamental shock, \( \beta_s \). Intuitively, the transient nature of noise trading shocks induces mean reversion in prices. A positive noise trading shock, for example, increases the price of an asset initially but the price reverts to the fundamental value. If transient shocks affect prices of many stocks then, in the absence of fundamental common shocks, one asset’s positive return will predict negative returns for other assets. Ultimately, cross-autocorrelation signs will depend on the relative importance of the fundamental and transient (noise trading) common factors.

\* The model generates the observed asymmetries in cross-autocorrelations (lead-lag patterns) if the number of traders with common information vary across assets, and as Bernhardt and Mahani (2007) show, mere private information cannot generate the asymmetry.
Our theoretical model assumes that information is short-lived, so that shocks to fundamental values and liquidity trades become publicly known at the end of each period. In reality, several periods may be needed before information is fully incorporated into prices. Other effects, such as market makers’ inventory costs, may also increase the time it takes for a shock’s effect to dissipate. Therefore, we consider the following generalized return generating process:

\[
(r_t^s - E r_t^s) = \alpha_F^s \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \alpha_N^s \sum_{k=1}^{\infty} (\gamma_N^s)^k (M_t - M_{t-k}) + \epsilon_t^s
\]

\[
= \beta_F^s (1 - \gamma_F^s) \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \beta_N^s (1 - \gamma_N^s) \sum_{k=1}^{\infty} (\gamma_N^s)^{k-1} (M_t - M_{t-k}) + \epsilon_t^s
\]

\[
\beta_F^s \equiv \frac{\alpha_F}{1 - \gamma_F}, \quad \beta_N^s \equiv \frac{\alpha_N}{1 - \gamma_N}
\]

Error terms are zero mean, \( E[\epsilon_t^s] = 0 \), and homoskedastic, \( \sigma_s^2 = E[(\epsilon_t^s)^2] \). Coefficients \( \alpha_F \) (short-term fundamental beta) and \( \beta_F \) (long-term fundamental beta) capture the immediate and cumulative responses to a fundamental factor shock \((m_t)\), respectively. In contrast, \( \beta_N \) captures the initial response to a transient factor shock \((M_t)\) and \( \alpha_N \) captures the portion of the shock that is resolved in the first period after. Parameter \( \gamma_F^s \) describes how long it takes for a fundamental factor shock to become fully incorporated into the price of asset \( s \), and parameter \( \gamma_N^s \) captures the time necessary for the effect of a transient factor shock to disappear from the price. The transient factor, \( M_t \), enters return processes in a time-differenced form and has no permanent price effect even though it may take a long time for its shocks to dissipate. An equivalent representation of return dynamics is more convenient in some cases:

\[
(r_t^s - E r_t^s) = \alpha_F^s \mu_{t-1}^s + \alpha_N^s \mu_t^s + \epsilon_t^s,
\]

\[
\begin{align*}
\mu_t^s & \equiv \gamma_F^s \mu_{t-1}^s + m_t , \\
M_t^s & \equiv \gamma_N^s M_{t-1}^s + \frac{1}{1 - \gamma_N} (M_t - M_{t-1}) .
\end{align*}
\]

The two representations (in terms of \( \alpha \) or \( \beta \) coefficients) are equivalent and we use them interchangeably.
The new AR(1) factors, $\mu_t$ and $M_t^s$, are asset-specific because their corresponding persistence parameters, $\gamma_F^s$ and $\gamma_N^s$, vary across stocks. Yet, their underlying sources of randomness, $m_t$ and $M_t$, are the same for all stocks.

We use the following unconditional second-order moment conditions later:

**Lemma 2** Suppose returns are generated by the process in equation 9, where we normalize factors to have zero mean, $E[m_t] = E[M_t] = 0$, and unit variance, $E[(m_t)^2] = E[(M_t)^2] = 1$. Also, suppose that $E[m_t M_{t-k}] = 0$, $\forall k$, $E[m_t m_{t-k}] = E[M_t M_{t-k}] = 0$, $\forall k \neq 0$, and finally, $E[\epsilon_t^s \epsilon_{t-k}^{s'}] = 0$, $\forall k, s \neq s'$. Then

1. $\text{var}(r_t^s) = \frac{(\alpha_F^s)^2}{1 - (\gamma_F^s)^2} + \frac{2(\alpha_N^s)^2}{(1 - (\gamma_N^s)^2)(1 - \gamma_N^s)} + \sigma_s^2$

2. $E[r_t^s r_{t-l}^{s'}] = \frac{\alpha_F^s \alpha_F^{s'}}{1 - \gamma_F^s \gamma_F^{s'}} (\gamma_F^s)^k - \frac{\alpha_N^s \alpha_N^{s'}}{1 - \gamma_N^s \gamma_N^{s'}} \frac{1 - \gamma_N^s}{1 - \gamma_N^{s'}} (\gamma_N^s)^{k-1}$

3. $E[r_t^s r_{t-l}^{s'}] = \frac{\alpha_N^s \alpha_N^{s'}}{1 - \gamma_N^s \gamma_N^{s'}} \frac{2 - \gamma_N^s - \gamma_N^{s'}}{(1 - \gamma_N^s \gamma_N^{s'}) (1 - \gamma_N^s) (1 - \gamma_N^{s'})}$

3 Empirics and Estimation Results

Section 3.1 provides evidence that negative cross-autocorrelation are pervasive in data. In section 3.2 we estimate our model parameters and recover fundamental and transient factors.

3.1 Negative Cross-Autocorrelations

We now examine cross-autocorrelation signs using daily returns on 25 size×BM, 25 size×momentum, and 30 industry portfolios (all value-weighted), covering July 1, 1963 through December 29, 2006 (10951 observations). Data are from Kenneth French’s on-line data library.

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10 To avoid making assumptions on dynamics of idiosyncratic components, we do not use moment conditions based on own-autocovariances, $E[r_t^s r_{t-k}^s]$. 

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Each panel in Table 1 shows, for one of the three sets of portfolios, the fractions of negative and positive cross-autocovariances among all cross-autocovariances of the same order. The cross-autocovariance of order $L$ between returns on portfolio $i$ and returns on portfolio $j$ is estimated by

$$\text{cov}\left( R_{t}^{i}, R_{t+L}^{j} \right) \equiv \frac{\sum_{n=1}^{N-L} \left( R_{n}^{i} - \bar{R}^{i} \right) \left( R_{n+L}^{j} - \bar{R}^{j} \right)}{N-L} \quad (i \text{ leading } j),$$

where $\bar{R}^{i}$ and $\bar{R}^{j}$ are appropriately defined sample means. First-order cross-autocovariances in Table 1 are positive almost everywhere. Second-order cross-autocovariances show more incidences of negative signs, but negative cross-autocovariances become less frequent for lags of order three and four. As the lag-order increases to six and seven, the fractions of negative cross-autocovariances reach their maximum of 0.38–0.72 (depending on portfolio set), and negative signs become as frequent as positive signs.

To assess the statistical significance of point estimates, we compute the corresponding standard errors adjusted for serial correlation in returns using a GMM approach (Newey-West method, 22 lags). We then construct one-sided significance intervals (at the 5% and 20% levels) and compute fractions of significantly negative and positive cross-autocovariances among all cross-autocovariances of the same order. We find that 5%–9% of the cross-autocovariances of order six and 10%–12% of the cross-autocovariances of order seven are significantly negative at the 5% level (depending on the portfolio set), quite comparable to the corresponding positive ratios (1%–22% for lag six and 0.2%–20% for lag seven).

