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On Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns

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Abstract

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In this paper, we shed theoretical and empirical light on short-horizon return reversals. We provide a model of price formation where risk averse agents absorb the order flow from outside investors. This framework captures both behavioral and inventory effects, and allows us to obtain analytical implications for the conditions required to obtain reversals in returns. Key to distinguishing between inventory and overreaction explanations for such reversals is the role of order flow. The inventory rationale requires a relation between returns and past order flow, whereas a reversion in beliefs of biased agents can cause reversal in returns independent of order flow. Our theoretical analysis further implies that lagged returns dominate lagged order flows in explaining current returns only if belief reversion is the dominant driver of return reversals. The empirical results indicate that, at monthly horizons, current returns are more strongly related to lagged returns than to lagged order imbalances. This suggests that monthly reversals are not completely captured by inventory effects and may be driven, in part, by belief reversion. We do find that returns are related to lagged imbalance innovations at horizons longer than a month. Finally, while the statistical significance of the reversal is quite strong, its magnitude is modest enough to not present substantial profit opportunities for individual investors.

1 Introduction

The predictability of stock returns has received considerable attention in the literature. Prominent among controversies regarding this issue is the finding of reversals in stock returns that occur at horizons ranging from a week to a month. Evidence of this phenomenon appears in papers by Cootner (1964), Fama (1964), Jegadeesh (1990), Lehmann (1990), and Kaul and Nimalendran (1990). Since this empirical finding contradicts the notion that stock prices follow a random walk, and thus is *prima facie* reason to suspect a violation of weak-form market efficiency, as defined by Fama (1970), it deserves a deep understanding by finance scholars.

Extant research suggests that the source of short-horizon return reversals remains an unresolved debate. Some authors, e.g., Conrad, Kaul, and Nimalendran (1990) and Jegadeesh and Titman (1995) take the position that market microstructure phenomena such as inventory control effects[1] or bid-ask bounce are the causes of these reversals. Others, such as Cooper (1999) and Mase (1999), suggest that market overreaction and correction drive the predictability of monthly returns. Those leaning towards the former cause generally relate return reversals to a measure of the bid-ask bounce such as that developed by Roll (1984), whereas those subscribing to the latter source point to a relation between unsigned trading activity (i.e., volume) and the strength of the reversal to support their position.

We take the view that further progress can be made on resolving the above debate in the presence of a specific equilibrium model that incorporates both microstructure

[1] The inventory theory of price formation has been elucidated by Stoll (1978), Ho and Stoll (1983), O'Hara and Oldfield (1986), Grossman and Miller (1988), and Spiegel and Subrahmanyam (1995).

and behavioral effects. The implications from such a model could potentially go a long way in helping us develop a better understanding of what drives short-horizon predictability.[2] Motivated by this observation, in this paper we construct a model where risk averse, possibly biased, agents absorb order flow from outside investors. To the best of our knowledge, such a framework has not yet appeared in the literature. Our theoretical analysis indicates that the key to distinguishing between the two explanations (inventory and overreaction) for return reversals is the role of order flow.

In particular, since market making agents with inventory concerns absorb order flow at a premium, any inventory-based explanation for short horizon reversals in returns should involve a discernible relation between returns and lagged order imbalances. On the other hand, we show that overreaction due to belief misperceptions relates current returns negatively to lagged returns without requiring any relation between order flow and past returns. We also find that in the expectation of returns conditional on lagged order flow and lagged returns, order flow dominates return completely if it contains exogenous liquidity orders as well as the trades of biased agents. When the order flow consists solely of exogenous liquidity orders and biased agents take the other side of the order flow, however, the coefficient on order flow captures reversal due to inventory, whereas the coefficient on lagged return captures reversals due to overreaction. Thus, overall, when inventory concerns are relevant, lagged order flow is an important driver of future returns. Further, our model suggests that lagged returns dominate lagged

[2]Our theoretical analysis can also be motivated by Lo and MacKinlay's (1990, p. 176) observation in the context of short-horizon predictability that "[an] equilibrium theory of overreaction with sharp empirical implications has yet to be developed." While models of overreaction (e.g., Odean, 1998) have indeed been developed since then, the interaction of behavioral effects with microstructure phenomena such as inventory control have not yet been examined explicitly.

order flow in predicting returns only when belief reversion is the dominant driver of return reversals.

The above implications can potentially be explored in depth if one has order flow data in addition to return data. We use order imbalance data for NYSE stocks during the period 1988-1998, in conjunction with return data based on quote mid-point returns, to shed light on the sources of short-horizon return reversals.[3] The use of mid-point returns allays concerns about bid-ask phenomena affecting the results. Further, due to issues surrounding the drawing of conclusions based on portfolio returns (Lo and Mackinlay, 1990; Brennan, Chordia, and Subrahmanyam, 1996), we focus on individual security returns in our analysis. Our empirical work is of independent interest because it presents evidence on the interaction between returns and order flows at horizons longer than those explored in the microstructure literature.[4]

We confirm that the reversals documented by Jegadeesh (1990), which were based on pre-1988 data, obtain out-of-sample for the 1988-1998 period, suggesting that they are not an artifact of data-mining. Nor do they appear to be completely captured by bid-ask bounce, since they obtain for the quote mid-point return series we use in our analysis. The monthly reversal also survives the use of beta, book-to-market ratio, size, and longer lags of returns as controls. In addition, the phenomenon is robust to cross-

[3]Several papers (e.g., Gallant, Rossi, and Tauchen, 1992, Campbell Grossman and Wang, 1993, Llorente, Michaely, Saar, and Wang, 2002, and Pastor and Stambaugh, 2003) have explored the relation between returns and trading volume. We use data on order imbalance because this variable more closely corresponds to the driver of signed returns in our theoretical work. Also, the preceding papers consider rational paradigms to link volume with returns, whereas our model allows for biased expectations as well as inventory concerns.

[4]For example, Hasbrouck and Seppi (2001) and Chordia, Roll, and Subrahmanyam (2003) use intraday intervals, whereas Chordia and Subrahmanyam (2003) consider daily horizons to analyze the return-imbalance relation.

sectional, time-series, and panel regression approaches. Our empirical work further indicates that at a monthly horizon, current returns bear a stronger relation to lagged returns than to lagged order flows. Based on our theoretical framework, this leads us to conclude that return reversals at monthly horizons are not completely captured by inventory-related phenomena, and are possibly a consequence of reversion in investor beliefs.[5] We also find that the magnitude of the reversal is modest, and while it is statistically significant, it does not appear to represent a dramatic violation of market efficiency after consideration of transaction costs faced by individual investors.

As a by-product of our analysis, we uncover an intriguing stylized fact; specifically, that in the cross-section, order flow innovations at lags of two and three months have predictive power for current returns that is independent of lagged returns. This result does not, however, obtain in our time-series analysis, and neither does it obtain for small companies, where inventory concerns are most likely to be relevant, suggesting that the phenomenon is not a manifestation of inventory pressures in individual stocks.

This paper is organized as follows. In the next section we present our model. Section 3 describes the data. Section 4 presents the empirical analysis. Section 5 concludes. All proofs appear in Appendix A.

[5]This, of course, does not preclude the possibility that inventory effects are present at other horizons. For example, Chordia and Subrahmanyam (2003) provide evidence of order-flow induced price pressures on daily returns.

2 The Theory

2.1 The Basic Model

Consider a risky security which trades at dates 1 and 2, and pays off a random amount θ at date 3, where θ is normally distributed with mean zero. There is a mass unity of risk averse agents who absorb liquidity shocks that appear in the market. Each such agent has CARA utility with coefficient R. These agents receive a signal $\theta + \epsilon$ at date 2, where ϵ is normally distributed, independent of θ and has variance v_ϵ. To capture overreaction and correction, we assume that overconfidence causes the variance of ϵ to be misassessed at a level $v_c < v_\epsilon$.[6] A demand shock of z arrives at the market on date 2; z is normally distributed with mean 0 and variance v_z, and is independent of all other random variables in the model. For now, we assume that no information is possessed by agents at date 1, and that there are no liquidity shocks to be absorbed at this date. We relax this assumption in Section 2.3. We let P_i denote the price at date i, with $P_3 = \theta$.

In this model the following lemma holds.

Lemma 1 *The equilibrium value of the price at date 2, P_2, is given by*

$$P_2 = Rkv_\theta z + k(\theta + \epsilon), \tag{1}$$

where $k \equiv v_\theta/(v_\theta + v_c)$. The date 1 price is nonstochastic, i.e., it does not depend on any of the random variables, θ, ϵ, or z.

As can be seen, the price has two components. The first one is the premium de-

[6]A similar construct is used by Odean (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998).

manded for absorbing the liquidity shock, and the second one is the (biased) conditional expectation of the asset's value. Both components cause reversals in price changes, as indicated in the following proposition:

Proposition 1 *The equilibrium value of the serial covariance* $\mathrm{cov}(\theta - P_2, P_2 - P_1)$ *is given by*

$$\mathrm{cov}(P_3 - P_2, P_2 - P_1) = -\frac{v_\theta^2}{v_\theta + v_c}(v_\epsilon - v_c) - \frac{R^2 v_\theta^2 v_c^2 v_z}{(v_\theta + v_c)^2}. \tag{2}$$

Thus, the two terms on the right-hand side of Eq. (2) capture the two reasons for which reversals occur, namely, overreaction-correction and the natural inventory effect, respectively. Note that when agents are rational, i.e., $v_c = v_\epsilon$, the first component goes to zero, and as the risk aversion coefficient becomes vanishingly small, so does the second component.

