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Order Imbalance and Individual Stock Returns

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Abstract

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This paper studies the relation between order imbalances and daily returns of individual stocks. Our tests are motivated by a model which explicitly considers how market makers dynamically accommodate autocorrelated imbalances emanating from large traders who optimally choose to split their orders. Price pressures caused by autocorrelated imbalances cause a positive relation between lagged imbalances and returns, which reverses sign after controlling for the current imbalance. We find empirical evidence consistent with these implications. We also find that imbalance-based trading strategies yield statistically significant returns. Our results shed light on the role of inventory effects in daily stock price movements.

1. Introduction

Why financial market prices move is a central issue which has preoccupied financial economists for decades. With a view to gaining a better understanding of this issue, much research has been devoted to exploring the relation between stock price movements and trading activity, where the latter is usually represented by trading volume. Thus, a large literature has studied volume and its association with stock market returns (Hiemstra and Jones, 1994; Gallant, Rossi, and Tauchen, 1992; Lo and Wang, 2000; see also the studies summarized in Karpoff, 1987). Trading volume, however, can be high either due to a preponderance of buyer-initiated or seller-initiated trades, or because there is generally a large amount of trading interest on a given day, which is about evenly distributed across buyers as well as sellers. Intuition suggests that the implications of a reported volume of 1 million shares generated by 500,000 shares of seller initiated trades and 500,000 shares of buyer initiated trades are very different from that generated by 1 million shares of seller (or buyer) initiated trades. In particular, there are at least two reasons why order imbalances can provide additional power beyond trading activity measures such as volume in explaining stock returns. First, a high absolute order imbalance can alter returns as market makers struggle to re-adjust their inventory. In addition, order imbalances can signal excessive investor interest in a stock, and if this interest is autocorrelated, then order imbalances could be related to future returns.

Obviously, the concept of order imbalance over an interval makes sense only in a paradigm of an intermediated market, where market makers accommodate buying and selling pressures from the general public (otherwise one could use the time-honored adage "for every buyer, there's a seller" to argue that order imbalances are irrelevant).

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However, much of modern finance theory is based on this intermediation paradigm and suggests that price changes are strongly associated with order imbalance. For example, the well-known Kyle (1985) model of price formation relates price changes to net (pooled) order flow. It can be argued that the Kyle setting is more naturally applicable in the context of signed order imbalances over a time interval, as opposed to trade-by-trade data, since the theory is not one of sequential trades by individual traders. Similarly, the dynamic inventory models of Ho and Stoll (1981) and Spiegel and Subrahmanyam (1995) also deal with how market makers accommodate buying and selling pressures from outside investors.

The natural appeal of order imbalances as a determinant of returns notwithstanding, most existing studies analyze imbalances only for specific agents, or over short periods of time.[1] Thus, for example, Lakonishok, Shleifer, and Vishny (1992), Kraus and Stoll (1972), Wermers (1999), and Sias (1997) analyze institutional order imbalances, Lauterbach and Ben-Zion (1993) and Blume, MacKinlay, and Terker (1989) analyze order imbalances around the October 1987 crash, Lee (1992) examines order imbalances around earnings announcements, while Stoll (2000) considers the return-order imbalance relation for individual stocks over a two-month sample period. Ours is the first study to analyze long-term order imbalances on a comprehensive cross-sectional sample of New York Stock Exchange (NYSE) stocks.

Specifically, we estimate daily order imbalances for each of a comprehensive sample of NYSE stocks for the period 1988-1998. Using data from the Institute for the Study of Security Markets (1988-1992) and the TAQ database provided by the NYSE, we sign

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[1]Recent work by Chordia, Roll, and Subrahmanyam (2002) examines a long series of market-wide order imbalances; the focus in this paper is on order imbalances at the individual stock level.

trades in each stock in our sample using the Lee and Ready (1991) algorithm. We then calculate measures of the daily order imbalance in each stock using both the number of buys and sells, as well the quantity bought or sold. In the end, we have measures of the daily order imbalance for each company in our sample.

Our study focuses on the daily time-series relation between order imbalances and individual stock returns. The issue of short-horizon return movements has been the focus of several well-known papers, e.g., Lo and MacKinlay (1990), Lehmann (1990), and Conrad, Hameed, and Niden (1994). A large part of this debate has focused on the importance of microstructure effects on short horizon returns. By examining the relation between returns and a very intuitive microstructure variable, namely, imbalance, we shed new light on this debate.

We motivate our empirical study by an intertemporal model of how prices react to imbalances when market makers have inventory and adverse selection concerns. The distinguishing feature of our framework is that it explicitly examines how risk averse market markers with inventory concerns accommodate autocorrelated trader demands. In our model, traders find it optimal to split their orders over time to minimize the price impact of trades,[2] thus causing positive autocorrelation in equilibrium imbalances. In turn, this autocorrelation causes intertemporal correlation in price pressures which give rise to a positive predictive relation between imbalances and future returns. Intuitively, this relation captures the idea that the current price pressure is correlated with lagged imbalances because contemporaneous and lagged imbalances are correlated. Of course, as the continuing price pressure is eventually reversed, prices exhibit reversals over

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[2]Chan and Lakonishok (1995)and Keim and Madhavan (1995) document that institutional traders often fill an order over a number of days.

longer horizons.

Our model also implies that after controlling for the current imbalance, lagged imbalances are negatively related to current price movements. The intuition is as follows. The expected price move conditional on the net current imbalance alone assigns equal weight to the price pressure created by history-dependent trades as well as current trades that are independent of past trades. However, the price pressure induced by the history-dependent trades is smaller than that created by the innovation in trades, since earlier rounds of trade partially incorporate the price pressure induced by trades that are autocorrelated with past ones. The negative coefficient on lagged imbalances arises because of this "over-weighting" of history-dependent trades in the current imbalance.

In our empirical work, we find that daily imbalances are positively autocorrelated, which is consistent with our theoretical model. Thus, buy (sell) imbalances are likely to be followed by further days of buy (sell) imbalances. Lagged imbalances bear a positive predictive relation to current day returns, which is consistent with continuing price pressures caused by positively autocorrelated imbalances. Contemporaneous imbalances are also positively related to returns, and, as predicted by the model, the positive relation between lagged imbalance and returns disappears after controlling for the current imbalance.

We directly analyze the profitability of an imbalance-based trading strategy that buys (at the ask) if the previous day's imbalance is positive, and sells (at the bid) if the previous day's imbalance is negative. The position is held from open to close of trade within a day and reversed at the bid (ask) if the morning trade was at the ask (bid). Thus, the trading strategy accounts for the bid-ask spread. The evidence indicates

that while such strategies yield statistically significant profits, individual investors may not be able to profit from them after accounting for brokerage commissions. However, institutional traders with low trading costs may be able to earn an extra return. Such activity is not necessarily inconsistent with market efficiency, because the inventory paradigm suggests that buyers may face favorable terms of trade following days of heavy selling or buying as market makers struggle to offload their inventory. Overall, therefore, our empirical findings are consistent with a model of market equilibrium where market makers with inventory concerns accommodate positively autocorrelated imbalances.

While analyzing the imbalance-return relation, we are aware that bid-ask bounce in daily returns (Blume and Stambaugh, 1983) is particularly relevant to our study. This is because a high buy order imbalance, for example, would imply a preponderance of trades on the ask side of the market, which would naturally contaminate any attempt to relate the next day's return to a given day's order imbalance. We address this issue by relating imbalances to a set of returns calculated from open-to-close bid-ask mid-points. In particular, we pass through the entire transactions database to calculate, for each stock, the mid-point of the quoted bid and ask prices corresponding to the first and last transaction of each day. We then calculate returns for each stock using the mid-point of the bid and ask prices. Throughout our empirical work, we focus these open-to-close return series.

This paper is organized as follows. Section 2 presents a theoretical model which derives empirical implications for the relation between price movements and imbalance. Section 3 describes the data and documents the degree of autocorrelation in imbalances.

Section 4 documents the time-series relation between daily returns and current as well as past order imbalances. Section 5 documents the predictive ability of imbalances, and Section 6 concludes.

2.   A Theoretical Framework

In order to motivate our tests of the relation between imbalance and returns, we provide an intertemporal setting with both inventory and asymmetric information effects. Motivated by the studies of Chan and Lakonishok (1995), and Keim and Madhavan (1995), who document that institutional traders often fill an order over a number of days, we model traders (e.g., financial institutions) who can split their orders over time, together with informed traders and market makers. For simplicity, we model two trading dates, with a final liquidation date, but the intuition generalizes to many periods.

In our model, a security trades at dates 1 and 2, and then has a liquidation payoff of

$$F = \bar{F} + \theta + \epsilon \tag{1}$$

where $\bar{F} > 0$ is the ex ante mean of the asset, and θ as well as ϵ are independent and normally distributed random variables with zero mean and variances given by v_θ and v_ϵ, respectively. F can be viewed as the long-term liquidation value of the asset, so that v_ϵ can be viewed as the long-term risk from holding the asset.

We assume that there are two types of utility-maximizing traders: informed traders who learn precisely the realization of θ just prior to trade at date 2, and uninformed "market makers" who have no knowledge of θ. No agent receives information about ϵ at any of the trading dates. In order to keep the model tractable, and to obtain a closed-

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form solution, we only allow for informed trading at date 2. The model can be viewed as the limit of a framework where some informed traders receive information later than others; in our limit, no informed trader receives information early. However, numerical analysis (available from the authors) suggests that similar results obtain when there is informed trading in both rounds.

We assume informed traders and market makers behave competitively. In addition, we model a discretionary liquidity trader with a demand $2z_1$, who can either split his demands equally among the two periods, or concentrate his trading in period 1 or period 2.[3] For now, we work with the assumption that he allocates his trading equally across the two periods. Then, we will show that this is indeed his optimal strategy, in that the expected trading costs of the agent are minimized by splitting the order across periods.

We also assume that an exogenous (non-discretionary) liquidity trade of z_2 arrives at the market at date 2.[4] The variables z_1 and z_2 are normally distributed with zero mean and common variance v_z, and are mutually independent and independent of θ and ϵ. The mass of informed traders is M, and the mass of market makers is $1 - M$, so that the total mass of all informed traders and market makers is normalized to unity. Both informed traders and market makers have negative exponential utility over final wealth with a common risk aversion coefficient R.