Finally, we study time variation in the fractions. We compute cross-autocovariances from 3-year windows of daily returns and we roll windows one quarter forward, covering the period of 1965 to 2006. We compute negative and positive cross-autocorrelation fractions for each 3-year window. We also find standard errors (as explained before) and fractions of significantly negative, and positive, cross-autocorrelations at the 5% level (one-sided). These fractions are plotted in Figure 1 for 25 size×BM, and in Figure 2 for 30 industry portfolios. Clearly, negative cross-autocorrelations are

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11 Cross-autocovariances are not symmetric in $i$ and $j$ and to be more precise we have to identify which portfolio is leading the other.
pervasive, consistent with the predictions of our model and confirming a transient factor in returns.

### 3.2 Estimation Results

We use the moment conditions derived in lemma 2 in a GMM setup to estimate the parameters \( \{\alpha_F^s, \gamma_F^s, \alpha_N^s, \gamma_N^s\} \) from daily returns on three value-weighted “size” portfolios. Our only instrument is a vector of ones and we use cross-autocovariances of order five and less as moment conditions. Details are in Appendix B.1. Panel A in Table 2 shows coefficient estimates. The “5% – \( \tau \)” column shows the “time to hit the 5% level”, \( \frac{\log(0.05)}{\log(\gamma)} \), calculated from a decay coefficient, \( \gamma \). It takes one to five days before 95% of a fundamental shock’s effect appears in prices. In contrast, three to nine days is needed for 95% of a transient shock’s effect to disappear from prices. This is broadly consistent with our previous observation (Table 1) that cross-autocorrelations of order four and less are mostly positive, and that frequency of negative signs reaches a maximum at lags of six and seven.

We use coefficient estimates for three “size” portfolios and recover fundamental and transient return factors with an OLS-based method. Basically, we regard estimated coefficients as data and factor values at each point in time as parameters to be estimated. Details are in Appendix B.2. To evaluate our recovered factors, we estimate the model (equation (10)) with recovered factors as observable explanatory variables. We use a variant of nonlinear least-squares (implemented with a GMM method) with daily returns on three size portfolios and five lags of the factors as instruments. Our choice of instruments closely resembles our choice of cross-autocorrelations of order five and less to estimate the coefficients initially. Panel B in Table 2 summarizes these estimates and is directly comparable to Panel A. Coefficient estimates in the two panels are quite close, which validates our recovered factors. Moreover, estimates in Panel B are robust to different choices of the instruments and weighting matrix.
4 Transient Factor’s Significance

Section 4.1 deals with the “statistical” significance of the transient factor, and sections 4.2 and 5 with the “economic” significance.

4.1 Statistical Significance

We first examine what portion of the time-series variation in daily returns is explained by the transient factor. Using our recovered factors, we estimate our model (equation (10)) for 25 size×BM portfolios. Table 3 reports coefficient estimates and $R^2$'s. Our two factor model explains more than 65% of the time-series variation in returns on each of these portfolios. Excluding the lowest two $R^2$'s, the explanatory power exceeds 74%. The last column, $R^2_N$, shows the ratio of the transient component variance to total variance. This ratio declines from an upper bound of about 43% for smaller firms to a lower bound of about 13% for larger firms, indicating that the transient factor explains a significant part of the time-variation in returns.

Given the central role of cross-autocovariances in our work, we next study the transient factor’s contribution to explaining the cross-section of return cross-autocovariances. In table 4 we compare how well two models, our two factor model and its restricted form with only the fundamental factor, explain cross-autocovariances of daily returns on 25 size×BM (value-weighted) portfolios. We first compute sample cross-autocovariances of “actual” returns for a range of lag-orders (lag-order $\leq 3$ for the first three rows and lag-order $\leq 9$ for the second three rows). We then use the fitted returns from each of the two models (two factor and one factor) to compute “model-based” cross-autocovariances. We run a cross-sectional regression of “actual” on “model-based” cross-autocovariances when intercept and slope are set to zero and one, respectively, and report $R^2$'s. Because intercept is forced to zero, an $R^2$ can be negative, indicating that the residual variance is higher than the dependent variable variance. Given the importance of a transient factor

\[ \text{In equation (10) the AR factors, } \mu^s \text{ and } M^s, \text{ are independent and we can think of } \alpha^sF^s \mu^s \text{ and } \alpha^sN^s M^s \text{ as projections of the return of portfolio } s \text{ on fundamental and transient factors, respectively.} \]
for negative cross-autocovariance signs, we repeat the same analysis for two sub-samples of cross-autocovariances based on their signs. Our two-factor model explains cross-autocovariances very well ($R^2$’s more than 99%) and much better than the traditional one-factor model (an improvement of about 13% in $R^2$’s). The improvement is more significant in the subsample of negative cross-autocovariances. Negative $R^2$’s of the one-factor model confirm that a fundamental factor alone is not able to generate negative cross-autocovariance signs.

To add perspective, we note that extant studies of return cross-autocorrelation use a market factor highly correlated with our fundamental factor. Table 5 provides the correlation matrix for the following six factors: our fundamental and transient factors, market ($MRKT$), size ($SMB$), book-to-market ($HML$), and momentum ($MOM$). Our fundamental factor is highly correlated with excess return on market (correlation coefficient = 0.87) and less correlated with size (correlation coefficient = −0.47) and book-to-market (correlation coefficient = −0.49). Our transient factor is more correlated with size (correlation coefficient = 0.32) and less correlated with market (correlation coefficient = 0.29) and book-to-market (correlation coefficient = −0.15). The momentum factor shows very small correlations with other factors. The high correlation between market and fundamental factors implies that models with only the market factor cannot generate negative cross-autocorrelation signs. Ubiquitous presence of negative cross-autocovariance signs (see Figure 1 and Figure 2) makes it, in turn, less likely that such models properly capture the dynamics of daily returns. Practically, to match negative cross-autocorrelations these models allow arbitrary signs for loadings of market lags. Moreover, negative loadings are sometimes interpreted as evidence for “overreaction”. Our model imposes a structure on signs of factor loadings and provides an alternative interpretation that negative cross-autocorrelations reflect the time prices need to recover from transient (noise trading) shocks.
4.2 Coefficient Patterns

To assess the transient factor’s “economic” significance, we examine factor loading patterns with size and BM characteristics for possible differences between fundamental and transient factors. Table 3 reports coefficient estimates using daily returns on 25 size×BM portfolios, and figures 3 and 4 offer a graphical representation. Coefficient patterns with BM are generally non-monotonic (for $\beta_F$ and $\beta_N$) or simply irregular (for $\gamma_F$ and $\gamma_N$). Fundamental loadings ($\beta_F$’s) and transient loadings ($\beta_N$’s) are convex, and U-shaped, in BM. Ultimately, growth (low BM) portfolios are riskier than value (high BM) portfolios with both measures of exposure, fundamental and transient betas, which seems consistent with existing literature. Neither decay coefficient ($\gamma_F$ or $\gamma_N$) shows a clear pattern with BM, indicating that BM is not closely related to information processing characteristics.