It is important to note that the inventory effect necessarily involves a relation between lagged order flow and returns. Specifically, the return reversal occurs because a conditional risk premium is reversed out of asset returns. This conditional risk premium causes a negative relation between price changes and lagged imbalance. In particular, $\mathrm{cov}(P_3 - P_2, Q_2) = -Rkv_\theta v_z < 0$, where $Q_2 = z$ is the date 2 order flow absorbed by market makers. Belief reversion, however does not require a relation between lagged imbalance and returns. In particular, under risk-neutrality, there are no inventory effects, and only the first term in Eq. (2) contributes to reversal. In this situation, the date 2 price is simply the biased expectation $P_2 = [v_\theta/(v_\theta + v_c)][\theta + \epsilon]$, and there also is no relation between returns and lagged order flow because there are no risk premia required to absorb the flow. The proposition below follows directly from the above discussion:

Proposition 2 *1. If market making agents are risk-averse (i.e., there are inventory effects), there is return reversal and also a relationship between lagged order flow and returns.*

2. If market making agents are risk-neutral and rational, there is no return reversal and no relationship between order flow and returns.

3. If market making agents are risk-neutral but overreact to information, there is return reversal but no relationship between order flow and returns.

Note that in our specification, the order flow emanates only from liquidity traders and not from biased agents (who are assumed to take the other side of the order flow as market makers). Because of this, if one regresses price changes on lagged price changes as well as order flow, the lagged price change picks up the reversal in beliefs, while the lagged order flow captures the inventory effect. More specifically, we can write

$$E(P_3 - P_2 | P_2 - P_1, Q_2) = \alpha(P_2 - P_1) + \beta Q_2, \tag{3}$$

where

$$\alpha = -\frac{v_\epsilon - v_c}{v_\epsilon + v_\theta}, \tag{4}$$

and

$$\beta = -\frac{R v_\theta^2}{v_\epsilon + v_\theta}. \tag{5}$$

The above expressions directly lead to the following proposition.

Proposition 3 *Consider a multivariate regression of price changes on lagged price changes and lagged order flow, where the order flow does not contain the trades of biased agents. This regression is linear, and both coefficients are, in general, negative. The coefficient on order flow is zero if there are no inventory effects (market makers are risk-neutral) while the coefficient on price change is zero if agents are rational.*

Thus, a regression of the type indicated in the above proposition can potentially shed light on inventory and overreaction effects. The result in the proposition is sensitive to model specification, however, as the next subsection illustrates.

2.2 Rational Market Makers

In the previous model, overconfident market making agents interact with price-inelastic liquidity traders. In case the construct of just these two types of agents is not appealing to the reader, let us now consider a slightly more complicated model where rational market makers trade with utility-maximizing overconfident agents, and also absorb liquidity shocks. Thus, suppose that there are two equal (unit) masses of agents, each with CARA utility and a common risk aversion coefficient R; the first class assesses the variance of ϵ correctly, whereas the second class, as before, assesses it at $v_c < v_\epsilon$. The first class is assumed to absorb the order flow of the other investors. Standard mean-variance analysis indicates that demands of the rational and overconfident agents are respectively given by $\frac{k_r(\theta+\epsilon)-P_2}{Rv_r}$ and $\frac{k_c(\theta+\epsilon)-P_2}{Rv_o}$, where $k_r \equiv v_\theta/[v_\theta+v_\epsilon]$, $k_c \equiv v_\theta/[v_\theta+v_c]$, $v_r \equiv v_\theta v_\epsilon/[v_\theta+v_\epsilon]$, and $v_o \equiv v_\theta v_c/[v_\theta+v_c]$. In this case, we can write the market clearing condition as

$$\frac{k_r(\theta+\epsilon)-P_2}{Rv_r}+\frac{k_c(\theta+\epsilon)-P_2}{Rv_o}+z=0.$$

This implies that

$$P_2=\frac{\theta+\epsilon}{1/v_r+1/v_o}\left[\frac{k_r}{v_r}+\frac{k_c}{v_o}\right]+\frac{Rz}{1/v_r+1/v_o}. \tag{6}$$

From the above expression for the price, we obtain the following proposition:

Proposition 4 *In the version of the model where rational market makers absorb the trades of overconfident agents and price-inelastic liquidity traders, the equilibrium value of the serial covariance is given by*

$$\mathrm{cov}(P_3-P_2,P_2-P_1)=-\frac{v_\theta^2 v_\epsilon(v_\epsilon-v_c)(v_\epsilon+v_c)}{[v_c(2v_\epsilon+v_\theta+v_\epsilon v_\theta)]^2}-\frac{R^2v_\epsilon^2v_c^2v_\theta^2v_z}{[v_c(2v_\epsilon+v_\theta+v_\epsilon v_\theta)]^2}. \tag{7}$$

One learns from the above expression that the intuition in Section 2.1 also applies to this case. Since the rational agents are risk averse, they are not able to completely arbitrage the mispricing component illustrated in the first term. At the same time the second term indicates that the standard inventory effect also contributes to reversal.

Note that the order flow at date 2, denoted by Q_2, is given by $Q_2=\frac{k_c(\theta+\epsilon-P_2)}{Rv_o}+z$. Thus, in this case the covariance between price changes and lagged order flow is given by

$$\mathrm{cov}\left[P_3-P_2,\frac{k_c(\theta+\epsilon-P_2)}{Rv_o}+z\right],$$

which reduces to

$$-\frac{Rv_c^2v_\epsilon v_\theta v_z(v_\epsilon+v_\theta)}{[v_c(2v_\epsilon+v_\theta+v_\epsilon v_\theta)]^2}-\frac{v_\epsilon v_\theta(v_\epsilon-v_c)^2}{R[v_c(2v_\epsilon+v_\theta+v_\epsilon v_\theta)]^2}.$$

Thus, even if agents are rational ($v_c = v_\epsilon$), there is a relation between returns and lagged imbalance. The basic point we wish to reiterate is the following. For return reversals to be caused by inventory effects, there should be a relation between returns and lagged imbalances. The overreaction-correction phenomenon also causes reversals, but this reversal in beliefs does not require an imbalance-return relation.

We now turn to the multivariate regression of price moves on lagged price changes and order flow. In this case, the following proposition obtains.

Proposition 5 *The regression of $P_3 - P_2$ on $P_2 - P_1$ and Q_2 is linear. The conditional expectation may be expressed as*

$$E(P_3 - P_2 | P_2 - P_1, Q_2) = \alpha'(P_2 - P_1) + \beta' Q_2, \tag{8}$$

where

$$\alpha' = 0, \tag{9}$$

and

$$\beta' = -\frac{R v_\epsilon v_\theta}{v_\epsilon + v_\theta}. \tag{10}$$

Thus, in this case, where the order flow contains overreaction as well as exogenous liquidity trades, the conditional expectation has zero loading on lagged price changes and a negative loading on order flow. This is because the order flow completely captures both sources of reversal, belief reversal as well as the inventory effect.

As another extension, we also provide expressions for the covariances when irrational agents and market makers have differing degrees of risk aversion (denoted by R_c and R_m, respectively). The analysis for this case is a simple extension of the preceding derivations, and is therefore omitted. In this case, we have

$$\begin{aligned}\operatorname{cov}(P_3 - P_2, P_2 - P_1) &= -\frac{R_m^2 R_c^2 v_\epsilon^2 v_\theta^2 v_c^2 v_z}{[R_c v_c(v_\epsilon + v_\theta) + R_m v_\epsilon (v_c + v_\theta)]^2} \\ &- \frac{(v_\epsilon - v_c)(R_c v_c + R_m v_\epsilon)}{[R_c v_c(v_\epsilon + v_\theta) + R_m v_\epsilon (v_c + v_\theta)]^2}, \end{aligned} \tag{11}$$

and the covariance between imbalance at date 2 and the price move across dates 2 and 3 reduces to

$$-\frac{R_m v_\epsilon v_\theta [R_c^2 v_c^2 v_z (v_\epsilon + v_\theta) + (v_\epsilon - v_c)^2]}{[R_c v_c(v_\epsilon + v_\theta) + R_m v_\epsilon (v_c + v_\theta)]^2}.$$

It can be seen from the above expression that as inventory effects become vanishingly small ($R_m \to 0$), the covariance between lagged order flow and returns approaches zero. On the other hand, as the risk aversion of the irrational agents approaches zero ($R_c \to 0$), the covariance does *not* approach zero, because while the risk-neutral but biased agents absorb the order flow, the risk-neutral price in that case approaches the biased price set by irrational agents, and the imbalance is negatively related to the subsequent reversal. The expression for the coefficients of the conditional expectation in Eq. (8) remain the same, except that R in Eq. (9) is replaced by R_m.