Let P_1 and P_2 denote the date 1 and date 2 equilibrium prices for the security. We will consider linear equilibria implied by the model. Thus, let us postulate that P_1 and

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[3]See Subrahmanyam (1994) for similar modeling of discretionary liquidity trading.

[4]Allowing for non-discretionary liquidity trades at both dates complicates the algebra, but does not change the conclusions in a substantive sense.

P_2 are linearly related to the observables at each date such that

$$P_2 = \bar{F} + a\theta + bz_1 + cz_2, \tag{2}$$

$$P_1 = \bar{F} + fz_1, \tag{3}$$

In the ensuing analysis we verify that these conjectures are consistent with the equilibrium we derive.

Let x_{Ii} and x_{Mi} respectively denote the holdings of each informed trader and each market maker, respectively, at date i. Standard mean-variance arguments yield

$$x_{I2} = \frac{\bar{F} + \theta - P_2}{Rv_\epsilon}$$

and

$$x_{M2} = \frac{E(\theta|P_1, P_2) - P_2}{R \, \text{var}(\theta + \epsilon|P_1, P_2)}$$

The date 1 demands of the agents, x_{I1} and x_{M1}, are more complicated and their derivation is confined to Appendix A. At each date, the market makers take the negative of the positions of the other traders to clear the markets, so that in equilibrium, the prices satisfy the conditions:

$$(1 - M)x_{M1} = -(Mx_{I1} + z_1)$$

$$(1 - M)(x_{M2} - x_{M1}) = -[M(x_{I2} - x_{I1}) + z_1 + z_2]$$

The complete solution for the prices is given in the following Lemma (which is proved in Appendix A).

Lemma 1 *Given that the discretionary liquidity trader splits his order across periods, the unique linear equilibrium of the model is given by*

$$a = \frac{M[Mv_\theta + R^2 v_\epsilon v_z(v_\epsilon + v_\theta)]}{D} \tag{4}$$

$$b = \frac{2Rv_\epsilon[M^2v_\theta + R^2v_\epsilon v_z(v_\epsilon + v_\theta)]}{D} \tag{5}$$

$$c = \frac{Rv_\epsilon a}{M} \tag{6}$$

$$f = \frac{R[M^2v_\theta(2v_\epsilon + v_\theta) + (2MR^2v_\epsilon v_\theta v_z + R^2v_\epsilon^2 v_z)(v_\epsilon + v_\theta) + 2]}{D + MR^2v_\epsilon v_\theta v_z + R^4v_\epsilon^2 v_z^2(v_\epsilon + v_\theta)}, \tag{7}$$

with $D \equiv M^2v_\theta + MR^2v_\epsilon v_\theta v_z + R^2v_\epsilon^2 v_z$.

The coefficients b and f in the above equation represent the effect of the discretionary liquidity trader z_1. In particular, when $b > f$, the price at date 2 continues to move in the direction of z_1, as opposed to reversing out the effect of the date 1 liquidity trade. This happens because there is autocorrelated liquidity trading which causes temporal dependence in price pressures. Generally, b can be greater or less than f. This is because while the arrival of correlated liquidity orders causes continuing price pressure, the arrival of traders with information about θ reduces price pressure by decreasing the risk borne by the market maker. If the long-term risk v_ϵ is large relative to the variance of information v_θ, however, the former effect dominates.

We define imbalances to be the negative of the market makers' trades in each period. Thus, the period 1 imbalance is given by $Q_1 = Mx_{I1} + z_1$ and the period 2 imbalance is given by $Q_2 = M(x_{I2} - x_{I1}) + z_1 + z_2$. Even in this relatively simple setting, deriving unambiguous relations between price changes and imbalances is quite difficult. Hence we impose reasonable parameter restrictions. In particular, we assume that equal masses of the utility-maximizing agents are informed traders and market makers, so that $M = 0.5$. Furthermore, since ϵ represents the risk associated with holding the asset long-term, we derive results under the plausible condition that v_ϵ is sufficiently high relative to the other model parameters.

In the above analysis, we have assumed that the discretionary trader splits his order across periods. Of course, if the discretionary trader changes his strategy, the price coefficients in Lemma 1 will change because prices will be set to clear markets in accordance with the new strategy. Consideration of the expected trading costs under the pricing coefficients associated with the various strategies allows us to obtain the optimal strategy of the discretionary trader. The following proposition is derived in Appendix A.

Proposition 1 *As long as the long-term risk from holding the asset, v_ϵ, is sufficiently high, the following results hold:*

1. *In equilibrium, the discretionary liquidity trader splits his order across the two periods, so that equilibrium order imbalances are positively autocorrelated.*

2. *Lagged imbalances are positively related to price changes, i.e., the regression coefficient $\text{cov}(P_2 - P_1, Q_1)/\text{var}(Q_1) > 0$. This coefficient is increasing in the risk aversion coefficient, R.*

3. *The expectation of the price change $P_2 - P_1$ conditional on the contemporaneous and lagged imbalances Q_2 and Q_1 is linear in these variables. The coefficient of Q_2 is positive while that on Q_1 is negative.*

Part 1 of the proposition obtains because the liquidity trader finds that splitting orders across periods minimizes his overall expected price impact, which creates autocorrelated imbalances in equilibrium. Part 2 indicates that price movements are positively related to lagged imbalance. This finding can be explained as follows. Since market makers are risk averse, an imbalance at date 1 creates price pressure at this date in the direction

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of the imbalance. However, since liquidity demands are autocorrelated in this dynamic setting, there is further price pressure at date 2 that is *correlated* with the date 1 price pressure. This leads to a positive predictive relation between lagged imbalance and future price movements, the strength of which increases in the degree of price pressure, and which, in turn, is related to the risk aversion coefficient R.[5]

The predictability of price movements from imbalances will *not* obtain if there are no inventory effects (i.e., if market makers are risk-neutral), because agents will not demand premia for bearing inventory risk, so that there will be no price pressures.[6] Thus, our tests of whether order imbalances predict future price movements are direct tests of whether there are price pressures due to inventory effects in the stock market.

Part 3 of Proposition 1 shows that in the presence of the contemporaneous imbalance, the coefficient of the lagged imbalance reverses sign. Intuition for this is as follows. Suppose for the moment that there is no informed trading. Then the price change incorporates two effects: the premium for the independent liquidity shock that arrives at date 2 (i.e., the shock z_2), and an incremental premium for the liquidity shock at date 2 that is correlated with past shocks. The incremental premium arises because the premiums charged by the market for absorbing the period 1 and 2 discretionary liquidity trades differ. Specifically, the market charges the initial autocorrelated liquidity trade more than if there were no trades following in the same direction because the

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[5]There is a countervailing effect to this phenomenon (described in Holden and Subrahmanyam, 2002), which is that the information conveyed by the trades of informed agents at date 2 reduces the risk of holding the asset, and consequently also reduces the price pressure at date 2. Nevertheless, if, as assumed, the long-term risk associated with holding the asset is sufficiently large relatively to the variance of information, and if the proportion of informed agents is sufficiently small (we have assumed it is 50%), the result in part 2 will hold.

[6]A formal proof of this assertion is available from the authors. However, the result obtains simply because under risk-neutrality, prices are martingales, and increments to such a martingale cannot be predicted from public information already impounded in the current price.

market maker incorporates the fact that trading in a certain direction is more likely to be followed by more trading, and hence, more inventory pressure, in the same direction. At the same time, the premium for the initial trade is not equal to what it would be were the entire discretionary liquidity trade to happen in that period, because the risk averse market maker has an opportunity to rebalance next period when more trade follows in the same direction. This future opportunity to rebalance is reflected in the premium precisely because the market maker can partially anticipate the next period's imbalance due to the correlated liquidity trading.

Thus, the price response to the contemporaneous imbalance, is composed of two parts, (i) a large independent premium which we term the innovation part, and (ii) a smaller autocorrelated portion which is termed the history-dependent part. Conditioning only on the total contemporaneous imbalance assigns the same weight to both the history-dependent part and the innovation part of the current imbalance. The negative coefficient on the lagged imbalance (after controlling for the current imbalance) compensates for this "over-weighting" of the autocorrelated portion of the contemporaneous imbalance. Of course, the arrival of traders with private information attenuates price pressures overall by reducing the conditional risk borne by the market maker. Nevertheless, if the long-term risk of the asset is large enough, and if the position taken by the informed traders is sufficiently small, then the negative coefficient on the lagged imbalance still obtains in the presence of the contemporaneous imbalance.

Note that the coefficient on the lagged imbalance can reverse sign in the presence of the contemporaneous imbalance only when imbalances are autocorrelated. If imbalances were serially uncorrelated, the sign and magnitude of the multivariate regression

coefficient of lagged imbalance would be the same as that of the univariate coefficient. Thus, the manner in which the coefficient of lagged imbalance changes in the presence of the current imbalance critically depends on the degree of autocorrelation in imbalance.

In sum, it is worth reiterating that the positive bivariate relation between current price moves and lagged imbalances simply accounts for the continuing price pressure caused by autocorrelated imbalances. At the same time, the negative relation between price moves and lagged imbalances, after controlling for the current imbalance, accounts for the fact that price pressure caused by the history-dependent portion of the current imbalance has partially been incorporated into prices in previous trading rounds. That portion, therefore, must be reversed out when one conditions the current price move on the current imbalance as well as the lagged imbalance.

Of course, it is worth noting that the continuing price pressures caused by auto-correlated imbalances should eventually be reversed, giving rise to reversals in longer horizon price movements. Indeed, it can easily be shown that under the condition of Proposition 1, the "long-term" covariance $\text{cov}(F - P_2, P_2 - P_1)$ is negative (see Appendix A). Thus, over longer horizons, lagged price movements should be negatively related to future price movements. This implication is consistent with the results of Lehmann (1990) and Jegadeesh (1990) who find reversals in weekly and monthly individual stock returns respectively.

We test the implications for the relation between imbalances and price movements in Proposition 1 using a comprehensive data set on daily order imbalances which encompasses more than 1100 stocks over more than 2700 trading days. To preserve normality and hence tractability, we analyze price changes in the model, which is standard prac-

tice in the microstructure literature on informed trading. However, as per empirical convention, and to preserve comparability in the cross-section, 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.[7]

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.[8] We use only NYSE stocks to avoid any possibility of the results being influenced by differences 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 the firm changed exchanges from Nasdaq to NYSE during the year (no firms switched from the NYSE to the Nasdaq during our sample period), it was dropped from the sample for that year.