Coefficient patterns with “size” are very strong. Smaller firms have higher fundamental loadings, as $\beta_F$ is monotonically decreasing in “size” for all BM groups. Moreover, larger firms are faster in incorporating fundamental information, as $\gamma_F$ is monotonically decreasing in “size” for all BM groups. “Size” patterns in transient factor coefficients are even more interesting. We find a concave pattern for $\beta_N$ as it first increases and then decreases with “size”. The following expression for $\beta_N$ (from equations 3 and 4) offers some insights into this puzzling observation:

$$\beta_N^s = \frac{\lambda_s B_s}{N_m + 1} = \left(\frac{n_s \omega_s^2}{(n_s + 1)^2} + \frac{n_m \beta_s^2}{(n_m + 1)^2}\right)^{1/2} \left(1 + \frac{\left(\frac{(N_m + 1) \Omega_s}{(N_s + 1) B_s}\right)^2}{1 + \left(\frac{(N_m + 1) \Omega_s}{(N_s + 1) B_s}\right)^2} \right)^{-1/2}.$$ 

(12)

The transient factor exposure, $\beta_N^s$, consists of two components: a measure of stock’s illiquidity, $\lambda_s$ (Kyle lambda), and a measure of its noise trading sensitivity to the common factor, $B_s$. We expect the first effect, $\lambda_s$, to be decreasing in firm “size” as stocks of larger firms are more liquid. The second effect, $B_s$, is likely to be increasing in firm “size”, as stocks of larger firms are more heavily traded by institutional traders (such as mutual funds and pension funds) who are, in turn, important sources of commonality in liquidity trading. The concave pattern of $\beta_N$ with “size” is consistent with the second effect (sensitivity to liquidity trading) being dominant initially for smaller firms and the first effect (illiquidity) becoming dominant for larger firms.
Most puzzling is an increasing pattern in decay coefficient, $\gamma_N$, with “size”, indicating that daily returns of larger firms require more time to recover from transient shocks than smaller firms. Information frictions, however, are interpreted differently for the two factors: Fundamental friction measures the length of time fundamental shocks require to be fully reflected in a stock price, whereas transient friction measures the length of time transient shocks take to be completely filtered out. Ex-ante, the two shocks are not distinguishable and effects that reduce fundamental friction may increase transient friction. For example, if momentum trading is more prevalent in larger stocks then recovering from liquidity trading shocks becomes slower for larger firms. This process also facilitates fundamental shocks’ incorporation into prices of larger stocks, which is consistent with their smaller fundamental decay coefficients, $\gamma_F$.

If stocks of larger firms are subject to more momentum trading than smaller firms then trade volumes of larger firms will feature more persistence over time as well. Therefore, in Table 6 we study trade volume autocorrelations for different firm sizes. For each year in the 1963–2007 period, we use previous December’s market capitalizations to sort individual stocks into ten equally numbered size groups. Within each group, we use daily trade volumes in the calendar year to run a time-series regression of trade volumes on their past 20 lags. We construct four measures of autocorrelation, (1) sum of lag coefficients, (2) regression $R^2$, (3) sum of lag coefficients significant at the 5% level, and (4) regression $R^2$ with $F$ statistic significant at 5% level. We average each autocorrelation measure within ten size groups and find the difference between large and small groups, $AC_{large} - AC_{small}$.

Panel A in Table 6 shows fractions of positive, positive and significant at 5%, negative, negative and significant at 5% incidences of each of four relative autocorrelation measures ($AC_{large} - AC_{small}$) in the 45 years from 1963 to 2007. In most years, larger stocks feature higher autocorrelations in their trade volume than smaller stocks, which is consistent with our hypothesis that there is more momentum trading in larger firms. Our hypothesis also implies that higher momentum trading in larger firms is accompanied by higher transient friction ($\gamma_N$) and lower fundamental friction.

---

13 This paragraph presumes a positive autocorrelation in trade volumes, which is easily confirmed in data.
Therefore, for each year, we estimate equation (10) with daily returns in a four year window (centered around that year) to obtain fundamental and transient frictions for each “size” portfolio. Then, we compute annual changes in relative autocorrelation measure, \( \Delta t(AC_{\text{large}} - AC_{\text{small}}) \), relative fundamental friction, \( \Delta t(\gamma^F_{\text{large}} - \gamma^F_{\text{small}}) \), and relative transient friction, \( \Delta t(\gamma^N_{\text{large}} - \gamma^N_{\text{small}}) \), and run a regression of the first variable on the latter two. Panel B in Table 6 shows regression coefficients. Clearly, an increase in large firms’ trade volume autocorrelation relative to small firms is associated with an increase in large firms’ transient frictions, and a decrease in their fundamental frictions, relative to small firms. The association between relative measures of trade volume autocorrelation and transient friction is stronger in both magnitude and statistical significance.

5 Fundamental and Transient Friction Premia

To the extent that a stock’s price deviation from its fundamental value (expected discounted cash flow given available information) lessens an investor’s utility, we expect stocks with higher frictions to compensate investors. Hou and Moskowitz (2005) show that firms with most delay in information incorporation offer a large premium (in the form of expected returns) that is not explained by size, liquidity, or microstructure effects. If fundamental and transient factors are economically distinct, then they may feature different premia. To study this, we first use daily returns on 100 size×BM portfolios to estimate our model (equation (10)). Figure 4 shows the patterns in friction estimates (\( \gamma^F \) and \( \gamma^N \)) with “size” and BM. Consistent with our previous findings, fundamental friction is decreasing, and transient friction is increasing, in “size”. Neither friction shows a strong pattern with BM.

To control for “size” and BM effects on expected returns, we use a conditional sort method. Specifically, we sort the 100 portfolios into five “size” groups and then into two BM subgroups, such that each size–BM cell contains ten portfolios. We then sort portfolios within each size–BM cell based on their fundamental friction (\( \gamma^F \)). Each fundamental friction portfolio then equally weights
portfolios in the corresponding fundamental friction decile across ten size–BM cells. For example, the first friction portfolio encompasses the lowest friction portfolios from each of the ten size–BM cells. This procedure isolates the influence of size and BM. We compute expected monthly returns, calculated as average return over the entire sample period, for each of the ten fundamental friction portfolios. To control for risk, we also run time-series regressions of portfolio returns on various risk factors utilized in the previous literature. Specifically, we find intercepts from the CAPM model, the Fama-French three-factor model, and the four-factor model (Fama-French three factors plus a momentum factor). We repeat the same exercise for the transient friction. Results are reported in the panel A of Table 7.

Expected returns increase with fundamental friction and the difference in expected returns between the tenth and the first group is 0.28% per month ($\approx 3.4\%$ annual). The probability of observing the difference randomly (p-value) is computed using GMM (Newey-West method, 8 lags) to allow for autocorrelation. The difference is significant at the 0.03% level. Expected returns do not show a clear pattern with transient friction. The overall increase in expected returns from the first to the tenth group is 0.13% per month ($\approx 1.6\%$ annual), which is less than one half of the fundamental friction premium and insignificant at the 20% level. Our controls for risk reveal interesting properties of friction premia. Adding a market factor increases fundamental friction premium to 0.34% per month ($\approx 4.1\%$ annual), significant at the 0.01% level, and transient friction premium to 0.23% per month ($\approx 2.8\%$ annual), significant at the 2% level. Therefore, friction premia are countercyclical, higher when the excess market return is lower. Adding size (SMB) and BM (HML) factors, however, reduces the magnitudes of the friction premia by one-half, and makes the transient friction premium negative and insignificant. This indicates that friction premia positively covary with size and BM, paying off better when SMB and HML premia are higher. Including the momentum factor increases fundamental friction premium to 0.33% per month ($\approx 4\%$ annual), significant at the 0.5% level, and transient friction premium to 0.15% per month ($\approx 1.8\%$ annual), insignificant at the 25% level. Friction premia, therefore, negatively covary with momentum premium.
Finally, we study friction premia conditional on “size” by repeating our analysis within five “size” quintiles. Panels B through D in Table 7 show the results for three of them. Friction premia are significantly higher among smaller firms. In the first “size” quintile, fundamental friction premium increases to 0.48%–1.14% per month (5.8%–13.7% annual), significant at the 0.01% level, depending on the control for risk. Moreover, the transient friction premium increases to 0.35%–0.69% per month (4.2%–8.3% annual), significant at the 0.05% level, depending on the control for risk. For portfolios of large firms (the fifth quintile), in contrast, the friction premia essentially disappear: Point estimates are close to zero (sometimes negative) and standard deviations increase such that all estimates are insignificant at the 5% level.