The basic point still obtains: inventory effects necessitate a relation between lagged imbalances and returns. It is worth noting, however, that the causality does not obtain in that same manner for behavioral effects: reversals due to overreaction and correction neither necessitate nor rule out the possibility of a relation between returns and lagged order flow.

2.3 A Model with Two Rounds of Trade

The preceding models have involved only one round of trade, but they suffice to explain the basic intuition. In order to make the analysis more convincing, and to explore the relations between price changes and order flows at lags greater than unity, we now consider a dynamic model where liquidity shocks arrive in each of two periods, with liquidation at date 3. In this model, liquidity shocks of z_1 and z_2 arrive at each of periods 1 and 2. These shocks are mutually independent with mean zero and a common variance v_z, and also are uncorrelated with all other random variables in the model. The initial date is now date 0, where no liquidity shocks arrive and no information signals are available. The functional form of the date 2 price remains unchanged from Eq. (1) and obtains by replacing z in this equation with $z_1 + z_2$:

$$P_2 = Rkv_\theta(z_1 + z_2) + k(\theta + \epsilon).$$

This immediately implies that the covariances and the coefficients of the conditional expectation at date 2 are unchanged from Eqs. (2), (4), and (5).

The calculation of the date 1 price is more complex. First, cumbersome algebra (which appears in Appendix A) demonstrates that the date 1 demand of the overconfident agents is given by

$$x_1 = \frac{E(P_2|z_1, \theta + \epsilon) - P_1}{R}\left[\frac{1}{\mathrm{var}(P_2|z_1, \theta + \epsilon)} + \frac{1}{v}\right] + E(x_2|\theta + \epsilon, z_1). \qquad (12)$$

Let $\mathrm{var}(P_2|z_1, \theta + \epsilon)$ and $\mathrm{var}(\theta|\theta + \epsilon)$ (as calculated by the overconfident agent) be denoted by v_{p2} and v, respectively. Then the above expression simplifies to

$$\frac{k(\theta + \epsilon) + Rkv_\theta z_1 - P_1}{Rv_{p2}} + \frac{k(\theta + \epsilon - P_1)}{Rv},$$

and the market clearing condition at date 1 therefore becomes

$$\frac{k(\theta+\epsilon)+Rkv_\theta z_1-P_1}{Rv_{p2}}+\frac{k(\theta+\epsilon-P_1)}{Rv}+z_1=0.$$

This implies that

$$P_1=k(\theta+\epsilon)+k'z_1,$$

where

$$k'=\frac{R}{D}\left(1+\frac{kv_\theta}{v_{p2}}\right),$$

with $D\equiv\frac{1}{v}+\frac{1}{v_{p2}}$.

This implies that

$$\mathrm{cov}(P_3-P_2,P_1-P_0)=-\frac{kv_\theta(v_\epsilon-v_c)}{v_\theta+v_c}-Rkk'v_\theta v_z.$$

The two terms in the above expression again have an interpretation similar to that in the static models; the first captures overreaction due to overconfidence, while the second captures the inventory effect. The additional result is that the dynamic model permits reversals lasting over longer lags. Letting Q_1, as before, represent the date 1 order flow, we also note that $\mathrm{cov}(P_3-P_2,Q_1)=-Rkv_\theta vv_z<0$.

The multiple regression of P_3-P_2 on P_1-P_0 and the date 1 order flow z_1 is linear in these variables. With the coefficients being denoted by $\alpha^\dagger$ and $\beta^\dagger$, respectively, we have (see the Appendix)

$$\alpha^\dagger=-\frac{v_\epsilon-v_c}{v_\epsilon+v_\theta}, \tag{13}$$

and

$$\beta^\dagger=-\frac{Rv_\theta^2\left[R^2v_\theta^2v_z\left\{v_c(v_c-v_\epsilon)+v_\theta(v_\epsilon+v_\theta)\right\}+v_c(v_c+v_\theta)^2\right]}{\left[R^2v_\theta^3v_z+v_c(v_c+v_\theta)\right][v_c+v_\theta][v_\epsilon+v_z]}. \tag{14}$$

While $\alpha^\dagger$ is negative, $\beta^\dagger$ can be negative or positive. The reason is that the risk averse, overconfident agents have a tendency to reverse their positions at date 2 to reduce their risk exposure. Since their trades can be negatively correlated with the price move across dates 2 and 3, and they take the opposite side of z_1, the date 1 order flow can be positively correlated with the price move across dates 2 and 3. The greater the risk aversion, the stronger is the tendency for this positive autocorrelation. As can be seen from (14), however, the coefficient is negative under a wide range of parameter values since only one of the terms, $v_c - v_\epsilon$, attenuates the negative relation.[7] We conclude that in the dynamic setting, the multivariate regression of returns on lagged returns and lagged order flow generally implies negative coefficients for both, and returns continue to pick up the belief reversal, whereas the coefficient on order flow picks up a combination of belief reversal and the inventory effect.

Overall, our analysis indicates that an order flow-return relation is necessary for inventory effects to cause short-horizon return reversals. This is simply because the inventory phenomenon is manifested in a premium demanded by the market makers for bearing inventory risk, and this premium is necessarily a function of the order flow. The additional insight yielded by the analysis is that in a multivariate regression of returns on lagged returns and lagged order flow, the latter dominates the former if it contains

[7] With regard to the price move across dates 1 and 2 the following results hold. First the covariance between $P_2 - P_1$ and $P_1 - P_0$ is $-k'^2 v_z$ and is negative. The covariance between $P_2 - P_1$ and the date 1 order flow, z_1, is

$$-\frac{R^3 v_\theta^4 v_z (v_c - v_\theta)}{[R^2 v_\theta^3 v_z + v_c(v_c + v_\theta)]\,[v_c + v_\theta]},$$

and is negative so long as v_θ is small relative to v_c. The multivariate regression of $P_2 - P_1$ on both $P_1 - P_0$ and the date 1 order flow is multicollinear because both the regressors are linear in z_1 and no other random variable. Generally, the notion that price changes load both on lagged price changes and order flow still holds.

the trades of biased investors as well as exogenous order flow. If biased investors take the other side of the order flow, however, then the coefficient on order flow captures the reversal due to inventory effects, while the coefficient on returns principally captures the reversal in beliefs, and both variables, in general, have nonzero coefficients. Further, our model suggests that lagged returns dominate lagged imbalances in explaining current returns only when belief reversion is the dominant driver of return reversals.

One way of potentially shedding light on the two types of explanations for short-horizon return reversals is to examine the interplay between current returns, lagged returns, and lagged order flows. In the remainder of the paper, we focus on these empirical relations. To preserve normality and hence tractability, we analyze price changes in the model, which is standard practice in the microstructure literature on informed trading. As per empirical convention, and to preserve comparability in the cross-section, however, we analyze returns in our tests to follow. This distinction, of course, is of no material consequence in that the economic forces in the model apply equally to price changes and returns.[8]

3 Data

The transactions data sources are the Institute for the Study of Securities Markets (ISSM) and the NYSE Trades and Automated Quotations (TAQ) databases. The ISSM data cover 1988-1992 inclusive while the TAQ data are for 1993-1998. We use only NYSE stocks to avoid any possibility of the results being influenced by differences

[8]See for instance, Hong and Stein (1999) who also model price changes but draw implications for returns that are tested in Hong, Lim, and Stein (2000).

in trading protocols.

3.1 Inclusion Requirements

Stocks are included or excluded depending on the following criteria:

1. To be included in any given year, a stock had to be present at the beginning and at the end of the year in both the Center for Research in Security Prices (CRSP) and the intraday databases.

2. If a firm changed exchanges from Nasdaq to NYSE during the year (no firms switched from the NYSE to the Nasdaq during our sample period), it is dropped from the sample for that year.

3. Since their trading characteristics might differ from those for ordinary equities, assets in the following categories are also expunged: certificates, American Depositary Receipts, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and Real Estate Investment Trusts.

4. To avoid the influence of unduly high-priced stocks, if the price at any month-end during the year was greater than $999, the stock was deleted from the sample for the year.

5. Stock-days on which there are stock splits, reverse splits, stock dividends, repurchases or a secondary offering are eliminated from the sample.

Next, intraday data are purged for one of the following reasons: trades out of sequence, trades recorded before the open or after the closing time, and trades with special settlement conditions (because they might be subject to distinct liquidity considerations). Our preliminary investigation revealed that auto-quotes (passive quotes by secondary market dealers) were eliminated in the ISSM database but not in TAQ. This caused the quoted spread to be artificially inflated in TAQ. Since there is no reliable way to filter out auto-quotes in TAQ, only BBO (best bid or offer)-eligible primary market (NYSE) quotes are used in calculating imbalances and mid-point returns. Also, quotes established before the opening of the market or after the close were discarded. Negative bid-ask spread quotations, transaction prices, and quoted depths were discarded. Following Lee and Ready (1991), any quote less than five seconds prior to the trade is ignored and the first one at least five seconds prior to the trade is retained.

3.2 Imbalance and Return Data

We sign trades using the Lee and Ready (1991) procedure: if a transaction occurs above the prevailing quote mid-point, it is regarded as a purchase and vice versa. If a transaction occurs exactly at the quote mid-point, it is signed using the previous transaction price according to the tick test (i.e., buys if the sign of the last non-zero price change is positive and vice versa).[9] For each stock we then define OIBVOL, the estimated monthly buyer-initiated minus seller-initiated dollar volume of transactions.