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[7]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).

[8]To assess the robustness of our results over time, and to address the issue that the ISSM portion of our sample from 1988 through 1992 is more prone to data errors, we ran the regressions separately for the TAQ portion of the data and confirmed all our results for the TAQ sample.

3. Since their trading characteristics might differ from ordinary equities, assets in the following categories were also expunged: certificates, ADRs, shares of beneficial interest, units, companies incorporated outside the U.S., Americus Trust components, closed-end funds, preferred stocks and REITs.

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 were 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. 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.

We then 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). For each stock we then define the following variables:

OIBNUM: the estimated daily number of buyer-initiated minus seller-initiated trades scaled by the total number of trades.

OIBVOL: defined as above for estimated daily buyer-initiated minus seller-initiated dollar volume of transactions scaled by total dollar volume.

Order imbalance is scaled by the total number of trades or by the total dollar trading volume so as to eliminate the impact of total trading activity. Actively traded stocks with higher total number of trades per day or a larger daily dollar trading volume are likely to have higher imbalances. The scaling standardizes the imbalance measures. We use order imbalance measured in the natural unit of dollars as well as in number of transactions. Jones, Kaul, and Lipson (1994) show that the total number of transactions is more influential in determining stock price movements than trading volume.

3.2. Summary Statistics

In Table 1, we present some descriptive statistics of the daily data. Panel A presents the cross-sectional averages of the time-series means of scaled and unscaled imbalances in number of transactions and in dollars, the number of transactions, and trading volume, for the entire sample of stocks. The mean value of imbalance in number of transactions across the stocks is about 5 transactions per day. This is in relation to the mean value of the total number of transactions, which is about 113 transactions per day. The average order imbalance in dollars is about $432,000. The respective grand averages of the

absolute order imbalance are 20 transactions and \$1.7 million, respectively. The order imbalance measures have positive means and medians. This finding relates to the fact that we sign only market orders in our analysis, so that the excess of buy market orders over sell market orders is accommodated by the limit order book.[9] At the same time, we see that scaled imbalances have small but negative means, indicating that there are more days with large selling pressure than with large buying pressure.

Panel B of Table 1 presents the cross-sectional averages of daily time-series correlations between the unscaled order imbalance measures, the number of transactions, and the daily return. The correlation between the unscaled number and volume measures of order imbalance is low (about 0.29), but is much higher for the corresponding scaled imbalance measures. In addition, the correlation between the total number of daily transactions and imbalance in number of transactions is only about 0.26; this correlation is even lower for the scaled imbalance measure. Finally, the correlation between returns and order imbalance is positive, suggesting that order imbalance and returns are strongly related. However, the correlation between return and order imbalance in number of transactions is much higher than that between return and order imbalance measured in dollar terms, which is consistent with the analysis of Jones, Kaul, and Lipson (1994).

In Panel C of Table 1, we present the cross-sectional average autocorrelations of order imbalance measures in each stock, for both scaled and unscaled versions of imbalance.[10]

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[9]This assumes that specialists maintain a more or less constant inventory.

[10]Since the analysis of Chordia, Roll, and Subrahmanyam (2002) indicates that aggregate market autocorrelations are substantially positive for up to five lags, we depart from our two-period model and use multiple lags in the computation of the autocorrelations and in our regressions, while noting that the intuition behind our theoretical results generalizes to many periods. Our basic conclusions are not substantively altered when we use only one lag.

As can be seen, order imbalance as measured by the excess number of buyer-initiated transactions is highly positively autocorrelated; the first-lag autocorrelation is about 33%. The autocorrelations for the scaled versions of imbalance in transactions are smaller, but the first lag autocorrelation is still substantial: about 23%. Thus, there is strong evidence that a significant number of trades in one direction is followed by further trading activity in the same direction. The correlation also decays fairly slowly. This evidence is consistent with our theoretical analysis, wherein traders split their orders over time to minimize their price impact.

The autocorrelation in dollar imbalance is significantly smaller in magnitude for both scaled and unscaled measures. The difference between the autocorrelations for the two types of imbalances likely reflects the notion that imbalance in number of transactions more effectively captures the small orders of institutions who split up their demands across trading days (see also Keim and Madhavan, 1995; and Chan and Lakonishok, 1995).

4. Daily Time-Series Regressions

4.1. Regression Specification and Results

In this section, we use the hypotheses developed in Section II to explore the relation between realized daily returns and current as well as past daily levels of order imbalance. Of course, short-horizon return computations are subject to the well-known bid-ask bounce bias. We use a return series which calculates the one-day-ahead daily returns using quote midpoints associated with the first and last transactions on that day (ex-

cluding the opening batch auction).[11] Using open-to-close returns allows for a trading strategy wherein the previous day's order imbalance is estimated overnight and used to forecast returns the following day.[12]

In our time-series return regressions, we include the contemporaneous imbalance and four lags of order imbalance. We do not include lagged returns, because imbalance and returns could be collinear and thereby affect our inferences. Further, we use market-adjusted returns as our dependent variable in order to reduce cross-correlations in error terms across stocks. Specifically, we run the following regression for each stock i,

$$R_{it} - R_{mt} = a_i + \sum_{k=0}^{5} b_{ik} OIB_{i,t-k} + e_i, \tag{8}$$

where R_{it} denotes the open-to-close returns for stock i on date t, R_{mt} the equally weighted open-to-close return across all stocks, and $OIB_{i,t}$ denotes the scaled order imbalance for stock i on day t (either OIBNUM or OIBVOL). While we present results for the individual stock regressions in equation (8)), we have checked for robustness using a number of different variations of the above equation. For instance, the results are not significantly affected by the inclusion or exclusion of market returns. Further, controlling for lags of unsigned trading activity (either in number of transactions or in dollar volume) and lagged returns makes no substantive difference to the results. In addition, results for unscaled imbalance measures are substantively similar to the scaled measures. These results are available upon request.

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[11]We exclude the opening batch auction because the differing protocol at the open could unduly influence our results. For example, all orders submitted to the auction will generally impact the opening price, whereas during regular trading, orders that are smaller than the posted depth may not have a material impact on the price.

[12]We find that the results are robust to different return choices including the CRSP returns and the close-to-close, bid-ask mid-point returns. In fact, the predictability results were stronger when using the close-to-close mid-point returns.

In aggregating the estimates for this regression, we note that the residuals could continue to exhibit cross-correlation after adjusting for the market return because of various omitted factors. To address this issue, we first estimate the cross-correlation in residuals from the regression. Ideally, we would like to estimate the cross-correlation between each pair of residuals but our large sample precludes this. Instead, we estimate the true correlation by computing the correlation between adjacent residuals across stocks sorted alphabetically. Since there is no bias inherent in alphabetical sorting, this should provide with us with a reasonable estimate of the residual cross-correlation.[13] Our examination of these cross-correlations indicate that their magnitudes are relatively small, reaching a maximum of 0.03 across all of the regressions reported in this paper. Nevertheless, we adjust the standard errors of our coefficients for cross-correlated residuals using the procedure that is described in Appendix B. We report the average values together with the corresponding correlation-adjusted t-statistics for the coefficients a and b in Table 2, together with our estimate of the cross-correlation. Panel A presents results using number of transactions, whereas Panel B presents results for dollar imbalances.

The results in Panel A indicate in the current imbalance is positive and significant for virtually all the firms. Further, whereas the average coefficients on the lagged imbalances are negative and significant, and about 80% of the coefficients on these imbalances are negative, with about 30% being negative and significant. The contemporaneous relation between imbalance and returns is consistent with both inventory and asymmetric information effects of price formation, and with our model that encompasses both of

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[13]See Chordia, Roll, and Subrahmanyam (2001) for a similar procedure to obtain an estimate of the residual cross-correlation across regressions with correlated errors.

these phenomena. The negative coefficients on lagged imbalances are consistent with our model in the previous section, wherein autocorrelated imbalances cause the effect of the lagged imbalance to be reversed out in the current day's return.

Note that lagged imbalances affect returns for up to five days, implying that the effect of autocorrelated imbalances on returns is quite long-lived. This can be explained as follows. Recall that the negative coefficient of lagged imbalances arises because conditioning on total current imbalance overweights the impact of current trades that are autocorrelated with past trades. Since the smaller the current price pressure induced by these trades, the *greater* the overweighting and the *stronger* the reversal, and since current price pressure induced by long lags of imbalance is small, we see negative and significant coefficients on these longer lags as well.

It also is worth noting that the cross-correlation in adjacent residuals for the alpha-betically-sorted sample is quite small in both cases (0.008 and 0.006), suggesting that cross-equation correlation, while relevant, is not a major factor influencing the statistical significance.[14] The effects of lagged imbalance, while significant in many cases, are stronger for OIBNUM than those for OIBVOL (in Panel B), which is consistent with our finding that autocorrelation in imbalances is larger for the former measure of imbalance.

4.2. Size-stratified Results

It is plausible that inventory pressures induced by daily order imbalances could differentially affect the returns for large, frequently-traded stocks and those of small, infrequently-traded stocks. Alternatively, differential patterns of imbalance autocor-

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[14]We also estimated a panel data regression allowing for cross-correlation in the residuals, using the Parks (1967) procedure. Since the procedure requires a balanced panel, wherein every stock has to have an equal number of time-series observations, we applied it to the 177 stocks that were present every day in our sample. The results were qualitatively identical to the ones reported here.

relations could induce different degrees of dependence between returns and lagged imbalances. To investigate these possibilities, we sorted firms into four size groups based on market capitalization as follows. For each firm, we calculated market capitalization at the beginning of each year. Then, we sorted all size-days into four groups based on market capitalization. The results from regression (8) are presented in Table 3.

Summary statistics of coefficients using OIBNUM are presented in Panels A through D of Table 3 (the results for OIBVOL are qualitatively similar to those for OIBNUM and are omitted for brevity). Overall, the earlier results of positive contemporaneous coefficient and negative lagged coefficients of returns on order imbalance are not driven by only the smallest or the largest firms. The results are generally robust and obtain for all size groups. This is consistent with the third result in Proposition 1. The size-stratified results demonstrate, however, that the average positive coefficient on the contemporaneous OIBNUM increases with firm size. Also, the average coefficient on the first lag is the most negative for the largest firms. In particular, for the largest firm group, about 87% of the coefficient of the first lag are negative, and about 43% are negative and significant, while the corresponding numbers for the smallest firm group are 64% and 15%, respectively. Thus, the price impact of the contemporaneous imbalance is highest in the largest firms as is the reversal in the lagged imbalances, suggesting that the stock price of the largest firms reacts quickest to order imbalances.