6 Concluding Remarks

This study improves our understanding of commonality in noise trading. Our economic model links such commonality to a transient return factor and indicates that a transient factor is essential in capturing negative and positive signs of return cross-autocorrelations. Negative signs for return cross-autocorrelations are pervasive in data, consistent with our model’s prediction. Our time-series model generalizes the return generating process from the economic model. We estimate the time-series model, and recover fundamental and transient return factors. Finally, we study basic properties of the two factors, highlight their differences, and study transient factor’s statistical and economic significance.

Our study opens many new research questions. In this work, we limit ourselves to basic questions and relatively straightforward econometric techniques. Cross-auto-covariances are symmetric in the direction of shocks, our return generating process is a linear approximation of what is implied by our model, and we use time-invariant estimates of moments and broad portfolios (with many stocks) in our estimations. All these and possibly other aspects of our work can be generalized. In addition, we uncover interesting, and sometimes puzzling, results. Among them, a concave pattern
in transient factor loading with firm “size”, increasing pattern in transient friction coefficient with firm “size”, and lack of premium to transient friction except for portfolios of small firms. We provide explanations for some of them, yet a fuller understanding requires more research.

Finally, commonality in noise trading is exogenous in this paper. Mahani and Bernhardt (2007) offer a rational model for noise trading in which agents trade to learn about their trading skills. Unskilled traders in their model use “signals” uncorrelated to fundamental values and effectively become noise traders. These “uninformative signals” can be correlated across assets and hence induce commonality in noise trading. Under such a scenario, strength of the common noise trading component (e.g., its variance) depends on small novice traders’ in- and outflows. Alternatively, commonality in noise trading may be induced by large institutions’ simultaneous trades in many assets as the result of their cash in- and outflows. Investigating possible links between the noise trading factor and such flows is an interesting question for future research.
References


Dimson, Elroy (1979) “Risk measurement when shares are subject to infrequent trading,” *Journal of Financial Economics* 7(2), 197–226


A Proofs

Proof of Proposition 1. First, we assume a linear pricing function and compute optimal trades. The computations for four groups of informed traders are similar, so we only derive the result for traders with private information about idiosyncratic component of liquidity trading. Their conditional expected profits are:

$$\mathbb{E}\left[ (V_s^t - P_s^t) X_s^t \mid G_t^s \right] = -\lambda_s \left( X_s^t + (N_s - 1) \hat{X}_s^t + \Omega_s G_t^s \right) X_s^t,$$

resulting in the first order condition: 

$$(N_s + 1) X_s^t + \Omega_s G_t^s = 0,$$

and hence equation 5.

Next, the zero profit condition of market makers implies that

$$P_s^t = \mathbb{E}_{t-1}[V_s^t \mid Z_t^s] = V_{t-1}^s + \mathbb{E}_{t-1}[\omega_s g_t^s + \beta_s m_t \mid Z_t^s],$$

and the joint normality of \((g_t^s, m_t, Z_t^s)\) implies that the pricing of stock \(s\) is characterized by

$$\text{var}(\lambda_s Z_t^s) = \text{cov}(\lambda_s Z_t^s, \Delta_t V^s),$$

where \(\Delta_t V^s = \omega_s g_t^s + \beta_s m_t\), and \(\lambda_s Z^s = \frac{n_s}{n_s + 1} \omega_s g_s + \frac{n_m}{n_m + 1} \beta_s m + \frac{\lambda_s}{N_s + 1} \Omega_s G_s + \frac{\lambda_s}{N_m + 1} B_s M\). Hence,

$$\text{var}(\lambda_s Z^s) = \left( \frac{n_s}{n_s + 1} \right)^2 \omega_s^2 + \left( \frac{n_m}{n_m + 1} \right)^2 \beta_s^2 + \frac{\lambda_s^2}{(N_s + 1)^2} \Omega_s^2 + \frac{\lambda_s^2}{(N_m + 1)^2} B_s^2,$$

$$\text{cov}(\lambda_s Z^s, V^s) = \frac{n_s}{n_s + 1} \omega_s^2 + \frac{n_m}{n_m + 1} \beta_s^2.$$

Solving for \(\lambda_s\) gives equation 3.

Proof of Lemma 1: (1) We are interested in \(\Delta_t P^s\):

$$\Delta_t P^s = \Delta_{t-1} V^s + \lambda_s \Delta_t Z^s,$$

$$\Delta_{t-1} V^s = \omega_{s-2} g_{t-2} + \beta_{s-2} m_{t-2},$$

$$\Delta_t Z^s = \Omega_s \Delta_t G^s + B_s \Delta_t M + n_s \Delta_t x^s + n_m \Delta_t y^s + N_s \Delta_t X^s + N_m \Delta_t Y^s.$$
Therefore,

\[
\Delta_t P^s = \omega_s g_{t-1}^s + \beta_s m_{t-1} + \lambda_s \left\{ \Omega_s \Delta_t G^s + B_s \Delta_t M \right\}
\]

\[
+ \frac{n_s \omega_s}{\lambda_s (n_s + 1)} \Delta_t g^s + \frac{n_m \beta_s}{\lambda_s (n_m + 1)} \Delta_t m - \frac{N_s \Omega_s}{N_s + 1} \Delta_t G^s - \frac{N_m B_s}{N_m + 1} \Delta_t M \]

\[
= \frac{n_s + 1}{n_s + 1} \frac{\omega_s g_t^s}{\lambda_s (n_s + 1)} \Delta_t g^s + \frac{n_m + 1}{n_m + 1} \frac{\beta_s m_t}{\lambda_s (n_m + 1)} \Delta_t m - \frac{N_s \Omega_s}{N_s + 1} \Delta_t G^s - \frac{N_m B_s}{N_m + 1} \Delta_t M
\]

(2) For \( s \neq s' \) we have:

\[
\mathbb{E} \left[ \Delta_{t+1} P^s \Delta_t P^{s'} \right] = \beta_s \mathbb{E} \left[ m_t \left( \lambda_s' Z_t^{s'} \right) \right] - \mathbb{E} \left[ \left( \lambda_s Z_t^s \right) \left( \lambda_s' Z_t^{s'} \right) \right]
\]

\[
= \beta_s \left( \frac{n_m}{n_m + 1} \right) \beta_s' - \left( \frac{n_m}{n_m + 1} \right)^2 \beta_s \beta_s' + \lambda_s \lambda_s' \frac{B_s B_s'}{(N_m + 1)^2}
\]

\[
= \frac{n_m}{(n_m + 1)^2} \beta_s \beta_s' - \lambda_s \lambda_s' \frac{B_s B_s'}{(N_m + 1)^2}
\]

Next, we substitute for \( \lambda \) after re-writing equation (3) as

\[
\lambda_s = \frac{\beta_s}{B_s} \sqrt{n_m} \frac{N_m + 1}{n_m + 1} \frac{1 + \frac{n_s}{n_m} \left( \frac{n_m + 1}{n_s + 1} \omega_s \right)^2}{1 + \left( \frac{N_m + 1}{N_s + 1} \frac{\Omega_s}{B_s} \right)^2}
\]

(16)

Simple algebra gives the second line in equation (8). \( \blacksquare \)