We recognize that our algorithm generally allows us to sign only market orders, so

[9] Odders-White (2000) and Lee and Radhakrishna (2000) argue that the Lee and Ready (1991) algorithm correctly classifies more than between 85%-93% of trades, which indicates that the rule is more than adequate for our purposes.

that our net imbalance measures the aggregate demand of agents that require immediacy. While this caveat is worth mentioning, we believe that the standard microstructure paradigm is of patient market makers (which include limit order traders) who absorb the demands of traders that have relatively urgent needs to trade. As such, we believe that it is hard to argue that inventory effects, if any, would not manifest themselves in premia required to bear the imbalance caused by submitters of market orders.

Of course, short-horizon return computations are subject to the well-known bid-ask bounce bias. We therefore do *not* use returns obtained from CRSP data in our empirical analysis. Instead, we use a series which calculates the daily returns using quote midpoints associated with the last transaction on a particular day (which are not necessarily the same as closing quote midpoints).[10] Throughout, these midpoint returns are used in the analysis.

Since we run time-series as well as cross-sectional regressions in the paper, we need enough observations per stock to estimate the parameters reliably. We therefore require a stock to have at least 48 monthly observations of returns as well as imbalances to be included in the database. Table 1 presents the summary statistics for the pooled time-series, cross-sectional sample of 156,752 firm-months. The average monthly return in the sample is 1.3%, whereas the average imbalance is $9.8 million. The mean proportional imbalance is about 0.40%. The average of the absolute level of the proportional imbalance is quite high, about 17.8%. The standard deviations indicate adequate variations relative to the mean to allow us to capture relationships between returns and order flow.

[10] Monthly returns are calculated by cumulating the daily mid-point returns.

4 Empirical Results

Our theoretical model, for tractability, and to succinctly bring out the intuition, considers the case of a single security. In performing our analysis on individual securities, however, we have the choice of performing the time-series aggregation of estimated coefficients from cross-sectional regressions, or the cross-sectional aggregation of time-series regression estimates. We show in Appendix B that under certain plausible conditions, the sign of the coefficient estimate obtained from the two aggregation methods will coincide. Aggregation of the estimates obtained from time-series regressions presents econometric problems because the residuals are likely to be cross-correlated due to a systematic component in the independent variable (i.e., imbalance), which contaminates inferences from simple t statistics associated with the average estimates. We initially choose to focus on time-series aggregation of cross-sectional regression estimates because they represent the well-accepted Fama and MacBeth (1973) technique. We also report estimates using cross-sectional aggregation of time-series regression coefficients (using a procedure to correct the standard errors), as well as a panel approach, and find that the conclusions are broadly unaltered.

Our goal is to explore the relation between monthly returns and lagged returns as well as lagged order flow. We choose the monthly horizon because of its consideration in earlier papers which explore the inventory and overreaction explanations (e.g., Jegadeesh and Titman, 1995, Cooper, 1999, and Mase, 1999).[11] We begin by performing

[11]Hvidkjaer (2002) considers how longer-horizon predictability (specifically, momentum at six- to twelve-month horizons) is related to order imbalances. His focus is on linking momentum to the behavioral models of Daniel, Hirshleifer, and Subrahmanyam (1998), and Barberis, Shleifer, and Vishny (1998).

the simplest possible test. Specifically, we perform Fama-MacBeth regressions which involve regressing the current month's returns on the past month's return and the past month's imbalance.[12] We control for total dollar volume in order to isolate the effect of imbalances. The average number of stocks in these monthly regressions is 1,185. Note that our use of mid-point returns in these regressions mitigates concern about bid-ask bounce affecting our results. Hence the need to omit a certain time-period between months (Jegadeesh, 1990) is also reduced.

The results are presented in Panel A of Table 2. As can be seen, the first lag of the monthly return is significantly and negatively related to the current month's return, which is consistent with the analysis of Jegadeesh (1990) and Lehmann (1990).[13] Lagged imbalances, however, are not significant. Further, the sign, significance, and magnitude of the coefficient on lagged return is not materially affected by the inclusion of the lagged imbalance. An issue that arises here, of course, is how noise in the imbalance measure could affect our conclusions. In Appendix B, we analytical address this question and conclude that, as per the literature, the Lee and Ready (1991) algorithm is accurate enough to not alter our conclusions.[14]

We also stratify our sample by size terciles. Specifically, we rank all stocks each month based on their average market capitalization during the month. We then divide

[12]In Table 10, we presents results that control for longer (up to twelve) lags of monthly returns.

[13]At this point, we do not include other variables such as size or the book to market ratio in our regression. Haugen and Baker (1996) show that the monthly reversal is the strongest effect in the cross-section of monthly returns and survives a host of controls. Later in this section, we explore the robustness of our results to the inclusion of beta as well as book/market and market capitalization.

[14]In addition, we use the method proposed by Fama and French (1992) for addressing measurement error in beta by sorting stocks into six groups by their lagged imbalance, and assigning the average lagged imbalance for a group to every stock in that group. Such an exercise does not change our basic conclusions; the lagged imbalance variable is insignificant, while lagged returns continue to be significant.

these stocks into three equal groups in that month. In Panel B of Table 2, we present the regression results stratified by size.[15] Not surprisingly, the one month reversal is strongest for the small firm group. It is also present in the mid-cap group. While the coefficient for the large firm group is negative, it is not significant. However, imbalance innovations are not significant for any of the size terciles.

We next report the average monthly returns from sorting stocks into groups by lagged return as well as lagged imbalances. The results are reported in Table 3. Panel A demonstrates that the average return of stocks with the lowest and highest lagged monthly returns are 1.38% and 1.08%, respectively. This difference is statistically significant with an (unreported) t statistic of 4.00. In contrast, from Panel B, the returns of stocks in the extreme imbalance innovation groups are 1.33% and 1.25% respectively, and this difference is not significant at the 5% level.

Panel C of Table 3 presents the results from sorting stocks into three groups by lagged return and then, within each return group, into three groups by lagged imbalances. The rows and columns respectively represent imbalance and return sorts. The difference between the first and last numbers in the first row is significant at the 5% level (with an unreported t statistic of 2.48), while that for the second and third rows are not significant. In contrast the differences in the first and last column entries are significant for the first two columns (with t statistics of 2.92 and 4.35, respectively, which are again omitted from the table for brevity), whereas the corresponding difference for the third column are not significant. Overall, the evidence in Tables 2 and 3 indicates that current returns are more strongly associated with lagged returns than

[15]The average number of stocks in these terciles (large to small) are 383, 306, and 340.

with lagged imbalances.

We now consider longer lags of returns and imbalances to more completely capture the interaction between returns and order flows. Of course, one problem in regressing returns on multiple lags of imbalances is the multicollinearity caused by autocorrelations in imbalance (see Chordia, Roll, and Subrahmanyam, 2002).[16] To address this issue, we calculate imbalance innovations by regressing imbalances on twelve lags each of past returns and past imbalances. Table 4 presents the results of performing Fama-MacBeth regressions which involve regressing the current month's returns on the past three months' returns and three lagged imbalance innovations, together with three lags of total volume as controls.[17] The average number of stocks in these monthly regressions is 1,141.

As can be seen from Table 4, the first lag of the monthly return is significantly and negatively related to the current month's return, which is again consistent with the analysis of Jegadeesh (1990) and Lehmann (1990). The other lags of the return are not significant, suggesting that reversals in the cross-section do not obtain beyond

[16]For our sample, the cross-sectional averages of the autocorrelations for the first three lags of imbalance measured in number of transactions are 0.419, 0.296, and 0.055, whereas those for the imbalance measured in dollars are 0.112, 0.066, and 0.055, respectively. All are significant at the 5% level.

[17]Return reversal has be shown to obtain over monthly horizons, so including three lags of monthly imbalance innovations would appear to be enough to capture lagged adjustments to order flow. We performed regressions including the fourth through the twelfth lags of imbalance innovations, but found them to be insignificant; details are available upon request. Further, while the usage of twelve monthly lags to back out imbalance innovations imposes a stringent requirement on the continuity of the imbalance series for a stock, this exercise would seem to capture most of the lagged dependence in imbalance. Indeed, the absolute value of the average autocorrelation in dollar imbalances remains at or below 0.02 from the third lag through the twelfth lag, suggesting that longer lags would not materially assist in computing imbalance innovations more accurately. We also performed identification checks on the time-series of imbalances using the Bayesian information criterion for a random sample of fifty stocks. In no case was the indicated autoregressive lag length greater than twelve.

the monthly horizon. The coefficient on the first lag of imbalance innovations is not significant, whereas those on the second and third lags are negative and significant. This appears to indicate that imbalance shocks take longer to be reversed than the monthly horizon at which return reversals obtain. Further, the monthly return reversals appear to occur in a manner that is largely independent of imbalance innovations. On the face of it, these results appear to support the notion that monthly reversals are driven by belief reversions whereas inventory phenomena may possibly drive returns at longer lags. We will shed more light on this issue in the discussion of Table 5 below, and when we present our time-series regressions in Table 6.