Note from the discussion of Proposition 1 that the relation between returns and lagged imbalances arises due to autocorrelation in imbalances. To obtain more insight, we calculate the magnitudes of imbalance autocorrelations for the different size groups. We find that the first-lag autocorrelation of scaled (unscaled) imbalance in transactions

shows a monotonic progression from 0.309 (0.404) for the largest firm group to 0.177 (0.267) for the smallest firm group. The somewhat counter-intuitive finding of higher imbalance autocorrelation in large stocks obtains likely because institutions are more likely to trade the large firms, so that imbalance persistence caused by splitting of institutional orders is likely to be a stronger phenomenon for such firms. The differential effects of lagged imbalance on returns across small and large firms are thus consistent with differential autocorrelation in imbalances across these firms.

5. Predictability

5.1. Regression Evidence

Proposition 1 also indicates a predictive relation between returns and lagged imbalances when contemporaneous imbalances are not included in the regression. To test this implication, we run the same regressions as in equation (8), but omit the contemporaneous imbalance, and include five lags of imbalances. In separate regressions (not reported for brevity) we also included the first lag of the market return to account for non-synchronous adjustment of prices to market information, and found that the results are not sensitive to whether the lagged market return is included. The regression estimates, together with the correlation-corrected t-statistics, are reported in Table 4.

We find evidence to support Part 2 of Proposition 1, namely, that lagged imbalance is positively related to daily open-to-close returns. In particular, about 77% of the coefficients on the first lag OIBNUM are positive, and more than a quarter are positive and significant. The results for OIBVOL are very similar to those for OIBNUM in that the first lag of imbalance has significant predictive power for daily open-to-close

returns.[15]

In Table 5, we present the regressions by size grouping. About 70-75% of the coefficients on the first lag are positive across the size groups, while the percentage of positive and significant coefficients is in the vicinity of 20%. However, the average coefficient on the first lag of imbalance is statistically significant only for the three smallest size groups. This indicates that persistent inventory price pressures induced by autocorrelated imbalances are most relevant for smaller firms, because as we saw in Table 3, markets for large firms accommodate persistent imbalances more expeditiously.[16]

Our results in this section are related to those of Huang and Stoll (1994) who analyze whether intraday returns can be predicted from transactions within day. They also find some evidence that returns within a trading day are predictable using past signed orders. We show that there is evidence of predictability at longer (i.e., daily) horizons. Our findings lend support to the notion that inventory effects last for time intervals greater than a trading day.

As a final point, the analysis in Section I indicates that the positive predictability of returns using imbalances arises because of continuing price pressure caused by autocorrelated trader demands. This suggests that even without controlling for current imbalance, very long lags of imbalances should be negatively related to current returns, as this persistent price pressure should eventually reverse. To examine this possibility, in Table 6 we present the results of pure forecasting regressions that include up to ten lags of imbalances. As can be seen, while the first lag, as before, is positive and sig-

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[15]We checked the robustness of this result by including lagged returns in addition to lagged imbalances, and found that the coefficient of lagged imbalance continued to be positive and significant.

[16]See Chordia and Swaminathan (2000) who document different speeds of adjustment to information across stock portfolios.

nificant, four of the sixth through tenth lags are negative and significant, though the magnitude of the latter coefficients is much smaller than that of the first lag. This implies that price pressure caused by autocorrelated imbalances reverses itself rather slowly through time. In this sense, our study can be interpreted as providing evidence to support the view (see Hasbrouck and Sofianos, 1993 and Madhavan and Smidt, 1993) that inventory effects persist for horizons of several trading days.

5.2. Profitability of Imbalance-Based Trading Strategies

Given the evidence of return predictability using imbalances, a natural question is whether one can form a profitable trading strategy based on the previously-presented regression results. Also, this exercise provides an estimate of the economic significance of our findings. We now discuss different imbalance-based trading strategies.

We first calculate the average return to a strategy that buys a share at the opening ask (the ask quote matched to the first transaction of the day) and sells at the closing bid (the bid quote matched to the last transaction of the day) if the previous day's imbalance was positive. The trades are reversed if the previous day's imbalance was negative. The results in the first row of Table 7 indicate that such a strategy would have yielded a statistically significant daily average return of 0.09% for the entire sample. For a trade of one round lot on an $40 stock, this translates to a profit of $3.60 per round-trip trade.[17] The average returns decline monotonically from about 0.23% for the smallest firm quartile to about 0.03% for the largest firm quartile.

We also form strategies based on extreme values of imbalances (one or two standard

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[17]The profits will be higher if quoted depths at the open and close are larger than one lot. We restrict ourselves to a one-lot trade to account for the fact that quoted depth at the close cannot be known in advance.

deviations away from zero), and calculate returns to both types of imbalances. The variability in imbalances is estimated in the prior three-month period and held constant in each three-month period (the first three-month period in the sample is therefore omitted from the profit calculation). The strategy based on extreme imbalances (more than two standard deviations away from zero) for small firms yields the highest average return of 0.55%. This translates to a profit of $22 for a one lot round-trip trade for a $40 stock. The profitability of strategies is similar for both types of imbalances.

While the size and significance of the profits indicates that the predictability of returns using imbalance is not illusory, it also suggests that brokerage commissions could nullify the profitability of such strategies to individual investors (online trades usually cost $10-$20, enough to virtually nullify the profit on a one-lot round-trip trade in each case). Nevertheless, professional investors with low trading costs do appear to have some room for designing profitable trading strategies. However, these strategies are not inconsistent with market efficiency because inventory paradigms of market microstructure do indeed predict that following days of heavy selling, for example, it can be profitable to buy because market makers offer favorable terms to buyers for a period of time in order to facilitate inventory offloading. Overall, our results are consistent with a model of market equilibrium where market makers with inventory concerns dynamically accommodate positively autocorrelated imbalances.

6. Conclusion

With a view to better understand why financial market prices move, the literature has extensively explored the relation between trading activity and stock market returns.

But trading activity has usually been proxied by volume, whereas order imbalance could bear a more meaningful relation to direction and magnitude of price changes. This study undertakes an analysis of the relation between estimated order imbalances and individual stock returns for a comprehensive sample of NYSE stocks over a relatively long sample period of eleven years (1988-1998). We mitigate bid-ask bias in returns by passing through the entire transactions database and recording the mid-points of bid and ask prices corresponding to the first and last transactions during each trading day. We then construct an open-to-close return series using these midpoints.

We derive implications for the relation between imbalances and price movements by developing an intertemporal model of how prices react to imbalances. Our model contributes to the microstructure literature by allowing an explicit analysis of how market makers accommodate autocorrelated imbalances. In our analysis, liquidity traders split their orders across periods to minimize price impact. This causes persistence in equilibrium order imbalances and positively autocorrelated price pressures. In turn, this phenomenon results in a positive predictive relation between imbalance and equilibrium price changes.

Consistent with theory, our empirical study finds that individual stock order imbalances are strongly positively autocorrelated. Further, the relation between lagged imbalances and returns is significantly positive at a one-day horizon. In addition, contemporaneous imbalances are strongly related to contemporaneous returns, but the positive relation between lagged imbalance and returns disappears after controlling for the contemporaneous imbalance.

We also find that strategies based on taking a position in the direction of the pre-

vious day's imbalance yield positive and statistically significant profits. However, the magnitude of the profits are small and are unlikely to be much larger than brokerage commissions for individual investors. In general, our study supports our model as well as the inventory paradigm of Stoll (1978) and O'Hara and Oldfield (1986), wherein risk averse market makers with inventory concerns charge premia to accommodate order imbalances. Our results are consistent with equilibrium in a securities market where persistent imbalances induce autocorrelated price pressures.

Our analysis also underscores the importance of imbalance as a measure of trading activity, and emphasizes the impact of microstructure effects on short-horizon returns. From a practical standpoint, our results suggest that access to information about imbalance can be valuable for designing trading strategies. For example, professional floor traders' interests would be best served by keeping track of daily buy/sell imbalances, as opposed to monitoring volume. This can be done by noting the proportion of orders executing above and below posted quote-midpoints.

In addition, our study suggests a few directions for further empirical work. For example, specific events that drive extreme order imbalance days still need to be determined. A large order imbalance prior to an informational event (e.g., a merger) could denote informed trading. However, large order imbalances following information events signal portfolio rebalancing trades owing to a change in investor expectations. The differential impact of these sources of imbalance on returns would form an interesting study. Analyzing imbalances caused by different categories of agents (institutions vs. individual investors) would help identify informed traders and liquidity traders in a more precise manner. Exploration of such issues is left for future research.

Appendix A

Proof of Lemma 1: We begin by conjecturing that all trader demands and both date 1 and date 2 prices are normally distributed. In the linear equilibrium we derive, this conjecture is confirmed to be correct.

Using mean variance analysis, it can be shown that

$$x_{I2} = \frac{\bar{F} + \theta - P_2}{Rv_\epsilon}, \tag{9}$$

$$x_{U2} = \frac{\bar{F} + E(\theta|P_1, P_2) - P_2}{R \, \text{var}(\theta + \epsilon|P_1, P_2)}. \tag{10}$$

We next show that the date 1 demands of the informed and uninformed agents are given by

$$x_{I1} = \frac{E(P_2|P_1) - P_1}{RS_I} + k_I E(x_{I2}|P_1) \tag{11}$$

$$x_{U1} = \frac{E(P_2|P_1) - P_1}{RS_U} + k_U E(x_{U2}|P_1), \tag{12}$$

where S and the k coefficients are exogenous constants. We begin by stating the following lemma, which is a standard result on multivariate normal random variables (see, for example, Brown and Jennings [1989]).