B Econometric Procedure

B.1 GMM Estimation with Unobserved Factors

To implement a GMM estimation of the return generating model in equation (9), we use the moment conditions specified in Lemma 2. The objective function is highly nonlinear in coefficients, and to deal with this nonlinearity, we use the observation that fixing \( \gamma \)'s makes the return generating process linear in \( \alpha \)'s. This is more clearly seen in equation (10) perhaps, where fixing \( \gamma \)'s is
equivalent to fixing the AR factors, $\mu^s$ and $M^s$, and results in a linear equation in $\alpha$’s. Therefore, we solve the optimization in two steps. In the first step (inner loop) we fix $\gamma$’s and we find the optimizing $\alpha$’s, which is a very straightforward problem with very short optimization time. In the second step (outer loop) we search on the $\gamma$ space to find the optimizing coefficients. A second complication is an identification problem. The objective function seems to have numerous local optima, and at the same time, the optimization routine often hits boundaries of parameter space. The most important boundary comes from the positivity of variance condition. Based on this observation, we impose tighter limits on the variance of errors to obtain better identification. To obtain these limits we run the following regressions for each of three size portfolios and then find the variance of the residuals:

$$r^s_t = \sum_{k=0}^{L} (a_k MRKT_{t-k} + b_k SMB_{t-k}) + e^s_t$$: Two Factor Model

$$r^s_t = \sum_{k=0}^{L} (a_k MRKT_{t-k} + b_k SMB_{t-k} + c_k HML_{t-k}) + e^s_t$$: Three Factor Model

Here, $MRKT$, $SMB$, and $HML$, are daily return on Fama-French market, size, and BM factors, respectively. The following results are obtained for $L = 5$:

<table>
<thead>
<tr>
<th>Size</th>
<th>two-factor</th>
<th>Three-factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Small (bottom 30%)</td>
<td>0.024702</td>
<td>0.033579</td>
</tr>
<tr>
<td>Medium (mid 40%)</td>
<td>0.024181</td>
<td>0.027744</td>
</tr>
<tr>
<td>Large (top 30%)</td>
<td>0.0029747</td>
<td>0.003057</td>
</tr>
</tbody>
</table>

Based on these number, we impose the following bounds on the idiosyncratic variance of the small, medium, and large portfolios. Small (bottom 30%): $[0.023, 0.035]$; Medium (mid 40%): $[0.022, 0.029]$; Large (top 30%): $[0.002, 0.005]$. With these restrictions, optimization becomes more straightforward and very robust to initial values.
B.2 Factor Recovery

We use our estimates, \( \{ \hat{\alpha}_F^s, \hat{\gamma}_F^s, \hat{\alpha}_N^s, \hat{\gamma}_N^s \}_{s=1,\ldots,S} \), for \( S = 3 \) size portfolios to recover the factors, \( m_t \) and \( M_t \). To make this operational, we use the first \( L = 40 \) lags of both factors in equation (9). The result is a linear system of three equations in factors and their lags at each time \( t \),

\[
[r_t - Er_t] = \left[ \hat{\alpha}_F, \hat{\alpha}_F \bullet \hat{\gamma}_F, \ldots, \hat{\alpha}_F \bullet \hat{\gamma}_F^L, \hat{\alpha}_N \sum_{j=1}^{L} \hat{\gamma}_N^j, -\hat{\alpha}_N \bullet \hat{\gamma}_N, \ldots, -\hat{\alpha}_N \bullet \hat{\gamma}_N^L \right] \begin{pmatrix}
m_t \\
m_{t-1} \\
\
\vdots \\
M_t \\
M_{t-1} \\
\vdots \\
M_{t-L}
\end{pmatrix} + e_t
\]

(18)

Note that \( \hat{\gamma}_F^L \equiv \hat{\gamma}_F \bullet \hat{\gamma}_F \bullet \cdots \hat{\gamma}_F \), where the bullet product, \( \bullet \), is a component-wise product of two vectors of the same length, \( [\hat{\alpha}^1, \ldots, \hat{\alpha}^S] \bullet [\hat{\gamma}^1, \ldots, \hat{\gamma}^S] \equiv [\hat{\alpha}^1 \hat{\gamma}^1, \ldots, \hat{\alpha}^S \hat{\gamma}^S] \). The presence of factors’ lags links cross-sectional equations through time. Therefore, we stack up the equations for the whole \( T \) periods, \( t = 1, \ldots, T \), and estimate (recover) the underlying factors with OLS. This approach is closely related to the factor recovery procedure described in Campbell, Lo and MacKinlay (1997) in the context of APT models. Alternatively, it is possible to apply the Kalman-filter method to recover the latent factors. We prefer the OLS method because it requires less distributional assumptions, consistent with the GMM approach we adopt in the rest of this paper.
Table 1:
Negative and Positive Cross-Autocorrelations

Each panel shows the fraction of negative and positive cross-autocovariances among all cross-autocovariances computed from daily returns on each set of portfolios (25 size×BM, 25 size×momentum, 30 industry) as indicated. Also, fractions of significant negative and positive cross-autocovariances (at 5% and 20% levels) are shown. One sided significance intervals are computed with standard errors adjusted for serial correlation (using a GMM approach with Newey-West method and 22 lags).

**Panel A. 25 size × BM (value weighted) portfolios**

<table>
<thead>
<tr>
<th>Lag</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0.0017</td>
<td>0.265</td>
<td>0.19</td>
<td>0.1133</td>
<td>0.1633</td>
<td>0.445</td>
<td>0.4417</td>
<td>0.1483</td>
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<tr>
<td>Neg. &amp; sig. at 20%</td>
<td>0</td>
<td>0.1867</td>
<td>0.0733</td>
<td>0.0217</td>
<td>0.0517</td>
<td>0.2533</td>
<td>0.245</td>
<td>0.015</td>
</tr>
<tr>
<td>Neg. &amp; sig. at 5%</td>
<td>0</td>
<td>0.085</td>
<td>0.0033</td>
<td>0</td>
<td>0.0133</td>
<td>0.09</td>
<td>0.1083</td>
<td>0</td>
</tr>
<tr>
<td>Positive</td>
<td>0.9983</td>
<td>0.735</td>
<td>0.81</td>
<td>0.8867</td>
<td>0.8367</td>
<td>0.555</td>
<td>0.5583</td>
<td>0.8517</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 20%</td>
<td>0.9917</td>
<td>0.64</td>
<td>0.7733</td>
<td>0.765</td>
<td>0.7183</td>
<td>0.355</td>
<td>0.3533</td>
<td>0.5</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 5%</td>
<td>0.9833</td>
<td>0.515</td>
<td>0.6517</td>
<td>0.6883</td>
<td>0.52</td>
<td>0.1683</td>
<td>0.175</td>
<td>0.2883</td>
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</table>

**Panel B. 25 size × momentum (value weighted) portfolios**

<table>
<thead>
<tr>
<th>Lag</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
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</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0</td>
<td>0.295</td>
<td>0.1633</td>
<td>0.0733</td>
<td>0.1617</td>
<td>0.385</td>
<td>0.3967</td>
<td>0.2367</td>
</tr>
<tr>
<td>Neg. &amp; sig. at 20%</td>
<td>0</td>
<td>0.185</td>
<td>0.0717</td>
<td>0.005</td>
<td>0.0533</td>
<td>0.165</td>
<td>0.235</td>
<td>0.0433</td>
</tr>
<tr>
<td>Neg. &amp; sig. at 5%</td>
<td>0</td>
<td>0.1067</td>
<td>0.0067</td>
<td>0</td>
<td>0.0083</td>
<td>0.0533</td>
<td>0.12</td>
<td>0</td>
</tr>
<tr>
<td>Positive</td>
<td>1</td>
<td>0.705</td>
<td>0.8367</td>
<td>0.9267</td>
<td>0.8383</td>
<td>0.615</td>
<td>0.6033</td>
<td>0.7633</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 20%</td>
<td>1</td>
<td>0.56</td>
<td>0.7783</td>
<td>0.82</td>
<td>0.69</td>
<td>0.3933</td>
<td>0.3817</td>
<td>0.48</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 5%</td>
<td>0.9883</td>
<td>0.445</td>
<td>0.7033</td>
<td>0.73</td>
<td>0.4983</td>
<td>0.2217</td>
<td>0.2017</td>
<td>0.2683</td>
</tr>
</tbody>
</table>