Next, we perform regressions analogous to Table 4, but stratified by three size groups, constructed, as before, by ranking all stocks by their average market capitalization during a month.[18] Table 5 presents the results from this analysis. Not surprisingly, the one month reversal is strongest for the small firm group. It is also present in the mid-cap group. While the coefficient for the large firm group is negative, it is not significant. Interestingly, however, imbalance innovations are most strongly significant for the large firm group, indicating that the negative relation of long lags of imbalance innovations with returns is stronger in large stocks than in small stocks. Since lagged imbalance innovations are not significant in the small firm tercile, where inventory concerns are more likely to be relevant, we do not believe that inventory phenomena are the driver of the negative relations between returns and innovations at lags greater than unity. Further, given that large stocks are actively traded by individuals, this phenomenon is consistent with naïve, and possibly perverse, invest-

[18]The average number of stocks in these terciles (large to small) are 371, 285, and 321.

ing rules used by relatively unsophisticated individual investors. For example, such investors may follow strategies of buying stocks that have recently announced positive news such as better-than-expected product demand, but if the market overreacts to this announcement, such stocks will disappoint.[19]

We now present our results in a different way by performing individual stock time-series regressions and averaging the time-series coefficients. This allows us to infer whether lags of a stock's order flow and return are useful in inferring its current return in isolation, as opposed to its price performance *relative* to that of other stocks. In this case, we need to account for the notion that the residuals could be cross-correlated across stocks, thus contaminating inferences drawn from the t statistic for the average coefficient, which assumes independence across regressions. To address this issue we proceed as follows. First, we identify the 470 firms that were present every month in the sample. Then, for this set of firms we run a regression with three lags each of returns and imbalance innovations, with the contemporaneous and three lags of the CRSP value-weighted index return, as well as three lags of total volume as controls. The average cross-correlation of residuals from this regression is a fairly small 0.010. Nonetheless, we adjust the t statistics of the regressions using a correction factor.

The specific formula for the correction that we employ, also mentioned in footnote 8 of Chordia, Roll, and Subrahmanyam (CRS) (2000), assumes that the residual cross-correlation and the residual variance are homogeneous across stocks. Under these

[19]The model of Barberis, Shleifer, and Vishny (1998) predicts possible overreaction to significant news events because, based on Griffin and Tversky (1992), agents may attach too much importance to the strength (i.e., vividness) of the event, as opposed to its statistical weighting in the determination of the expected value of the stock.

assumptions, an estimate of the amount by which the standard error is inflated is given by $\sqrt{1+\rho(N-1)}$ (the CRS formula contains an erroneous numeral 2), where ρ is the common cross-correlation in the residuals, and N is the number of firms (470). Approximating ρ by the average correlation (0.010) yields a deflation factor for the t statistic of 2.36. All t statistics are scaled downward by this amount. We recognize that this approach is imperfect, and therefore also correct inferences for the cross-correlation in residuals by way of the panel regression approach presented in Table 9. For now, we provide the coefficient estimates, together with the adjusted t-statistics, in Table 6.[20] As can be seen, the coefficients on the first two lags of returns are quite significant even after the deflation, while the imbalance innovations are not significant in any instance.[21]

Even though the significance tests for lagged returns are subject to debate because of residual cross-correlation, our inference on imbalance innovations remain unchanged before and after the correction factor is applied.[22] More specifically, since the average

[20]Note that the correlation between the coefficient estimates depends not only on the correlation in the residuals, but also on the cross products of the X matrices that represent the explanatory variables; and it also assumed that the X matrices are relatively homogeneous in the cross-section so that the variation in the cross-product across stocks can be ignored. A full-fledged correction is computationally cumbersome owing to the required inversion of large matrices; however, we implemented it using a random sample of 100 stocks, and found our conclusions on coefficient significance to be substantively unchanged. In particular, the deflation factor implied by this approach was lower than the one we use in Table 6 (which implied increased significance for the return coefficients), but it was not low enough to cause the imbalance innovations to become significant.

[21]It is also worth mentioning that 65.3% of the coefficients on the first lag of the return are negative, only 1.1% are positive and significant at the 5% level, whereas 10.2% are negative and significant. The corresponding numbers for the coefficients on the first lag of the imbalance innovation are 48.3%, 4.9%, and 2.3%, respectively.

[22]There is another potential econometric issue relating to the time-series regressions. In particular, Stambaugh (1999) points out the potential bias in regression coefficients when returns are regressed on lagged values of serially dependent predictors. In our case, while a control variable, total volume, is serially correlated, it not significant in the regressions. Thus it should have little impact on the results. We therefore ascertained the robustness of the results by running regressions first excluding total volume, but including volume innovations (calculated, as for imbalance, by regressing volume

residual cross-correlation is positive, the simple t statistics for the mean (that ignore the cross-correlation) are overstated. These unadjusted t statistics are insignificant for lagged imbalance innovations even before applying the deflation factor, so that correcting for cross-correlation does not alter our conclusion on the role of imbalance innovations in causing return reversals.

It also is worth noting that the magnitude of the coefficient on the first lag of the return in Table 6 is about 5%, which is not economically insignificant before transaction costs. In particular, the coefficient implies that a ten percentage point increase in the return of an individual stock, *ceteris paribus*, predicts a decrease in next month's return of 0.5%. Given a stock with a spread of 1/8, the percentage round trip transaction cost on a share price of $50 is only 0.25%, so it is arguable whether the magnitude of the reversal is within transaction cost bounds, though brokerage commissions, may of course, further attenuate profits.[23] In our view, the magnitude of the coefficient is not overwhelmingly high, so that it does not suggest a gross violation of market efficiency. Thus, from the perspective of individual investors, trading on the monthly reversal may not be profitable, though the same may not be true for institutions who face low transaction costs.

If inventory pressures were indeed a strong driver of returns, we would expect their manifestation in the time-series. Indeed, it would be difficult to conjure a story

on its own twelve lags as well as twelve lags of returns) instead of volume *per se*. The results were materially unaltered, and are available upon request.

[23]The monthly reversal we document does not extend to daily returns. Indeed, the average first-lag autocorrelation in daily mid-point returns within our sample is marginally *positive*. Furthermore, omitting the first day of the month from the computation of the monthly return makes no substantive difference to the results, suggesting that turn of the month effects do not capture the monthly reversals; details are available upon request.

where inventory concerns play a role in individual stock return reversals, but returns are not related to lagged order flow in a significant way. Specifically, the classical inventory paradigm (Stoll, 1978, Grossman and Miller, 1988) indicates that if a large unexpected buy imbalance hits a stock, given that individual specialists make markets in a relatively small number of stocks (Coughenour and Deli, 2002), the inventory phenomenon implies a future downward pressure on the price of that stock in largely an absolute sense, not in a relative (cross-sectional) sense. We do not find evidence of such price pressure reversals at any of the lags in Table 6. Indeed, the first lag of imbalance enters with a *positive* sign, with a t statistic of merely 0.08.[24] Therefore, the time-series results run counter to the notion that inventory concerns drive monthly reversals.

To confirm the robustness of our results, we perform a panel regression for the sample of firms that were present every day in the sample. We estimate a two-way random effects model, which allows for firm-specific shocks for each time-period, an overall firm-specific shock across time, and an overall time-specific shock across firms (see Fuller and Battese, 1974 or Hsiao, 2002, for estimation details).

The panel approach incorporates well-studied characteristics that are known to affect the cross-section of returns by including the book to market ratio and size in the regressions. We also control for risk by regressing each stock's monthly return on the

[24] A version of the regression in Table 6 with returns omitted does not materially change the coefficients of imbalance innovations: they remain insignificant in this scenario as well. Furthermore, the imbalance variables remain insignificant when imbalance innovations are replaced by raw imbalances, whether one lag at a time, or all three lags together. Finally, controlling for a possible January seasonality by omitting the month of January from the analysis also does not alter the conclusions: imbalance innovations remain insignificant, while the first lag of returns remains significant.

Fama and French (1993) factors (obtained from Wharton Research Data Services) and using the residuals (i.e., the risk-adjusted returns) as our dependent variable. Size is measured by market capitalization as of December of the previous year, and, following Fama and French (1992), returns in July of year n through June of year $n+1$ are associated with the book-to-market ratio as of the end of year $n-1$, which is calculated using end-of-year data on the Compustat tapes. Book-to-market ratios greater than the 99th percentile (less than the 1st percentile) in a given month are set equal to the 99th percentile (1st percentile).[25] We include twelve lags of returns to account for the Jegadeesh and Titman (1993) momentum effect (though, for brevity, the estimates of the individual coefficients are omitted beyond the third lag). Regression estimates from this approach are presented in Table 7, Panel A.

The regressions confirm a value-growth effect and the notion that large firms performed well in the 1990s. The most noteworthy result for our purposes is that the first lag of return remains highly significant after accounting for the characteristics, while the imbalance innovation lags remain insignificant.[26] We also perform a regression where book-to-market ratio and size are omitted, because the risk-adjustment is designed to account for their effects; estimates from this approach are presented in Table 7, Panel B. As can be seen, the coefficients on lagged returns and imbalance

[25]Omitting firms with negative book-to-market ratios made virtually no difference to the results.