Lemma 2 *Let $Q(\chi)$ be a quadratic function of the random vector χ: $Q(\chi) = C + B'\chi - \chi'A\chi$, where $\chi \sim N(\mu, \Sigma)$, and A is a square, symmetric matrix whose dimension corresponds to that of χ. We then have*

$$E[\exp(Q(\chi))] = |\Sigma|^{-\frac{1}{2}}|2A + \Sigma^{-1}|^{-\frac{1}{2}} \times$$

$$\exp\left(C + B'\mu + \mu'A\mu + \frac{1}{2}(B' - 2\mu'A')(2A + \Sigma^{-1})^{-1}(B - 2A\mu)\right).$$

Let ϕ_{ij} and x_{ij} denote the information set and demand, respectively, of an agent i ($i = I, U$), at date i. The date 2 demand of the agent (from maximization of the mean-variance objective) is given by

$$x_{i2} = \frac{E(F|\phi_{i2}) - P_2}{R \text{ var}(F|\phi_{i2})}. \tag{13}$$

Let $\mu_2 \equiv E(F|\phi_{i2})$. Note that in period 1, the trader maximizes the derived expected utility of his time 2 wealth which is given by

$$E[[-\exp\{-R[B_0 - x_{i1}P_1 + x_{i1}P_2 + [\mu_2 - P_2]^2/(2R\text{var}(F|\phi_{i2}))]\}]|\phi_{i1}]. \tag{14}$$

Let $\bar{P}_2$ and μ denote the expectations of P_2 and μ_2, and Π the variance-covariance matrix of P_2 and μ_2, conditional on ϕ_{i1}. Then, the expression within the exponential above (including terms from the normal density) can be written as

$$-\left[\frac{1}{2}y'Gy + h'y + w\right],$$

where

$$
\begin{aligned}
y' &= [\mu_2 - \mu, P_2 - \bar{P}_2], \\
h' &= [-Rx_{i1} + \frac{(\bar{P}_2 - \mu)}{\text{var}(F|\phi_{i2})}, \frac{(\mu - \bar{P}_2)}{\text{var}(F|\phi_{i2})}], \\
G &= \left[\Pi^{-1} + \begin{bmatrix} s^{-1} & -s^{-1} \\ -s^{-1} & s^{-1} \end{bmatrix}\right], \\
w &= Rx_{i1}(P_1 - \bar{P}_2) + g,
\end{aligned}
$$

where $s \equiv \text{var}(F|\phi_{i1})$, and where g is an expression which does not involve x_{i1}. From Lemma 2 and Bray (1981, Appendix), (14) is given by

$$-\frac{1}{(Det(\Pi))^{\frac{1}{2}}|Det(A)|^{\frac{1}{2}}}\exp\left(\frac{1}{2}h'G^{-1}h - w\right). \tag{15}$$

Thus, the optimal x_{i1} solves

$$\left[\frac{dh}{dx_{i1}}\right]' G^{-1}h - \frac{dw}{dx_{i1}} = 0.$$

Substituting for h and w, we have

$$x_{i1} = \frac{\bar{P}_2 - P_1}{RG_1} + \frac{\mu - \bar{P}_2}{R\text{var}(F|\phi_{i2})}\frac{G_1 - G_2}{G_1}, \qquad (16)$$

where G_1 and G_2 are the elements in the first row of the matrix G^{-1}. It follows that the demands x_{I1} and x_{U1} are given by (11) and (12), respectively, with the S coefficients being the G_1 coefficient above and the k coefficients being the term $(G_1 - G_2)/G_1$. We thus obtain (11) and (12).

Market clearing implies

$$Mx_{I1} + (1 - M)x_{M1} + z_1 = 0, \qquad (17)$$

$$Mx_{I2} + (1 - M)x_{M2} + 2z_1 + z_2 = 0. \qquad (18)$$

We can rewrite (18) as:

$$M\frac{\bar{F} + \theta - P_2}{Rv_\epsilon} + (1 - M)\frac{\bar{F} + E(\theta|\phi_2) - P_2}{R\,\text{var}(\theta + \epsilon|\phi_2)} + 2z_1 + z_2 = 0, \qquad (19)$$

where ϕ_2 is the date 2 information set of the uninformed. Now, the uninformed observe P_2 at date 2, which is equivalent to observing

$$\tau \equiv \theta + \frac{Rv_\epsilon}{M}(2z_1 + z_2).$$

In addition, since there is no private information at date 1, the uninformed also observe the date 1 demand shock z_1. Thus, we have

$$E(\theta|\phi_2) = E(\theta|\tau, z_1) = \frac{v_\theta}{v_\theta + k^2 v_z}(\theta + kz_2) \qquad (20)$$

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and

$$\text{var}(\theta + \epsilon|\phi_2) = v_\epsilon + \text{var}(\theta|\tau, z_1) \equiv v = v_\epsilon + \frac{k^2 v_\theta v_z}{v_\theta + k^2 v_z}, \qquad (21)$$

where $k \equiv \frac{R v_\epsilon}{M}$. Substituting for the above moments into the market clearing condition (19), for the price P_2 from (2), and equating coefficients of the variables θ, z_1, and z_2, we obtain a closed-form expression for the date 2 price.

Now, from the market clearing condition at date 1, (17), we can solve for f in terms of the k and S coefficients in (11) and (12). This exercise yields

$$f = \frac{b\left[\frac{M}{RS_I} + \frac{1-M}{RS_U} - \left\{\frac{Mk_I}{Rv_\epsilon} + \frac{(1-M)k_U}{Rv} + 1\right\}\right]}{\frac{M}{RS_I} + \frac{1-M}{RS_U}}. \qquad (22)$$

The G coefficients for the informed agents are given by the first row of the matrix

$$\left[\begin{pmatrix} a^2 v_\theta + c^2 v_z & a v_\theta \\ a v_\theta & v_\theta \end{pmatrix}^{-1} + \begin{pmatrix} v_\epsilon^{-1} & -v_\epsilon^{-1} \\ -v_\epsilon^{-1} & v_\epsilon^{-1} \end{pmatrix}\right]^{-1}. \qquad (23)$$

and those for the uninformed agents given by the first row of the matrix

$$\left[\begin{pmatrix} a^2 v_\theta + c^2 v_z & \frac{v_\theta(a v_\theta + k c v_z)}{v_\theta + k^2 v_z} \\ \frac{v_\theta(a v_\theta + k c v_z)}{v_\theta + k^2 v_z} & \frac{v_\theta^2}{v_\theta + k^2 v_z} \end{pmatrix}^{-1} + \begin{pmatrix} v^{-1} & -v^{-1} \\ -v^{-1} & v^{-1} \end{pmatrix}\right]^{-1}. \qquad (24)$$

where $v \equiv \text{var}(F|P_1, P_2)$. Substituting for a, b, and c, we find that

$$S_I = S_U = \frac{[M v_\theta + R^2 v_\epsilon^2 v_z(v_\epsilon + v_\theta)]^2}{M^2 v_\theta + 2M R^2 v_\epsilon v_\theta v_z + R^2 v_\epsilon^2 v_z[R^2(v_\epsilon + v_\theta) + 1]}$$

$$k_I = \frac{R^2 v_\epsilon^2 v_z}{M v_\theta + R^2 v_\epsilon v_z(v_\theta + v_\epsilon)},$$

and

$$k_U = k_I \frac{M^2 v_\theta + R^2 v_\epsilon v_z(v_\epsilon + v_\theta)}{M^2 v_\theta + R^2 v_\epsilon^2 v_z}.$$

Note that $k_U > k_I$. Using (21), it is easy to show that $k_I/v_\epsilon = k_U/v$. This implies that each informed agent and each market maker trades an equal amount at date 1. In

turn, from the market clearing condition, this implies that the aggregate informed order

at date 1 is $-Mz_1$, while the aggregate market maker order at date 1 is $-(1-M)z_1$.

Substituting for S_I, S_U, k_I, and k_U into (22) and performing some tedious algebra yields

(7). □

Proof of Proposition 1: First, let us show that it is optimal for the discretionary

trader to split his order across periods so long as v_ϵ is sufficiently high. In calculating

expected trading costs associated with switching to a particular strategy, the discre-

tionary trader uses the pricing coefficients associated with that strategy.[18] Now, if the

trader splits his order, the price impact is given by $E[(P_1 + P_2 - F)z_1] = (f+b)v_z$. If

he concentrates his order in period 2, the price impact is $E(P_2' - F)2z_1 = 2b'v_z$, where

P_2' is the period 2 price and b' is the period 2 coefficient of z_1 when the discretionary

trader concentrates his trades in period 2. It is easy to show that

$$b' = \frac{2Rv_\epsilon[Mv_\theta + 3R^2v_\epsilon v_z(v_\epsilon + v_\theta)]}{M^2v_\theta + 3MR^2v_\epsilon v_\theta v_z + 3R^2v_\epsilon^2 v_z} \tag{25}$$

Therefore, the liquidity trader will prefer splitting orders to concentrating in period 2

so long as $2b' > f + b$. From (25) and Lemma 1, the difference $2b' - (b+f)$ can be

written as A/B, where

$$B = D[D + MR^2v_\epsilon v_\theta v_z + R^4v_\epsilon^2 v_z^2(v_\epsilon + v_\theta)][M^2v_\theta + 3MR^2v_\epsilon v_\theta v_z + 3R^2v_\epsilon^2 v_z]$$

and where A is a complicated polynomial whose highest exponent in v_ϵ is to the eighth

power, and this term is given by $3R^9v_z^4 v_\epsilon^8$. Hence there exists a critical value of v_ϵ such

that above this value $2b' > b + f$.

If the discretionary trader concentrates his trades in period 1, his price impact is

$E(P_1' - F)2z_1 = 2f'v_z$, where P_1' and f' are the price and the pricing coefficient when the

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[18]See Admati and Pfleiderer (1988) or Subrahmanyam (1994) for a similar equilibrium concept.

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discretionary trader concentrates his trading in period 1. Straightforward calculations show that $f' = 2(v_\epsilon + v_\theta)$. The discretionary trader prefers splitting to concentrating in period 1 if $4(v_\epsilon + v_\theta) > b + f$. From Lemma 1, this is true when

$$
\begin{aligned}
R \quad & [8R^6 v_\epsilon^3 v_z^3 (v_\epsilon + v_\theta)(2v_\epsilon + v_\theta)(26v_\epsilon^2 + 41v_\epsilon v_\theta + 15v_\theta^2) \\
+ \quad & 12R^4 v_\epsilon^2 v_z^2 (32v_\epsilon^4 + 110v_\epsilon^3 v_\theta 139v_\epsilon^2 v_z^2 + 76v_\epsilon v_\theta^3 + 15v_\theta^4) \\
+ \quad & 2R^2 v_\epsilon v_\theta v_z (96v_\theta^3 + 236v_\epsilon^2 v_\theta + 184v_\epsilon v_\theta^2 + 45v_\theta^3) \\
+ \quad & 3v_\theta^2 (18v_\epsilon^2 + 14v_\epsilon v_\theta + 5v_\theta^2)]
\end{aligned}
$$

divided by

$$
[4R^4 v_\epsilon^2 v_z^2 (v_\epsilon + v_\theta) + 4R^2 v_\epsilon v_z (v_\epsilon + v_\theta) + v_\theta][2R^2 v_\epsilon v_z (2v_\epsilon + v_\theta) + v_\theta][2v_\epsilon + v_\theta]
$$

is positive, which is true. Hence, if v_ϵ is sufficiently large, the lowest cost strategy (and hence, the equilibrium strategy) for the discretionary trader is to split orders across periods.