**Panel C. 30 industry (value weighted) portfolios**

<table>
<thead>
<tr>
<th>Lag</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Negative</td>
<td>0.008</td>
<td>0.4862</td>
<td>0.3126</td>
<td>0.2724</td>
<td>0.3287</td>
<td>0.6172</td>
<td>0.7172</td>
<td>0.3885</td>
</tr>
<tr>
<td>Neg. &amp; sig. at 20%</td>
<td>0</td>
<td>0.2023</td>
<td>0.131</td>
<td>0.092</td>
<td>0.1046</td>
<td>0.2563</td>
<td>0.3655</td>
<td>0.0782</td>
</tr>
<tr>
<td>Neg. &amp; sig. at 5%</td>
<td>0</td>
<td>0.0563</td>
<td>0.0402</td>
<td>0.0241</td>
<td>0.0276</td>
<td>0.054</td>
<td>0.1057</td>
<td>0.0057</td>
</tr>
<tr>
<td>Positive</td>
<td>0.992</td>
<td>0.5138</td>
<td>0.6874</td>
<td>0.7276</td>
<td>0.6713</td>
<td>0.3828</td>
<td>0.2828</td>
<td>0.6115</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 20%</td>
<td>0.9724</td>
<td>0.2632</td>
<td>0.3851</td>
<td>0.4793</td>
<td>0.3287</td>
<td>0.1138</td>
<td>0.0414</td>
<td>0.231</td>
</tr>
<tr>
<td>Pos. &amp; sig. at 5%</td>
<td>0.9322</td>
<td>0.1126</td>
<td>0.1828</td>
<td>0.2575</td>
<td>0.0586</td>
<td>0.0126</td>
<td>0.0023</td>
<td>0.0368</td>
</tr>
</tbody>
</table>
This table shows coefficient estimates for the following return-generating process:

\[
(r_s^t - E_r^t) = \alpha_s F \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \alpha_N^s \sum_{k=1}^{\infty} (\gamma_N^s)^k (M_t - M_{t-k}) + \epsilon_s^t \\
= \beta_F^s (1 - \gamma_F^s) \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \beta_N^s (1 - \gamma_N^s) \sum_{k=1}^{\infty} (\gamma_N^s)^{k-1} (M_t - M_{t-k}) + \epsilon_s^t
\]

\[
\beta_F \equiv \frac{\alpha_F}{1 - \gamma_F}, \quad \beta_N \equiv \frac{\alpha_N}{1 - \gamma_N}
\]

using a GMM method. In Panel A factors are unobservable and moments are obtained from contemporaneous and cross-autocovariances up to lag order of 5, and \( \tau_{0.05} \equiv \frac{\log(0.05)}{\log(\gamma)} \) column is the “time to hit the 5% level”. In Panel B estimated factors are used (treated as observed) and lags of factors up to order 5 are used as instruments.

### Panel A. GMM Estimation with Unobserved Factors

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Fundamental</th>
<th></th>
<th>Transient</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \alpha_F )</td>
<td>( \beta_F )</td>
<td>( \gamma_F )</td>
<td>( \tau_{0.05} )</td>
</tr>
<tr>
<td>Small (bottom 30%)</td>
<td>0.61674</td>
<td>1.2212</td>
<td>0.49497</td>
<td>4.26</td>
</tr>
<tr>
<td>Mid–40 %</td>
<td>0.68014</td>
<td>1.0307</td>
<td>0.34012</td>
<td>2.78</td>
</tr>
<tr>
<td>Large (top 30%)</td>
<td>0.86946</td>
<td>0.98804</td>
<td>0.12002</td>
<td>1.41</td>
</tr>
</tbody>
</table>

### Panel B. GMM Estimation with Recovered Factors

<table>
<thead>
<tr>
<th>Portfolio</th>
<th>Fundamental</th>
<th></th>
<th>Transient</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>( \alpha_F )</td>
<td>( \gamma_F )</td>
<td>( \alpha_N )</td>
<td>( \gamma_N )</td>
</tr>
<tr>
<td>Small (bottom 30%)</td>
<td>0.58366</td>
<td>0.52179</td>
<td>0.19589</td>
<td>0.45683</td>
</tr>
<tr>
<td>Mid–40 %</td>
<td>0.71408</td>
<td>0.3626</td>
<td>0.15495</td>
<td>0.57678</td>
</tr>
<tr>
<td>Large (top 30%)</td>
<td>0.85628</td>
<td>0.088487</td>
<td>0.04688</td>
<td>0.81848</td>
</tr>
</tbody>
</table>

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Table 3: GMM Estimates with Recovered Factors

This table shows coefficient estimates and $R^2$'s for the return generating process,

\[(r_t^s - E(r_t^s)) = \alpha_F^s \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \alpha_N^s \sum_{k=1}^{\infty} (\gamma_N^s)^k (M_t - M_{t-k}) + \epsilon_t^s\]

\[= \beta_F^s (1 - \gamma_F^s) \sum_{k=0}^{\infty} (\gamma_F^s)^k m_{t-k} + \beta_N^s (1 - \gamma_N^s) \sum_{k=1}^{\infty} (\gamma_N^s)^{k-1} (M_t - M_{t-k}) + \epsilon_t^s\]

\[\beta_F \equiv \frac{\alpha_F}{1 - \gamma_F}, \quad \beta_N \equiv \frac{\alpha_N}{1 - \gamma_N}\]

using daily returns on 25 size×BM (value weighted) portfolios, 1963-07-01 to 2006-12-29 time period (10951 observations). Coefficients $\beta_F$ and $\beta_N$ represent the portfolio exposures (betas) for fundamental and transient factors, respectively. Coefficients $\gamma_F$ and $\gamma_N$ are the fundamental and transient friction measures, respectively.