[26]In unreported regressions, we include the Dimson (1979) beta (with one lead and one lag of the index return) as a separate characteristic in the regression. Our beta estimate is calculated using between 36 to 60 months of data ending in the previous year, using as much data as available, and is based on the CRSP value-weighted index. To reduce the impact of measurement error in the beta, we replaced each stock's beta by its portfolio beta, where the latter quantity is obtained by sorting stocks into five beta portfolios each month and assigning the portfolio beta to each stock in that portfolio (as in Fama and French, 1992). This exercise marginally increases the significance and preserved the sign of the first lag of returns, but imbalance innovations remain insignificant.

innovations are altered little by the omission of the characteristics. Thus, the results of the panel regressions generally are in agreement with the conclusions obtained from the time-series and cross-sectional regressions.

Overall, our empirical work indicates that lagged monthly returns bear a stronger relation to current monthly returns than lagged imbalance innovations. Indeed the lag of the monthly imbalance innovation is not statistically significant in any of our regressions, while the first lag of return is negative and significant in all of them.[27] Our theoretical framework, on the other hand, indicates that inventory effects imply a return-lagged order flow relation even after controlling for lagged return. Indeed, in our model, lagged returns dominate lagged order flow only when belief corrections are the dominant driver of return reversals. Based on the evidence, we conclude that inventory effects alone do not appear to fully account for monthly return reversals. Further, our analysis is consistent with the view that belief reversals play a significant role in causing this phenomenon.

5 Conclusion

We have attempted to shed light on an important regularity in stock return data: namely, reversals at the monthly horizon. An explicit model, which captures behavioral bias as well as inventory effects, allows us to obtain implications for the relation between

[27] We also perform our analysis over weekly horizons in order to relate our analysis with that of Lehmann (1990), where a week is defined as a Wednesday through the following Tuesday. If a week does not end by the last trading day of the year, it is truncated on the last trading day. This procedure avoids contamination by weekend and turn-of-the-year effects. The conclusions are qualitatively similar to the ones for monthly returns; i.e., there is strong evidence of return reversals, but there is no significant relation between returns and lagged imbalances (or imbalance innovations). These results are available upon request.

current returns, past returns, and past order flows. The model indicates that inventory effects are accompanied by a relation between current returns and past order flows, whereas no such relation is necessitated by the behavioral theory of overreaction and correction. Further, in our theoretical setting, lagged returns dominate lagged order flow in forecasting future returns only when belief reversion is the principal driver of return reversals.

By considering the 1988-1998 period in our empirical work, we provide out-of-sample support for the monthly return reversal effect illuminated, for example, by Jegadeesh (1990). Our data analysis is of independent interest because we link order flow with returns at monthly horizons, as opposed to the intraday or daily horizons that are the focus of much of the microstructure literature. We find that monthly returns, both in the cross-section and time-series, bear a stronger relation to lagged returns than to lagged order flow innovations. This indicates that inventory effects do not appear to completely account for the return reversal at the monthly horizon (though other authors, such as Madhavan and Smidt, 1993, do find some evidence of inventory-related phenomena at daily horizons). We also find an interesting stylized fact: that order flow innovations at horizons of two to three months are negatively related to current returns in the cross-section even after controlling for lagged returns. This result, however, does not extend to our time-series analysis, nor to small companies, where inventory concerns are most likely to be relevant, hinting that it is not driven by inventory pressures.

Our results accord with the notion that monthly reversals are caused, in substantial part, by reversals in beliefs of financial market agents. We note that our goal here is to advance our understanding of the source of the monthly reversal, and not to claim violation of market efficiency. Indeed, the magnitude of the reversal does not appear to present substantial profit opportunities for individual investors.

A puzzle that is raised by our paper is the issue of how beliefs evolve and are reflected in returns at various horizons. For example, Chordia, Roll, and Subrahmanyam (2003) show that serial correlation at intradaily horizons is close to zero. Nonetheless, there are reversals at monthly horizons (as documented in our work and in Cootner, 1964, Fama, 1964, Jegadeesh, 1990, and Lehmann, 1990), cross-sectional momentum effects at six-monthly and annual horizons (Jegadeesh and Titman, 1993), and reversals at three- to five-year horizons (DeBondt and Thaler, 1985).[28]

Of course, we cannot convincingly appeal to inventory effects in trying to explain predictability at annual and three-year horizons. Thus, behavioral models such as Daniel, Hirshleifer, and Subrahmanyam (1998), Barberis, Shleifer, and Vishny (1998), and Hong and Stein (1999) have been developed to address these phenomena. It is worth noting that these models are specifically designed to explain medium-term continuations and long-term reversals, and naturally raise the issue of how we can reconcile predictability at six to twelve month horizons with no predictability in the very short-term (intradaily and daily horizons). In general, why markets show an alternating pattern of reversal and continuation, and how they transit from no predictability in the very short-run to predictability in the longer run is an interesting challenge for future empirical and theoretical research.

[28] The analyses of Mackinlay (1995) and Brennan, Chordia, and Subrahmanyam (1998) suggest that these patterns may not readily be explicable by alluding to variations in risk premia.

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Appendix A

Proofs of Lemma 1 and Proposition 1: The mean-variance optimization owing to exponential utility implies that the demand of the overconfident agents, denoted by x, is given by

$$x = \frac{E(\theta|\theta+\epsilon) - P_2}{R\text{var}(\theta|\theta+\epsilon)},$$

where the expectation and the variance are calculated under overconfidence. Market clearing implies that

$$\frac{E(\theta|\theta+\epsilon) - P_2}{R\text{var}(\theta|\theta+\epsilon} + z_1 = 0.$$

Solving for P_2, we have Eq. (1).

Note that P_1 is non-stochastic. Hence the covariance $\text{cov}(P_3 - P_2, P_2 - P_1)$ becomes

$$\text{cov}[\theta - k(\theta+\epsilon) - Rkv_\theta z_1, k(\theta+\epsilon+Rkv_\theta z_1],$$

which reduces to (2). $\square$

Proofs of Propositions 2 and 3: Proposition 2 follows directly from Eq. (1). For proving Proposition 3, we use the well-known result that if there exist random vectors $\upsilon_\mathbf{1}$ and $\upsilon_\mathbf{2}$ such that

$$(\upsilon_\mathbf{1}, \upsilon_\mathbf{2}) \sim \mathbf{N}\left[(\mu_\mathbf{1}, \mu_\mathbf{2}), \begin{pmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{pmatrix}\right]$$

then the conditional distribution of $\upsilon_\mathbf{1}$ given $\upsilon_\mathbf{2} = \mathbf{X_2}$ is normal with a mean given by the vector

$$E(\upsilon_\mathbf{1}|\upsilon_\mathbf{2} = \mathbf{X_2}) = \mu_\mathbf{1} + \mathbf{\Sigma_{12}\Sigma_{22}^{-1}}(\mathbf{X_2} - \mu_\mathbf{2}), \tag{15}$$

and a variance given by

$$\text{var}(\upsilon_1|\upsilon_2 = \mathbf{X_2}) = \mathbf{\Sigma_{12}\Sigma_{22}^{-1}\Sigma_{21}}. \tag{16}$$

In our case, $\upsilon_1 = P_3 - P_2$ and $\upsilon_2 = [P_2 - P_1, Q_2]$, and the relevant unconditional means are all zero. A straightforward application of (15) yields the result that the coefficients α and β in the conditional expectation (3) are given by Eqs. (4) and (5). $\square$

Proof of Proposition 4: Note that $P_3 = \theta$ and

$$P_2 = \frac{\theta + \epsilon}{1/v_r + 1/v_o}\left[\frac{k_r}{v_r} + \frac{k_c}{v_o}\right] + \frac{Rz}{1/v_r + 1/v_o},$$

while P_1 is not a random variable. Substituting for P_3 and P_2 into $\text{cov}(P_3 - P_2, P_2 - P_1)$ and simplifying, we obtain Eq. (7). $\square$

Proof of Proposition 5: Let $k_c = v_\theta/(v_\theta + v_c)$, and $v_o = v_\theta v_c/(v_\theta + v_c)$. Further, let k_1 and k_2 be the coefficients of $\theta + \epsilon$ and z in Eq. (6). Then, we find that in the conditional expectation of (8), Σ_{12} in (15) has the elements

$$k_1(1 - k_1)v_\theta - k_1^2 v_\epsilon - k_2^2 v_z,$$

and

$$\frac{(1 - k_1)(k_c - k_1)v_\theta}{Rv_o} - \frac{k_1(k_c - k_1)v_\epsilon}{Rv_o} - k_2 v_z\left(1 - \frac{k_2}{Rv_o}\right),$$

while Σ_{22} is comprised of the three elements (in order)

$$k_1^2(v_\theta + v_\epsilon) + k_2^2 v_z,$$

$$(k_1 v_\theta + k_2 v_\epsilon)\left(\frac{k_c - k_1}{Rv_o}\right) + k_2 v_z\left(1 - \frac{k_2}{Rv_o}\right),$$

and

$$\left(\frac{k_c - a_1}{Rv_o}\right)^2 (v_\theta + v_\epsilon) + \left(1 - \frac{k_2}{Rv_o}\right)^2 v_z.$$