Given that the liquidity trader follows his optimal strategy, from Lemma 1, and, recalling that the period 1 imbalance is given by $Q_1 = (1 - M)z_1$, while the period 2 imbalance is given by $Q_2 = Mx_{I1} + [2 + (1-M)]z_1 + z_2$, the covariance in the imbalances Q_1 and Q_2 becomes

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

which is positive. This completes the proof of Part 1.

For Part 2, note that $\text{cov}(P_2 - P_1, Q_1)/\text{var}(Q_1) = (b - f)/2$. From Lemma 1, $b > f$ so long as

$$
\frac{R[8R^6 v_\epsilon^3 v_z^3 (v_\epsilon + v_\theta)^2 (2v_\epsilon - v_\theta) + 4R^4 v_\epsilon^2 v_\theta v_z^2 (v_\epsilon - 3v_\theta) - 2R^2 v_\theta^2 v_\epsilon v_z (2v_\epsilon + 3v_\theta) - v_\theta^3]}{[4R^2 v_\epsilon^2 v_z^2 (v_\epsilon + v_\theta) + 4R^2 v_\epsilon v_z (v_\epsilon + v_\theta)][2R^2 v_\epsilon v_z (2v_\epsilon + v_\theta)]}
$$

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is positive. Since the highest exponent of v_ϵ is to the sixth power and the coefficient on this exponent is positive, there exists a critical value of v_ϵ such that above this value $b > f$. In this case, the past period's imbalance is positively related to the current price change. Differentiating the coefficient with respect to R yields an expression A'/B', where

$$B' = [4R^2 v_\epsilon^2 v_z^2 (v_\epsilon + v_\theta) + 4R^2 v_\epsilon v_z (v_\epsilon + v_\theta)]^2 [2R^2 v_\epsilon v_z (2v_\epsilon + v_\theta)]^2$$

and where A is a complicated polynomial expression. The highest exponent of v_ϵ in this expression is to the eleventh power and the term involving this exponent is given by $256R^{12} v_z^6 v_\epsilon^{11}$. Hence there exists a cutoff level of v_ϵ such that above this cutoff, the derivative is positive. This completes the proof of Part 2.

Finally, to prove Part 3, we use the well-known result that if there exist random vectors v_1 and v_2 such that

$$(v_1, v_2) \sim \mathbf{N} \left[(\mu_1, \mu_2), \left(\begin{array}{cc} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{array} \right) \right]$$

then the conditional distribution of v_1 given $v_2 = \mathbf{X_2}$ is normal with a mean given by the vector

$$E(v_1 | v_2 = \mathbf{X_2}) = \mu_1 + \Sigma_{12} \Sigma_{22}^{-1} (\mathbf{X_2} - \mu_2) \tag{26}$$

In our case, $v_1 = P_2 - P_1$ and $v_2 = [Q_1, Q_2]$, and the relevant unconditional means are all zero. A straightforward application of (26) yields that the coefficient on Q_2 in the quantity $E(P_2 - P_1 | Q_1, Q_2)$ is given by

$$\frac{[4Rv_\epsilon v_z + v_\theta][2R^2 (v_\epsilon + v_\theta) + v_\theta)]}{v_z (4R^2 v_\epsilon^2 v_z + v_\theta)}$$

which is positive. Further, the coefficient on Q_1 is given by C/D, where

$$D = [4R^4 v_\epsilon^2 v_z^2 (v_\epsilon + v_\theta) + 4R^2 v_\epsilon v_z (v_\epsilon + v_\theta) + v_\theta][2R^2 v_\epsilon v_z (2v_\epsilon + v_\theta) + v_\theta][2v_\epsilon + v_\theta]$$

and where C is a complicated polynomial expression. The highest exponent of v_ϵ in this expression is to the seventh power and the term involving this exponent is given by $-32R^7v_\epsilon^7v_z^4(Rv_\theta+4)$. Hence there exists a cutoff level of v_ϵ such that above this cutoff, the coefficient of Q_1 is negative. This completes the proof of the proposition. $\square$

Proof that $\mathrm{cov}(F-P_2, P_2-P_1) < 0$ **if** v_ϵ **is sufficiently high:** The relevant covariance can be written as

$$a(1-a)v_\theta - [b(b-f+c^2]v_z.$$

Substituting for a, b, and c from Lemma 1, we find that the covariance can be written as G/H, where

$$H \equiv 4R^4v_\epsilon^2v_z^2(v_\epsilon+v_\theta) + 4R^2v_\epsilon v_z(v_\epsilon+v_\theta) + v_\theta][2R^2v_\epsilon v_z(2v_\epsilon+v_\theta)+v_\theta]^2$$

where G is a complicated polynomial whose highest exponent in v_ϵ is to the ninth power, and this term is given by $-192R^{10}v_zv_\epsilon^9$. Hence there exists a cutoff level of v_ϵ such that above this cutoff, the covariance is negative.

Appendix B

In this appendix we describe the procedure we use to adjust the standard errors of the average coefficients from our individual firm, time-series regressions. Let there be N firms, and K regressors for each firm. Further, let T denote the number of time-series observations per firm. Also, suppose that the residual variance for firm i is given by σ_i^2 and the cross-covariance in residuals for two firms i and j is σ_{ij}. Standard regression theory implies that the variance-covariance matrix of the vector of coefficients β_i for firm i is given by the $K \times K$ matrix $\text{var}(\beta_i) = \sigma_i^2(X_i'X_i)^{-1}$, where X_i is the $T \times K$ matrix of regressors for firm i. It also follows that the covariance between the regression coefficients across two stocks i and j is represented by the $K \times K$ matrix

$$\text{cov}(\beta_i, \beta_j) = \sigma_{ij}(X_i'X_i)^{-1}X_i'X_j(X_j'X_j)^{-1}$$

Thus, the variance-covariance matrix of the NK regressors is given by a matrix of dimensions $NK \times NK$, which can be written as

$$\begin{bmatrix} \text{var}(\beta_1) & \text{cov}(\beta_1, \beta_2) & \text{cov}(\beta_1, \beta_3) & \ldots \\ \text{cov}(\beta_2, \beta_1) & \text{var}(\beta_2) & \text{cov}(\beta_2, \beta_3) & \ldots \\ \ldots & \ldots & \ldots & \ldots \end{bmatrix}$$

Thus, the variance of the mean coefficient of, say regressor 1, is given by adding the element $[1,1]$, to twice the sum of the elements $[K+1,1]$, $[2K+1,1]$, ..., $[(N-1)K+1,1]$, and then dividing the overall sum by N^2. Similarly, the variance of the mean coefficient of regressor 2 is given by adding the element $[2,2]$ to twice the sum of the elements $[K+1,2]$, $[3K+1,2]$, ..., $[(N-1)K+1,2]$, and dividing by N^2, and so on. The square roots of these numbers provide an estimate of the corrected standard errors.

There are two issues we face in adapting the above procedure to our case. The first problem is that we have a large number of time-series and cross-sectional observations;

thus the matrices involved are of large dimension, and invertibility is hampered. In addition, we do not require the number of time-series observations to be equal across stocks, and lack of significant time-series overlap across stocks could create noise in the estimate of cross-correlations in our coefficient estimates. Taking into account these limitations, we obtain an estimate of the corrected standard errors as follows. We first estimate the standard errors for the 177 firms that traded every day in our sample using the above procedure. We then calculate the ratio of these standard errors to the standard errors for these stocks calculated assuming independence of the coefficients. This ratio provides us an estimate of the factor by which the standard errors are inflated. We apply this inflation factor to each of the standard errors in the full-sample regressions. The inflation factors are fairly small, suggesting that the influence of cross-correlated residuals on the standard errors of our estimates is quite small.

References

Admati, A., and P. Pfleiderer, 1988, A theory of intraday patterns: volume and price variability, Review of Financial Studies 1, 3-40.

Amihud, Y. and H. Mendelson, 1986, Asset pricing and the bid-ask spread, Journal of Financial Economics 17, 223-249.

Blume, M., A. MacKinlay, and B. Terker, 1989, Order imbalances and stock price movements on October 19 and 20, 1987, Journal of Finance 44, 827-848.

Blume, M., and R. Stambaugh, 1983, Biases in computed returns: An application to the size effect, Journal of Financial Economics 12, 387-404.

Chan, L., and J. Lakonishok, 1995, The behaviour of stock prices around institutional trades, Journal of Finance 50, 1147-1174.

Chordia, T., R. Roll, and A. Subrahmanyam, 2000, Commonality in liquidity, Journal of Financial Economics 56, 3-28.

Chordia, T., R. Roll, and A. Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, Journal of Financial Economics 65, 111-130.

Chordia, T., A. Subrahmanyam, and V. Anshuman, 2001, Trading activity and expected stock returns, Journal of Financial Economics 59, 3-32.

Chordia, T., and B. Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, Journal of Finance 55, 913-936.

Conrad, J., A. Hameed, and C. Niden, 1994, Volume and autocovariances in short-horizon individual security returns, Journal of Finance 49, 1305-1329.

Fama, E.F., and K.R. French, 1992, The cross section of expected stock returns, Journal of Finance 47, 427-466.

Gallant, A., P. Rossi, and G. Tauchen, 1992, Stock prices and volume, Review of Financial Studies 5, 199-242.

Glosten, P., and P. Milgrom, 1985, Bid, ask and transaction prices in a specialist market with heterogeneously informed traders, Journal of Financial Economics, 14, 71-100.

Hasbrouck, J. and G. Sofianos, 1993, The trades of market makers: An empirical analysis of NYSE specialists, Journal of Finance 48, 1565-1594.

Hiemstra, C., and J. Jones, 1994, Testing for linear and nonlinear Granger causality in the stock price-volume relation, Journal of Finance 49, 1639-1664.