<table>
<thead>
<tr>
<th>Portfolio size × BM</th>
<th>Coefficients</th>
<th>$R^2$</th>
<th>$R^3_N$</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$\beta_F$</td>
<td>$\gamma_F$</td>
<td>$\beta_N$</td>
</tr>
<tr>
<td>01 × 01</td>
<td>1.544</td>
<td>0.527</td>
<td>0.448</td>
</tr>
<tr>
<td>01 × 02</td>
<td>1.323</td>
<td>0.542</td>
<td>0.383</td>
</tr>
<tr>
<td>01 × 03</td>
<td>1.147</td>
<td>0.55</td>
<td>0.319</td>
</tr>
<tr>
<td>01 × 04</td>
<td>1.099</td>
<td>0.575</td>
<td>0.289</td>
</tr>
<tr>
<td>01 × 05</td>
<td>1.125</td>
<td>0.593</td>
<td>0.289</td>
</tr>
<tr>
<td>02 × 01</td>
<td>1.472</td>
<td>0.406</td>
<td>0.483</td>
</tr>
<tr>
<td>02 × 02</td>
<td>1.196</td>
<td>0.435</td>
<td>0.388</td>
</tr>
<tr>
<td>02 × 03</td>
<td>1.066</td>
<td>0.447</td>
<td>0.352</td>
</tr>
<tr>
<td>02 × 04</td>
<td>1.008</td>
<td>0.457</td>
<td>0.324</td>
</tr>
<tr>
<td>02 × 05</td>
<td>1.079</td>
<td>0.435</td>
<td>0.354</td>
</tr>
<tr>
<td>03 × 01</td>
<td>1.381</td>
<td>0.349</td>
<td>0.454</td>
</tr>
<tr>
<td>03 × 02</td>
<td>1.116</td>
<td>0.385</td>
<td>0.361</td>
</tr>
<tr>
<td>03 × 03</td>
<td>0.969</td>
<td>0.393</td>
<td>0.319</td>
</tr>
<tr>
<td>03 × 04</td>
<td>0.903</td>
<td>0.363</td>
<td>0.306</td>
</tr>
<tr>
<td>03 × 05</td>
<td>0.987</td>
<td>0.337</td>
<td>0.33</td>
</tr>
<tr>
<td>04 × 01</td>
<td>1.261</td>
<td>0.278</td>
<td>0.402</td>
</tr>
<tr>
<td>04 × 02</td>
<td>1.034</td>
<td>0.309</td>
<td>0.317</td>
</tr>
<tr>
<td>04 × 03</td>
<td>0.938</td>
<td>0.308</td>
<td>0.293</td>
</tr>
<tr>
<td>04 × 04</td>
<td>0.88</td>
<td>0.298</td>
<td>0.281</td>
</tr>
<tr>
<td>04 × 05</td>
<td>0.947</td>
<td>0.275</td>
<td>0.29</td>
</tr>
<tr>
<td>05 × 01</td>
<td>1.025</td>
<td>0.064</td>
<td>0.264</td>
</tr>
<tr>
<td>05 × 02</td>
<td>0.902</td>
<td>0.077</td>
<td>0.247</td>
</tr>
<tr>
<td>05 × 03</td>
<td>0.847</td>
<td>0.094</td>
<td>0.236</td>
</tr>
<tr>
<td>05 × 04</td>
<td>0.775</td>
<td>0.082</td>
<td>0.221</td>
</tr>
<tr>
<td>05 × 05</td>
<td>0.822</td>
<td>0.089</td>
<td>0.243</td>
</tr>
</tbody>
</table>
Table 4: **Explanatory Power in Cross-Section of Cross-Autocovariances**

This table shows the $R^2$’s of cross-sectional linear regressions of “actual” cross-autocovariances on “model-based” cross-autocovariances when intercept and slope are fixed to zero and one, respectively. “Actual” cross-autocovariances are computed from daily returns on 25 size×BM (value weighted) portfolios for 1963-07-01 to 2006-12-29 time period (10951 observations). “Model-based” cross-autocovariances are computed using predicted value from the following two factor model,

$$(r^s_t - E r^s_t) = \alpha^s_F \mu^s_t + \alpha^s_N M^s_t + \epsilon^s_t,$$

$$\begin{align*}
\mu^s_t & \equiv \gamma^s_F \mu^s_{t-1} + m_t, \\
M^s_t & \equiv \gamma^s_N M^s_{t-1} + \frac{1}{1-\gamma^s_N} (M_t - M_{t-1}),
\end{align*}$$

or a restricted, one-factor, version in which $\alpha_N \equiv 0$.

<table>
<thead>
<tr>
<th>Cross-Autocovariances</th>
<th>Lag-Order</th>
<th>Sign</th>
<th>Number of Observations</th>
<th>Explanatory Power ($R^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>Two-Factor Fund. &amp; Transient One-Factor Only Fund.</td>
</tr>
<tr>
<td>Lag ≤ 3</td>
<td>All</td>
<td>Positive</td>
<td>1300</td>
<td>99.356</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Negative</td>
<td>1254</td>
<td>99.362</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>46</td>
<td>19.797</td>
</tr>
<tr>
<td>Lag ≤ 9</td>
<td>All</td>
<td>Positive</td>
<td>3250</td>
<td>99.235</td>
</tr>
<tr>
<td></td>
<td></td>
<td>Negative</td>
<td>2782</td>
<td>99.268</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>468</td>
<td>14.718</td>
</tr>
</tbody>
</table>
Table 5: **Factor Correlation Matrix**

The table displays the correlation matrix for time-series of daily returns on the following portfolios, 1963-07-01 to 2006-12-29 time period (10951 observations). Recovered fundamental [**Fund.**] and transient (liquidity trading) [**Trans.**] factors, three Fama-French factors, excess market return [**MRKT**], size (Small Minus Big, [**SMB**]), book-to-market (High Minus Low, [**HML**]), and momentum factor [**MOM**].

<table>
<thead>
<tr>
<th></th>
<th>Fund.</th>
<th>Trans.</th>
<th>MRKT</th>
<th>SMB</th>
<th>HML</th>
<th>Mom</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fund.</td>
<td>1</td>
<td>-0.1442</td>
<td>0.8675</td>
<td>-0.4744</td>
<td>-0.4885</td>
<td>0.0034</td>
</tr>
<tr>
<td>Trans.</td>
<td>-0.1442</td>
<td>1</td>
<td>0.2923</td>
<td>0.3181</td>
<td>-0.1506</td>
<td>0.0082</td>
</tr>
<tr>
<td>MRKT</td>
<td>0.8675</td>
<td>0.2923</td>
<td>1</td>
<td>-0.2262</td>
<td>-0.5746</td>
<td>0.0485</td>
</tr>
<tr>
<td>SMB</td>
<td>-0.4744</td>
<td>0.3181</td>
<td>-0.2262</td>
<td>1</td>
<td>-0.0652</td>
<td>0.0856</td>
</tr>
<tr>
<td>HML</td>
<td>-0.4885</td>
<td>-0.1506</td>
<td>-0.5746</td>
<td>-0.0652</td>
<td>1</td>
<td>-0.0253</td>
</tr>
<tr>
<td>MOM</td>
<td>0.0034</td>
<td>0.0082</td>
<td>0.0485</td>
<td>0.0856</td>
<td>-0.0253</td>
<td>1</td>
</tr>
</tbody>
</table>
To compute measure of trade volume autocorrelation, we first run a time series regression of trade volume on its 20 lags using daily observations on individual stocks within each calendar year in 1963-2007 period. Our four measure are (1) sum of lag coefficients, (2) regression’s $R^2$, (3) sum of lag coefficients that are significant at 5% level, and (4) regression’s $R^2$ if the corresponding $F$ statistic is significant at 5% level. We average each of the four autocorrelation measures of individual stocks within ten size groups and compute the difference between large (size group ten) and small (size group one), $AC_{\text{large}} - AC_{\text{small}}$.

To compute friction measures, we estimate our model for 100 size×BM portfolios using four years of daily returns centered around each month in the 1965-01–2005-12 period and find average $\gamma^N$ and $\gamma^F$ coefficients within each size group and within each year. Then, we subtract the friction coefficients for the small firm group from large firm group to find $(\gamma^N_{\text{large}} - \gamma^N_{\text{small}})$ and $(\gamma^F_{\text{large}} - \gamma^F_{\text{small}})$.

**Panel A.** This panel shows the fraction of years with the specified sign condition on $AC_{\text{large}} - AC_{\text{small}}$ in the 1963–2007 period.

<table>
<thead>
<tr>
<th>Measure of</th>
<th>“Autocorrelation (large) - Autocorrelation (small)” Sign Ratios</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Volume Autocorrelation</td>
<td>Positive</td>
<td>Positive and Significant (5%)</td>
</tr>
<tr>
<td>1 (Coefficients’ Sum)</td>
<td>0.844</td>
<td>0.667</td>
</tr>
<tr>
<td>2 ($R^2$)</td>
<td>0.622</td>
<td>0.578</td>
</tr>
<tr>
<td>3 (Significant Coefficients’ Sum)</td>
<td>0.667</td>
<td>0.6</td>
</tr>
<tr>
<td>4 (Significant $R^2$)</td>
<td>0.711</td>
<td>0.6</td>
</tr>
</tbody>
</table>

**Panel B.** This panel shows the coefficients from the time series regression of $\Delta_t(AC_{\text{large}} - AC_{\text{small}})$ on an intercept, $\Delta_t(\gamma^F_{\text{large}} - \gamma^F_{\text{small}})$, and $\Delta_t(\gamma^N_{\text{large}} - \gamma^N_{\text{small}})$, where $\Delta_t(\cdot)$ denotes the time difference operator: $\Delta_t x \equiv x_t - x_{t-1}$.