Computing $\Sigma_{12}\Sigma_{22}^{-1}$ yields the expressions in (9) and (10). $\square$

Derivation of Eq. (12): Let $\bar{P}_2$ be the mean of P_2, conditional on the date 1 information set. Then, we have

$$\begin{aligned} W^E &= \frac{(\theta - P_2)}{Rv}(\theta + \epsilon) - \frac{(\theta - P_2)}{Rv}P_2 - x_1(P_1 - P_2) + B_0 \\ &= \frac{(\theta - P_2)^2}{Rv} + \frac{(\theta - P_2)\epsilon}{Rv} - x_1(P_1 - P_2) + B_0 \end{aligned}$$

Now, from the formula for the characteristic function of a normal distribution, it follows that if $u \sim N(\mu, \sigma^2)$, then $E(exp(vu)) = exp(\mu v + (1/2)\sigma^2 v^2)$. In our case, setting $u = W^E$, $v = -R$, we have

$$E(-exp(-RW^E)|\phi_2) = -exp\{-R[-x_1P_1 + x_1P_2 + (\theta - P_2)^2/(2Rv)]\}. \tag{17}$$

It follows that at date 1, the early-informed traders maximize the derived expected utility of their date 2 wealth

$$E[[-exp\{-R[x_1P_1 + x_1P_2 + (\bar{F} + \theta - P_2)^2/(2Rv)]\}]|\phi_1]. \tag{18}$$

Now, (18) can be written as

$$\begin{aligned} -[2\pi v_{P_2}]^{-\frac{1}{2}} \int_{-\infty}^{\infty} exp \Bigg\{ -R \left[x_1P_1 + x_1P_2 + \frac{(\bar{F} + \theta - P_2)^2}{(2Rv)} \right] \\ -\frac{1}{2}\frac{(P_2 - \bar{P}_2)^2}{v_{P2}} \Bigg\} d(P_2 - \bar{P}_2). \end{aligned} \tag{19}$$

Completing squares, the expression within the exponential above can be written as

$$-\frac{1}{2}w^2 s - hw - l, \tag{20}$$

where

$$\begin{aligned} w &= P_2 - \bar{P}_2 \\ h &= Rx_1 - \tfrac{(\theta - \bar{P}_2)}{v} \\ s &= \tfrac{1}{v_{P_2}} + \tfrac{1}{v} \\ l &= Rx_1(\bar{P}_2 - P_1) + \tfrac{(\theta - \bar{P}_2)^2}{2v} + RB_0, \end{aligned}$$

Define $u \equiv \sqrt{s}w + h/\sqrt{s}$. Then, expression (20) becomes $-(1/2)u^2 + (1/2)h^2/s - l$. The Jacobian of the transformation from w to u is $s^{-\frac{1}{2}}$, and thus the integral (19) becomes

$$-[2\pi v_{P_2} s]^{-\frac{1}{2}} \int_{-\infty}^{\infty} exp\left(-\frac{1}{2}u^2 + \frac{1}{2}\frac{h^2}{s} - l\right) du$$

$$= -\frac{1}{(v_{P_2} s)^{\frac{1}{2}}} exp\left(\frac{1}{2}\frac{h^2}{s} - l\right). \tag{21}$$

Solving for the optimal x_1 by maximizing the above objective, we obtain (12). $\square$

Derivation of Eqs. (13) and (14): In this case, we again apply Eq. (16). We have that Σ_{12} has the elements $k(1-k)v_\theta - k^2 v_\epsilon - Rkk' v_\theta v_z$ and $-Rkv_\theta v_z$. The symmetric matrix Σ_{22} has the three elements $k^2(v_\theta + v_\epsilon) + k'^2 v_z$, $k' v_z$, and v_z. Applying (16) and performing some tedious algebra yields the expressions (13) and (14). $\square$

Appendix B

In this appendix, we briefly discuss two issues. The first relates to alternative methods of estimation: Fama-Macbeth cross-sectional regressions with aggregation of the estimates through time, and individual stock time-series regressions with cross-sectional aggregation of the time-series estimates. The second discusses the likely impact of measurement error in order imbalances.

Cross-Sectional and Time-Series Estimation Methods

Letting c denote a cross-sectional expectation and t denote a time-series one, the Fama-Macbeth approach produces the following (population) expression for the coefficient from a regression of a random variable y on another random variable x (we omit subscripts on the variables for brevity):

$$E_t\left[\frac{E_c(xy) - E_c(x)E_c(y)}{E_c(x - E_c(x))^2}\right].$$

The time-series approach produces the expression

$$E_c\left[\frac{E_t(xy) - E_t(x)E_t(y)}{E_t(x - E_t(x))^2}\right].$$

Comparing the two approaches we find that whether the signs of the two expressions coincide depends, in part on the cross-sectional variation in $E_t(x - E_t(x))^2$, and the time-series variation in $E_c(x - E_c(x))^2$. If these are vanishingly small, for example, then the denominator in each case can be taken out of the expectation and signs of the two estimates will coincide. While no general results are available beyond this, we initially choose to adopt the Fama-Macbeth approach because it allows us to report the simple t statistic that assumes independence. The time-series estimates, on the other hand, are correlated across stocks so this approach is not possible, and we employ the standard error correction described in the main text. We also use a panel approach that explicitly corrects for cross-correlation in the error terms generated by the time-series regression.

In matrix notation, when a random variable Y is regressed on multiple variables represented by a random vector X, then the two centered expressions above can be written in matrix notation as

$$E_t\left[\Sigma_{cYX}\Sigma_{cXX}^{-1}\right],$$

and

$$E_c\left[\Sigma_{tYX}\Sigma_{tXX}^{-1}\right],$$

where Σ_{AB} denotes the covariance vector of the variable A with the vector B, Σ_{AA} is the variance-covariance matrix of the vector A, and the subscripts t and c are defined as before. A similar intuition holds in this case. If the elements of Σ_{tXX}^{-1} and Σ_{cXX}^{-1} exhibit vanishingly small variation in the cross-section and time-series, respectively, the expectation operator will have a negligible impact on these terms, and the signs of the two estimate vectors will coincide on an element-by-element basis.

Measurement Error in Order Imbalance

We now attempt to understand how the error-in-variable problem could affect our regression estimation. We conduct the analysis in number of transactions, rather than dollars, because this allows a tractable handling of the issue; however, this does not change the basic nature of the conclusions. Let O be the true imbalance, measured as

$$O = \rho V - (1-\rho)V = (2\rho - 1)V,$$

where V represents the total number of transactions, and ρ is the fraction of trades signed as buys. Suppose a fraction r of the trades are signed with error. Then, we can write the measured imbalance, $\hat{O}$, as

$$\hat{O} = (1-r)(2\rho - 1)V + rV(2\hat{\rho} - 1),$$

where $\hat{\rho}$ is the assigned fraction of buys in that part of the total number of transactions which are signed incorrectly. Let $2\rho - 1 \equiv k$ and $2\hat{\rho} - 1 = k'$. Then, we have

$$\hat{O} = kV + rV(k - k').$$

Suppose a dependent variable Y is regressed on $\hat{O}$ whereas its true relationship with imbalance is expressed as $bO + e$, where e is the usual OLS error term. Assume for simplicity that k and k' are independent of each other and of V and have the same variance σ_k^2. Let σ_V^2 denote the variance of V. This implies that

$$\text{cov}(Y, \hat{O}) = (1+r)b\sigma_k^2\sigma_V^2,$$

and

$$\text{var}(\hat{O}) = \sigma^2\sigma_V^2(1+r)^2 + r^2\sigma_k^2\sigma_V^2.$$

Thus, the probability limit of the measured regression coefficient, $\hat{b}$, can be written as

$$\text{plim}\ \ \hat{b} = \frac{(1+r)b}{(1+r)^2 + r^2},$$

so that the estimated coefficient is inconsistent. In papers by Lee and Radhakrishna (2002), Odders-White (2002), and Ellis, Michaely, and O'Hara (2000), the estimate of r ranges from about 7% to about 15%. The corresponding range for the inconsistency factor $(1+r)/[(1+r)^2 + r^2]$ is 0.93 to 0.86, with implied inflation factors (reciprocals) of 1.08 and 1.17. Such a range does not appear sufficient to alter our conclusions. As an example, the coefficient on the lagged imbalance in Table 2 is -0.052 with an associated t-statistic of -0.72 and increasing it by 8%-17% will not be sufficient to allow the variable to approach significance. Indeed, the t-statistic on lagged imbalance would need to be inflated by 172% to make it significant at the 5% level, and the measurement error problem in the imbalance does not seem to be sufficiently large to allow this. Within a multivariate setting, in general, we find that the coefficient of return is altered little by including imbalance innovations, and the imbalance innovation in the other regressions has t-statistics that are well below the 5% significance cutoff of 1.96, so that similar arguments apply to the other cases reported in the tables.