Ho, T., and H. Stoll, 1983, The dynamics of dealer markets under competition, Journal of Finance 38, 1053-1074.

Holden, C., and A. Subrahmanyam, 2002, News events, information acquisition, and serial correlation, Journal of Business 75, 1-32.

Hong, H., T. Lim, and J. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, Journal of Finance 55, 265-295.

Hong, H., and J. Stein, 1999, A unified theory of underreaction, momentum trading, and overreaction in asset markets, Journal of Finance 54, 2143-2184.

Huang, R., and H. Stoll, 1994, Market microstructure and stock return predictions, Review of Financial Studies 7, 179-213.

Jegadeesh, N., 1990, Evidence of predictable behaviour of security returns, Journal of Finance 45, 881-898.

Jegadeesh, N., and S. Titman, 1995, Short-horizon return reversals and the bid-ask spread, Journal of Financial Intermediation 4, 116-132.

Jones, C., G. Kaul, and M. Lipson, 1994, Transactions, volume, and volatility, Review of Financial Studies 7, 631-651.

Karpoff, J., 1987, The relation between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis, 22, 109-125.

Keim, D. B. and A. Madhavan, 1995, Empirical evidence on the behavior of institutional traders, Journal of Financial Economics 37, 371-399.

Kraus, A., and H. Stoll, 1972, Parallel trading by institutional investors, Journal of Financial and Quantitative Analysis 7, 2107-2138.

Kyle, A., 1985, Continuous auctions and insider trading, Econometrica 53, 1315-1335.

Lakonishok, J., A. Shleifer, and R. Vishny, 1992, The impact of institutional trading on stock prices, Journal of Financial Economics 32, 23-43.

Lauterbach, B., and U. Ben-Zion, 1993, Stock market crashes and the performance of circuit breakers: Empirical evidence, Journal of Finance 48, 1909-1925.

Lee, C., 1992, Earnings news and small traders: An intraday analysis, Journal of Accounting and Economics 15, 265-302.

Lee, C., and B. Radhakrishna, 2000, Inferring investor behavior: Evidence from TORQ data, Journal Of Financial Markets 3, 83-111.

Lee, C., and M. Ready, 1991, Inferring trade direction from intraday data, Journal of Finance 46, 733-747.

Lehmann, B., 1990, Fads, martingales, and market efficiency, Quarterly Journal of Economics 105, 1-28.

Lo, A., and C. MacKinlay, 1990, When are contrarian profits due to stock market overreaction, Review of Financial Studies 3, 175-205.

Lo A., and J. Wang, 2000, Trading volume: definitions, data analysis, and implications of portfolio theory, Review of Financial Studies 13, 257-300.

Madhavan, A., and S. Smidt, 1993, An analysis of changes in specialist inventories and quotations, Journal of Finance 48, 1595-1628.

Odders-White, Elizabeth R., 2000, On the occurrence and consequences of inaccurate trade classification, Journal of Financial Markets 3, 205-332.

O'Hara, M., and G. Oldfield, 1986, The microeconomics of market making, Journal of Financial and Quantitative Analysis 21, 361-376.

Parks, R., 1967, Efficient estimation of a system of regression equations when disturbances are both serially and contemporaneously correlated, Journal of the American Statistical Association 62, 500-509.

Spiegel, M., and A. Subrahmanyam, 1995, On intraday risk premia, Journal of Finance 50, 319-339.

Sias, R., 1997, Price pressure and the role of institutional investors in closed-end funds, Journal of Financial Research 20, 211-229.

Stoll, H., 1978, The supply of dealer services in securities markets, Journal of Finance 33, 1133-1151.

Stoll, H., 2000, Friction, Journal of Finance 55, 1479-1514.

Subrahmanyam, A., 1994, Circuit breakers and market volatility: A theoretical perspective, Journal of Finance 49, 237-254.

Wermers, R., 1999, Mutual fund herding and the impact on stock prices, Journal of Finance 54, 581-622.

Table 1: Descriptive Statistics
The summary statistics represent the time-series averages of the cross-sectional statistics for an average of 1322 NYSE -AMEX stocks over 132 months from Jan. 1988 through Dec. 1998. The included stocks were required to have daily data available on both CRSP and the transactions databases (ISSM and TAQ). The sample was reconstructed at the beginning of each year. The total number of unique stocks in the sample is 2378.   In Panels B and C, the correlations and autocorrelations are the cross-sectional averages of the time-series correlations.

Panel A: Descriptive Statistics

Variable	Mean	Std. Dev.
Order imbalance in number of transactions	4.67	7.89
Order imbalance in number of transactions scaled by total transactions (%)	-1.72	7.25
Order imbalance in millions of dollars	0.432	0.626
Order imbalance in dollars scaled by total dollar volume (%)	-0.539	7.36
Number of transactions	112.7	48.1
Dollar volume (millions)	7.322	3.769
Absolute value of order imbalance in number of transactions	19.61	6.15
Absolute order imbalance in number of transactions scaled by total transactions (%)	25.83	3.33
Absolute value of order imbalance (millions of dollars)	1.704	0.682
Absolute order imbalance in dollars scaled by total dollar volume (%)	36.62	3.93

Table 1, continued

Panel B: Correlations

	Order imbalance in number of transactions scaled by total transactions	Order imbalance in dollars	Order imbalance in dollars scaled by total dollar volume	Number of transactions	$volume	Return
Order imbalance in number of transactions	0.742	0.288	0.443	0.260	0.141	0.369
Order imbalance in number of transactions scaled by total transactions		0.220	0.637	0.131	0.069	0.343
Order imbalance in dollars			0.461	0.061	-0.001	0.221
Order imbalance in dollars scaled by total dollar volume				0.061	0.022	0.373
Number of transactions					0.558	0.080
$volume						0.048

Panel C: Daily Autocorrelations

Lag	Order imbalance (number of transactions)		Order imbalance (dollar volume)	
	Unscaled	Scaled by total transactions	Unscaled	Scaled by total dollar volume
1	0.331	0.229	0.062	0.091
2	0.237	0.179	0.037	0.054
3	0.202	0.163	0.027	0.043
4	0.184	0.153	0.022	0.035
5	0.172	0.144	0.027	0.031

Table 2: Daily regressions of open-to-close excess returns on contemporaneous and lagged order imbalances

This table presents the cross-sectional average coefficients from the following time-series regression for each stock,

$$R_{it} - R_{mt} = a + b_1 OIB_{it} + b_2 OIB_{it-1} + b_3 OIB_{it-2} + b_4 OIB_{it-3} + b_5 OIB_{it-4} ,$$

where R_{it} is the open-to-close return of stock i on day t calculated using the mid-point of the bid-ask spreads at the open and the close of trading, R_{mt} is the equally weighted open-to-close return on day t, and $OIB=\{OIBNUM,OIBVOL\}$. $OIBNUM_{it}$ ($OIBVOL_{it}$) is the order imbalance in number of transactions (dollar shares) divided by the total number of transactions (total dollar shares) for stock i on day t. The average coefficients are multiplied by 100, and the t-statistics (in parentheses) are obtained from standard errors that are corrected for cross-correlation across the individual stock regression residuals. An estimate of the average cross-correlation (ρ) in the residuals from the time-series regressions is also presented. "Significant" denotes significant at the 5% level (two-tailed test).

Panel A: Open-to-close excess returns on contemporaneous and lagged OIBNUM ($\rho = 0.0076$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it}$	2.326 (19.35)	99.92	99.58	0.00
$OIBNUM_{it-1}$	-0.233 (-5.11)	23.89	2.52	30.95
$OIBNUM_{it-2}$	-0.239 (-6.38)	19.05	1.05	34.86
$OIBNUM_{it-3}$	-0.207 (-5.85)	21.62	1.05	28.93
$OIBNUM_{it-4}$	-0.191 (-5.74)	20.98	1.43	28.97

Panel B: Open-to-close excess returns on contemporaneous and lagged OIBVOL ($\rho = 0.0057$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBVOL_{it}$	1.754 (21.70)	100.00	99.87	0.00
$OIBVOL_{it-1}$	-0.025 (-1.20)	44.58	5.55	11.52
$OIBVOL_{it-2}$	-0.070 (-4.14)	30.70	2.23	16.15
$OIBVOL_{it-3}$	-0.062 (-3.54)	34.15	2.40	13.79
$OIBVOL_{it-4}$	-0.047 (-2.69)	35.37	2.35	10.39

Table 3: Daily regressions of open-to-close excess returns on order imbalances, sorted by firm size
This table presents the cross-sectional average size sorted coefficients from the following time-series regression for each stock,

$$R_{it} - R_{mt} = a + b_1\, OIBNUM_{it} + b_2\, OIBNUM_{it-1} + b_3\, OIBNUM_{it-2} + b_4\, OIBNUM_{it-3} + b_5\, OIBNUM_{it-4}\,,$$

where R_{it} is the open-to-close return of stock i on day t calculated using the mid-point of the bid-ask spreads at the open and the close of trading, R_{mt} is the equally weighted open-to-close return on day t, and $OIBNUM_{it}$ is the order imbalance in number of transactions divided by the total number of transactions for stock i on day t. Stocks are sorted into groups based on market capitalization at the start of each year. Panels A through D present the results for the smallest through largest firm size quartiles. The average coefficients are multiplied by 100, and the t-statistics (in parentheses) are obtained from standard errors that are corrected for cross-correlation across the individual stock regression residuals. An estimate of the average cross-correlation (ρ) in the residuals from the time-series regressions is also presented. "Significant" denotes significant at the 5% level (two-tailed test).