<table>
<thead>
<tr>
<th>Measure of</th>
<th>Regression coefficients</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Trade Volume Autocorrelation</td>
<td>Intercept</td>
<td>Fundamental Friction</td>
</tr>
<tr>
<td>1 (Coefficients’ Sum)</td>
<td>0.009</td>
<td>-0.09</td>
</tr>
<tr>
<td>2 ($R^2$)</td>
<td>0.01</td>
<td>-0.042</td>
</tr>
<tr>
<td>3 (Significant Coefficients’ Sum)</td>
<td>0.007</td>
<td>-0.02</td>
</tr>
<tr>
<td>4 (Significant $R^2$)</td>
<td>0.008</td>
<td>-0.029</td>
</tr>
</tbody>
</table>

$^{***}$: Significant at 5% level, $^{**}$: Significant at 10% level, $^{*}$: Significant at 20% level
Table 7: Monthly Expected Returns and Alphas

<table>
<thead>
<tr>
<th>Return Variable</th>
<th>Friction Deciles</th>
<th>Difference</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>1 2 5 9 10</td>
<td>10–1 (8 lags)</td>
<td></td>
</tr>
<tr>
<td>Panel A: All Portfolios</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected Returns</td>
<td>0.9767 1.0788 1.1312 1.1997 1.2547</td>
<td>0.278</td>
<td>0.0003</td>
</tr>
<tr>
<td>CAPM α’s</td>
<td>0.4487 0.5948 0.6681 0.7527 0.7915</td>
<td>0.3428</td>
<td>0</td>
</tr>
<tr>
<td>F-F 3-factor α’s</td>
<td>0.3964 0.4122 0.4029 0.4882 0.5392</td>
<td>0.1428</td>
<td>0.0093</td>
</tr>
<tr>
<td>4-factor α’s</td>
<td>−0.1865 −0.15 −0.1796 0.0849 0.1405</td>
<td>0.3269</td>
<td>0.0059</td>
</tr>
<tr>
<td>Panel B: First Size Quintile (Small)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected Returns</td>
<td>1.0437 1.0801 1.1042 1.1043 1.1761</td>
<td>0.1324</td>
<td>0.2072</td>
</tr>
<tr>
<td>CAPM α’s</td>
<td>0.5036 0.559 0.6336 0.6416 0.73</td>
<td>0.2264</td>
<td>0.0183</td>
</tr>
<tr>
<td>F-F 3-factor α’s</td>
<td>0.4495 0.49 0.4326 0.4462 0.4237</td>
<td>−0.0258</td>
<td>0.742</td>
</tr>
<tr>
<td>4-factor α’s</td>
<td>−0.0522 −0.0014 −0.21 −0.0265 0.0951</td>
<td>0.1473</td>
<td>0.2636</td>
</tr>
<tr>
<td>Panel C: Third Size Quintile</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected Returns</td>
<td>0.9712 1.0222 1.1282 1.3787 1.4735</td>
<td>0.6384</td>
<td>0</td>
</tr>
<tr>
<td>CAPM α’s</td>
<td>0.2666 0.7869 0.6405 0.9252 1.0013</td>
<td>0.7347</td>
<td>0</td>
</tr>
<tr>
<td>F-F 3-factor α’s</td>
<td>0.2091 0.6036 0.4059 0.6665 0.6886</td>
<td>0.4796</td>
<td>0</td>
</tr>
<tr>
<td>4-factor α’s</td>
<td>−0.434 0.0261 −0.1323 0.4442 0.7094</td>
<td>1.1433</td>
<td>0</td>
</tr>
<tr>
<td>Panel D: Fifth Size Quintile (Large)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Expected Returns</td>
<td>1.1187 0.9988 1.2671 1.1974 1.3908</td>
<td>0.2721</td>
<td>0.0401</td>
</tr>
<tr>
<td>CAPM α’s</td>
<td>0.5487 0.4771 0.7797 0.7572 0.9216</td>
<td>0.3729</td>
<td>0.004</td>
</tr>
<tr>
<td>F-F 3-factor α’s</td>
<td>0.476 0.465 0.3692 0.4217 0.692</td>
<td>0.216</td>
<td>0.0728</td>
</tr>
<tr>
<td>4-factor α’s</td>
<td>0.0692 −0.0512 −0.33 −0.215 0.1532</td>
<td>0.084</td>
<td>0.6999</td>
</tr>
</tbody>
</table>

Note: Table 7 presents expected returns and alphas for different size quintiles, using various models such as CAPM, F-F 3-factor, and 4-factor models. The table includes friction deciles and interest rates for different variables, such as expected returns and CAPM α’s. The p-values indicate the significance of the differences between expected returns and alphas.
Figure 1: Time Patterns in Cross-Autocovariance Signs, 25 size×BM Portfolios
The two graphs to the left (right) show the fraction of negative (positive) cross-autocovariances among all cross-autocovariances of lag-order six in the top and lag-order seven in the bottom. The dashed line shows the fraction of significant negative (positive) cross-autocovariances at the 5% level, one-sided test, based on standard deviation computed from a GMM procedure with Newey-West method and 22 lags.
Figure 2: Time Patterns in Cross-Autocovariance Signs, 30 Industry Portfolios
The two graphs to the left (right) show the fraction of negative (positive) cross-autocovariances among all cross-autocovariances of lag-order six in the top and lag-order seven in the bottom. The dashed line shows the fraction of significant negative (positive) cross-autocovariances at the 5% level, one-sided test, based on standard deviation computed from a GMM procedure with Newey-West method and 22 lags.
Coefficient Patterns with “Size”

Figure 3: Coefficient Patterns with “Size”
Coefficient are estimated for the return generating process in equation (9) using daily returns on 25 size×BM (value weighted) portfolios, 1963-07-01 to 2006-12-29 time period (10951 observations). Coefficients $\beta_F$ and $\beta_N$ represent the portfolio exposures to fundamental and transient factors, respectively. Coefficients $\gamma_F$ and $\gamma_N$ are the fundamental and transient friction measures, respectively.
Figure 4: Coefficient Patterns with “BM”
Coefficient are estimated for the return generating process in equation (9) using daily returns on 25 size×BM (value weighted) portfolios, 1963-07-01 to 2006-12-29 time period (10951 observations). Coefficients $\beta_F$ and $\beta_N$ represent the portfolio exposures to fundamental and transient factors, respectively. Coefficients $\gamma_F$ and $\gamma_N$ are the fundamental and transient friction measures, respectively.
Figure 5: Friction Coefficients’ Patterns with “Size” and “BM”

Coefficient are estimated for the return generating process in equation (9) using daily returns on 100 size×BM (value weighted) portfolios, 1963-07-01 to 2006-12-29 time period (10951 observations). Coefficients $\gamma_F$ and $\gamma_N$ are the fundamental and transient friction measures, respectively. The “time to hit the 5% level”, $\tau_{0.05} = \frac{\log(0.05)}{\log(\gamma)}$, is computed for fundamental ($\gamma_F$) and transient ($\gamma_N$) frictions and is shown in the parenthesis on y-axis.