We add two more findings in support of our basic assertion that our inferences are not affected by measurement error. First, for lagged order flow to drive return reversals, its coefficient is generally expected to be negative within our theoretical specification. In some cases, however, the coefficient on the first lag of imbalance is insignificant but positive (last column of Panel A as well as all columns of Panel B of Table 2, and Table 6). While measurement error can attenuate a coefficient, it generally is not expected to cause a sign change in the coefficient. Second, in the cross-section, longer lags of imbalance innovations (beyond the monthly horizon at which reversals occur) are indeed significantly related to returns (Table 4), and there is no compelling reason why measurement error would materially attenuate the coefficient of the first lag of the imbalance but not those at longer lags. Overall, therefore, it appears implausible that measurement error in imbalance has a material effect on our conclusions.

Table 1: Summary Statistics

This table presents the summary statistics associated with the pooled cross-section and monthly time-series of NYSE stocks used in the analysis. The time-period is January 1988 to December 1998. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. Order imbalance is measured by the difference in dollar buys and dollar sells (in millions of dollars). Proportional order imbalance is obtained from dividing order imbalance by the total dollar values of buys and sells.

Variable	Mean	Median	Standard deviation
Return	0.0128	0.0090	0.1122
Absolute return	0.0746	0.0527	0.0849
Order imbalance	9.846	0.2224	60.41
Absolute value of order imbalance	17.81	3.02	58.56
Proportional imbalance	0.0040	0.0243	0.2139
Absolute value of proportional imbalance	0.1560	0.1161	0.1464

Table 2: Monthly Cross-Sectional Regressions for Lagged Returns and Lagged Imbalances

This table presents the results of cross-sectional Fama-Macbeth type regressions for monthly returns of NYSE stocks on three lags of monthly returns and three lags of imbalance innovations. The time-period is January 1988 to December 1998. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET and LOIB represent lags of the monthly return and dollar imbalance, respectively. The lag of the total dollar volume is included in the regressions, but its coefficient is not reported. Size terciles are formed by sorting all stocks into groups every month by their market capitalization as of the end of the previous month. All return and imbalance coefficients are multiplied by factors of 10^2 and 10^4, respectively.

Panel A: Full sample

Variable	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
LRET	-2.66	-3.13	-	-	-2.72	-3.23
LOIB	-	-	-0.052	-0.72	0.062	0.83

Panel B: By size tercile

	Small firm tercile		Mid-cap firm tercile		Large firm tercile	
Variable	Coefficient	t statistic	Coefficient	t statistic	Coefficient	t statistic
LRET	-5.10	-5.21	-2.13	-2.15	-1.86	-1.50
LOIB	0.417	1.64	0.144	0.24	0.076	1.00

Table 3: Monthly Average returns for Portfolios sorted by Lagged Returns and Lagged Imbalances

This table presents the average monthly returns (in percentages) for portfolios sorted by the first lag of the monthly return and the first lag of the imbalance innovation. The time-period is January 1988 to December 1998. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET and LOIB represent lags of the monthly return and dollar imbalance, respectively. The symbol * denotes that the entry is significantly different at the 5% significance level from the first entry in the relevant column, while † denotes that the entry is significantly different from the first entry in the relevant row.

Panel A: Return Sort

1	1.383
2	1.340
3	1.084*

Panel B: Imbalance Sort

1	1.326
2	1.235
3	1.245

Panel C: Return and Imbalance Sorts

LRET rank	LOIB Rank		
↓	1	2	3
1	1.471	1.516	1.161†
2	1.396	1.265	1.358
3	1.112*	0.924*	1.216

Table 4: Monthly Cross-Sectional Regressions for Lagged Returns and Lagged Imbalance Innovations

This table presents the results of cross-sectional Fama-Macbeth type regressions for monthly returns of NYSE stocks on three lags of monthly returns and three lags of imbalance innovations. The time-period is January 1988 to December 1998. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET, L2RET, and L3RET denote the first three lags of the monthly return. LROIB, L2ROIB, and L3ROIB represent the first three lags of imbalance innovations obtained from regressing imbalance on twelve lags each of returns and imbalances. Three lags of total volume are included in the regressions, but their coefficients are not reported. All return and imbalance coefficients are multiplied by factors of 10^2 and 10^4, respectively.

Variable	Coefficient	t-statistic
LRET	−2.55	−2.79
L2RET	−0.218	−0.28
L3RET	0.874	1.08
LROIB	−0.108	−1.37
L2ROIB	−0.241	−3.22
L3ROIB	−0.266	−3.49

Table 5: Monthly Cross-Sectional Regressions for Lagged Returns and Imbalance Innovations, Stratified by Market Capitalization

This table presents the results of cross-sectional Fama-Macbeth type regressions for monthly returns of NYSE stocks on three lags of monthly returns and three lags of imbalance innovations, stratified by monthly market capitalization. The time-period is January 1988 to December 1998. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET, L2RET, and L3RET denote the first three lags of the monthly return. LROIB, L2ROIB, and L3ROIB represent the first three lags of imbalance innovations obtained from regressing imbalance on twelve lags each of returns and imbalances. Three lags of total volume are included in the regressions, but their coefficients are not reported. All return and imbalance coefficients are multiplied by factors of 10^2 and 10^4, respectively.

Panel A: Small firm tercile

Variable	Coefficient	t-statistic
LRET	−4.66	−4.46
L2RET	−0.530	0.49
L3RET	−0.993	−0.94
LROIB	−0.111	−0.50
L2ROIB	−0.327	−1.64
L3ROIB	−0.290	−1.38

Panel B: Mid-cap firm tercile

Variable	Coefficient	t-statistic
LRET	−2.27	−2.17
L2RET	−2.69	−2.63
L3RET	1.20	1.25
LROIB	−0.638	−1.23
L2ROIB	−0.350	−0.59
L3ROIB	−1.42	−2.66

Panel C: Large firm tercile

Variable	Coefficient	t-statistic
LRET	−1.56	−1.25
L2RET	−0.741	−0.61
L3RET	0.567	0.57
LROIB	−0.006	−0.09
L2ROIB	−0.233	−3.19
L3ROIB	−0.207	−2.91

Table 6: Monthly Time-Series Regressions for Lagged Returns and Imbalance Innovations, for Stocks Present in Every Sample Month

This table presents the results of individual stock time-series regressions for monthly returns of NYSE stocks on three lags of monthly returns and three lags of imbalance innovations. The time-period is January 1988 to December 1998. Regressions are run for the 470 firms that were present every month in the sample period. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET, L2RET, and L3RET denote the first three lags of the monthly return. LROIB, L2ROIB, and L3ROIB represent the first three lags of imbalance innovations obtained from regressing imbalance on twelve lags each of returns and imbalances. Three lags of total volume as well as the contemporaneous and three lags of the CRSP value-weighted index return are included in the regressions, but their coefficients are not reported. Cross-sectional averages of the coefficients from the time-series regressions are reported, along with the t statistic (corrected for cross-correlation in the regressors) for the mean coefficient being different from zero. All return and imbalance coefficients are multiplied by factors of 10^2 and 10^4, respectively.

Variable	Coefficient	t statistic
LRET	−5.02	−4.06
L2RET	−4.64	−3.94
L3RET	−1.185	−0.99
LROIB	0.707	0.08
L2ROIB	−2.74	−0.34
L3ROIB	0.406	0.06

Table 7: Panel Data Regressions for Lagged Returns and Imbalance Innovations

This table presents the results of individual stock panel data regressions for monthly returns of NYSE stocks on three lags of monthly returns and three lags of imbalance innovations. The time-period is January 1988 to December 1998. Regressions are run for the 470 firms that were present every month in the sample period. Returns are cumulated using daily mid-points of the quoted spreads associated with the last transaction of each trading day. LRET, L2RET, and L3RET denote the first three lags of the monthly return. LROIB, L2ROIB, and L3ROIB represent the first three lags of imbalance innovations obtained from regressing imbalance on twelve lags each of returns and imbalances. Three lags of total volume as well as the contemporaneous and three lags of the CRSP value-weighted index return are included in the regressions, but their coefficients are not reported. BMR and Size respectively represent the book-to-market ratio and market capitalization. Returns in July of year n through June of year $n+1$ are associated with the book-to-market ratio as of the end of year $n-1$. Book-to-market ratios greater than the 99th percentile (less than the 1st percentile) in a given month are set equal to the 99th percentile (1st percentile). Market capitalization is calculated as of the end of the previous year. The dependent variable for each stock is the residual from the regression of its mid-point return series on the Fama and French (1993) factors. All BMR, return, and beta coefficients are multiplied by 10^2. The coefficient for imbalance is scaled by 10^4, whereas that for size is multiplied by 10^{10}.

Panel A: Including Fama and French (1992) characteristics

Variable	Coefficient	t statistic
LRET	−5.05	−11.01
L2RET	−2.25	−4.85
L3RET	−0.518	−1.11
LROIB	−0.071	−0.91
L2ROIB	0.048	0.57
L3ROIB	−0.100	−1.48
BMR	0.384	3.82
Size	2.61	5.53

Panel B: Excluding Fama and French (1992) characteristics

Variable	Coefficient	t statistic
LRET	−4.95	−10.94
L2RET	−2.25	−4.92
L3RET	−0.519	−1.13
LROIB	−0.072	−0.86
L2ROIB	0.031	0.38
L3ROIB	−0.100	−1.34