Panel A: Smallest size group ($\rho = 0.0101$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it}$	2.081 (16.35)	99.79	99.06	0.11
$OIBNUM_{it-1}$	-0.084 (-1.68)	36.35	3.99	14.50
$OIBNUM_{it-2}$	-0.134 (-3.29)	28.78	2.10	17.75
$OIBNUM_{it-3}$	-0.168 (-3.82)	28.78	1.79	15.65
$OIBNUM_{it-4}$	-0.144 (-3.33)	28.57	3.36	17.02

Panel B: Size group 2 ($\rho = 0.01443$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it}$	2.250 (12.99)	100.00	99.39	0.00
$OIBNUM_{it-1}$	-0.170 (-2.77)	32.99	3.73	18.84
$OIBNUM_{it-2}$	-0.193 (-3.32)	29.25	1.22	17.97
$OIBNUM_{it-3}$	-0.156 (-2.87)	30.82	1.74	15.45
$OIBNUM_{it-4}$	-0.141 (-2.73)	30.90	1.39	15.63

Table 3, continued

Panel C: Size group 3 ($\rho = 0.00875$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it}$	2.697 (16.52)	99.90	99.31	0.00
$OIBNUM_{it-1}$	-0.319 (-5.18)	24.61	2.06	26.47
$OIBNUM_{it-2}$	-0.294 (-5.77)	21.96	0.69	25.78
$OIBNUM_{it-3}$	-0.197 (-3.98)	26.37	2.25	21.37
$OIBNUM_{it-4}$	-0.196 (-4.10)	27.55	2.06	20.88

Panel D: Largest size group ($\rho = 0.0275$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it}$	3.282 (9.49)	99.85	99.69	0.00
$OIBNUM_{it-1}$	-0.620 (-3.89)	13.43	0.15	43.36
$OIBNUM_{it-2}$	-0.520 (-4.24)	10.49	0.31	47.22
$OIBNUM_{it-3}$	-0.370 (-3.75)	16.67	0.31	38.58
$OIBNUM_{it-4}$	-0.326 (-3.60)	15.74	0.46	35.34

Table 4: Daily regressions of open-to-close excess returns on lagged order imbalances
This table presents the cross-sectional average coefficients from the following time-series regression for each stock,

$$R_{it} - R_{mt} = a + b_1\,OIB_{it-1} + b_2\,OIB_{it-2} + b_3\,OIB_{it-3} + b_4\,OIB_{it-4} + b_5\,OIB_{it-5}\,,$$

where R_{it} is the open-to-close return of stock i on day t calculated using the mid-point of the bid-ask spreads at the open and the close of trading, R_{mt} is the equally weighted open-to-close return on day t, and $OIB=\{OIBNUM,OIBVOL\}$. $OIBNUM_{it}$ ($OIBVOL_{it}$) is the order imbalance in number of transactions (dollar shares) divided by the total number of transactions (total dollar trading volume) for stock i on day t. The average coefficients are multiplied by 100, and the t-statistics (in parentheses) are obtained from standard errors that are corrected for cross-correlation across the individual stock regression residuals. An estimate of the average cross-correlation (ρ) in the residuals from the time-series regressions is also presented. "Significant" denotes significant at the 5% level (two-tailed test).

Panel A: Open-to-close excess returns on lagged OIBNUM ($\rho = 0.0002$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it-1}$	0.214 (26.43)	77.38	25.95	1.35
$OIBNUM_{it-2}$	-0.019 (-2.48)	46.55	5.00	6.22
$OIBNUM_{it-3}$	-0.021 (-2.83)	46.13	3.78	5.97
$OIBNUM_{it-4}$	-0.007 (-1.01)	47.88	3.99	6.06
$OIBNUM_{it-5}$	-0.033 (-4.38)	45.42	4.00	6.69

Panel B: Open-to-close excess returns on lagged OIBVOL ($\rho = 0.0004$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBVOL_{it-1}$	0.131 (18.57)	75.57	23.80	1.68
$OIBVOL_{it-2}$	0.003 (0.59)	48.82	4.67	5.34
$OIBVOL_{it-3}$	-0.006 (-0.99)	49.29	4.50	5.93
$OIBVOL_{it-4}$	-0.003 (-0.50)	48.02	4.21	4.92
$OIBVOL_{it-5}$	-0.000 (-0.07)	50.76	4.88	4.25

Table 5: Daily regressions of open-to-close excess returns on lagged order imbalances, **sorted by firm size**
This table presents the cross-sectional average size sorted coefficients from the following time-series regression for each stock,

$$R_{it} - R_{mt} = a + b_1\, OIBNUM_{it-1} + b_2\, OIBNUM_{it-2} + b_3\, OIBNUM_{it-3} + b_4\, OIBNUM_{it-4} + b_5\, OIBNUM_{it-5},$$

where R_{it} is the open-to-close return of stock i on day t calculated using the mid-point of the bid-ask spreads at the open and the close of trading, R_{mt} is the equally weighted open-to-close return on day t, and $OIBNUM_{it}$ is the order imbalance in number of transactions divided by the total number of transactions for stock i on day t. Stocks are sorted into groups based on market capitalization at the start of each year. Panels A through D present the results for the smallest through largest firm size quartiles. The average coefficients are multiplied by 100, and the t-statistics (in parentheses) are obtained from standard errors that are corrected for cross-correlation across the individual stock regression residuals. An estimate of the average cross-correlation (ρ) in the residuals from the time-series regressions is also presented. "Significant" denotes significant at the 5% level (two-tailed test).

Panel A: Smallest size group (ρ = 0.0034)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it-1}$	0.257 (7.62)	75.32	21.01	1.68
$OIBNUM_{it-2}$	0.041 (1.53)	53.89	6.62	4.62
$OIBNUM_{it-3}$	-0.029 (-1.30)	49.16	4.73	3.99
$OIBNUM_{it-4}$	-0.011 (-0.46)	48.00	4.52	5.78
$OIBNUM_{it-5}$	-0.021 (-0.78)	48.63	5.15	4.73

Panel B: Size group 2 (ρ = 0.0056)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it-1}$	0.234 (6.50)	74.22	20.40	1.22
$OIBNUM_{it-2}$	-0.013 (-0.35)	48.35	5.82	5.21
$OIBNUM_{it-3}$	-0.013 (-0.39)	49.48	3.73	4.34
$OIBNUM_{it-4}$	0.004 (0.11)	50.87	3.91	5.73
$OIBNUM_{it-5}$	-0.025 (-0.78)	48.79	4.17	6.42

Table 5, continued

Panel C: Size group 3 ($\rho = 0.00103$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it-1}$	0.201 (10.50)	70.20	19.80	1.76
$OIBNUM_{it-2}$	-0.063 (-3.30)	45.69	3.43	5.88
$OIBNUM_{it-3}$	0.000 (0.04)	49.02	4.90	6.08
$OIBNUM_{it-4}$	-0.020 (-1.04)	49.51	4.61	6.37
$OIBNUM_{it-5}$	0.010 (0.57)	50.69	3.53	5.49

Panel D: Largest size group ($\rho = 0.0322$)

Variable	Average Coefficient (t-value)	% positive	%positive significant	%negative significant
$OIBNUM_{it-1}$	0.136 (1.27)	71.76	23.61	2.78
$OIBNUM_{it-2}$	-0.160 (-1.36)	35.96	2.78	9.41
$OIBNUM_{it-3}$	-0.053 (-0.50)	41.67	2.62	8.33
$OIBNUM_{it-4}$	-0.009 (-0.08)	49.38	3.55	5.56
$OIBNUM_{it-5}$	-0.019 (-0.18)	43.06	3.54	8.18

Table 6: Daily regressions of open-to-close excess returns on ten lags of order imbalances
This table presents the cross-sectional average coefficients from the following time-series regression for each stock,

$$R_{it} - R_{mt} = a + \sum_k b_k \, OIBNUM_{it-k} \,,$$

where k=1,...,10, R_{it} is the open-to-close return of stock i on day t calculated using the mid-point of the bid-ask spreads at the open and the close of trading, R_{mt} is the equally weighted open-to-close return on day t, and $OIBNUM_{it}$ is the order imbalance in number of transactions divided by the total number of transactions for stock i on day t. The average coefficients are multiplied by 100, and the t-statistics (in parentheses) are obtained from standard errors that are corrected for cross-correlation across the individual stock regression residuals. An estimate of the average cross-correlation ρ in the residuals (which is the average residual correlation across adjacent, alphabetically-sorted stocks from the time-series regressions) is -0.0004.

Variable	Average Coefficient (t-value)	Variable	Average Coefficient (t-value)
$OIBNUM_{it-1}$	0.201 (21.88)	$OIBNUM_{it-6}$	-0.017 (-2.14)
$OIBNUM_{it-2}$	-0.007 (-0.86)	$OIBNUM_{it-7}$	-0.025 (-3.27)
$OIBNUM_{it-3}$	-0.011 (-1.36)	$OIBNUM_{it-8}$	-0.024 (-2.92)
$OIBNUM_{it-4}$	0.005 (0.63)	$OIBNUM_{it-9}$	-0.000 (-0.03)
$OIBNUM_{it-5}$	-0.009 (-1.11)	$OIBNUM_{it-10}$	-0.026 (-3.31)

Table 7: Profits from trading strategy conditional on lagged order imbalance

This table reports the average returns over the 1993-1998 period resulting from a (i) trading strategy that buys if the previous day's imbalance was positive and vice versa, or (ii) buys if the imbalance was very positive (more than one or two standard deviations from zero) and vice versa. Returns are calculated on the basis of the first and last quotes of the day that correspond to actual trades, and are calculated on the day following the order imbalance. All buys take place at the ask and all sells at the bid. The standard deviation of imbalance each quarter is calculated using the imbalance data from the previous three months. OIBNUM is order imbalance in number of transactions divided by total number of transactions, OIBVOL, the order imbalance in dollars divided by total dollar volume. The size groups are formed using the market capitalization as of the close of the previous year. All returns are in percentage points and are calculated based on each transaction and then averaged across transactions and then across stocks. T-statistics are in parentheses.

	All	Small (size=0)	Size=1	Size=2	Large (Size=3)
OIBNUM positive or negative	0.0943 (46.24)	0.2257 (36.06)	0.0763 (20.93)	0.0575 (18.03)	0.0301 (10.83)
OIBNUM one standard deviation above or below zero	0.1085 (29.19)	0.2993 (26.65)	0.0759 (11.57)	0.0603 (10.35)	0.0109 (2.15)
OIBNUM two standard deviations above or below zero	0.1777 (23.08)	0.5471 (20.05)	0.1609 (10.62)	0.1450 (12.08)	-0.0048 (-0.54)
OIBVOL positive or negative	0.0943 (46.24)	0.2257 (36.06)	0.0763 (20.93)	0.0575 (18.03)	0.0301 (10.83)
OIBVOL one standard deviation above or below zero	0.1192 (32.65)	0.2946 (28.86)	0.0900 (15.07)	0.0541 (9.68)	0.0116 (2.26)
OIBVOL two standard deviations above or below zero	0.1462 (13.62)	0.4551 (12.68)	0.1606 (6.84)	0.0748 (4.45)	0.0101 (0.73)