Order flow and prices

Ekkehart Boehmer and Julie Wu*

Mays Business School
Texas A&M University
College Station, TX 77845-4218

March 14, 2006

Abstract

We provide new evidence on a central prediction of microstructure theory, that order flow is related to prices. We examine proprietary data on a broad panel of NYSE-listed stocks that reveal daily order imbalances by institutions, individuals, and market makers. We can further differentiate regular institutional trades from institutional program trades. Our results indicate that order imbalances from different trader types play distinctly different roles in price formation. Institutions and individuals are contrarians with respect to previous-day returns, but differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns, and we provide cross-sectional evidence that this relationship is likely to be the result of firm-specific information institutions have. Individuals, specialists, and other traders provide liquidity to these actively trading institutions. Our results also suggest a special role for institutional program trades. Institutions choose program trades when they have no firm-specific information and can afford to trade passively. As a result, program trades provide liquidity to the market. Finally, both institutional non-program and individual imbalances (information which is not available to market participants) have predictive power for next-day returns.

* Email addresses: eboehmer@mays.tamu.edu, jwu@mays.tamu.edu. We thank Kerry Back for his comments.

Order flow and prices

A central prediction of market microstructure theory is that order flow affects prices. This follows from inventory models, where market makers temporarily adjust prices in response to incoming orders (Garman, 1976; Amihud and Mendelson, 1980; Stoll, 1978; Ho and Stoll, 1981). It also follows from information-based models where some traders have information about future asset value, so their trades lead to permanent price adjustments (Glosten and Milgrom, 1985; Kyle, 1985; Easley and O'Hara, 1987). The prediction that order flow affects prices is robust to competition among informed traders (Holden and Subrahmanyam, 1992), endogenous order sizes (Back and Baruch, 2005), and the consideration of strategic uninformed traders (Admati and Pfleiderer, 1988; Spiegel and Subrahmanyam, 1992).

Empirical research is almost uniformly consistent with this basic prediction and generally supports both inventory and information effects. Ho and Macris (1984) document that an options specialist adjusts prices in a way that is consistent with inventory models. Other early studies compare stock return variance during the trading day with overnight variance. French and Roll (1986) find much higher variance while markets are open and attribute this finding to the activities of informed traders whose information is impounded into prices. Hasbrouck (1988, 1991a, 1991b) uses a VAR model to disentangle (transient) inventory effects from (permanent) information effects. He demonstrates significant information effects on prices and some evidence consistent with inventory adjustments. More recent studies focus on daily net order flow, the difference between buy and sell volume, to explain contemporaneous and next-day returns. Chordia, Roll, and Subrahmanyam (2002) show that aggregate order imbalance is positively associated with market returns, and Chordia and Subrahmanyam (2004) obtain comparable results in the cross-section of stocks.[1]

While microstructure theory clearly distinguishes among different trader types according to their information and motives for trading, data limitations typically limit empirical tests to analysis that pools all traders. In this paper, we use a unique dataset derived from NYSE audit trail data that allows us to distinguish

[1] A related literature focuses on the relation between trading volume and returns. See Baker and Stein (2004), Campbell, Grossman, and Wang (1993), Chordia, Roll, and Subrahmanyam (2001), Chordia, Huh, and Subrahmanyam (2004), and Karpoff (1987) for a survey of earlier work.

buys and sells from different trader types: individuals, institutions, non-NYSE market makers, and specialists. We further differentiate regular institutional trades, index arbitrage program trades, and other program trades.[2] These types are likely to differ in their trading motives and trading strategies and, in particular, in the quantity and quality of private information. Therefore, we expect that the relationship between order flow, liquidity, and returns differs across these trader types, and our tests are designed to measure these differences. Understanding how trader type-specific order flow affects prices and liquidity has important implications for modeling the evolution of liquidity, trader behavior, and market design. Moreover, analyzing these differences allows us to refine inferences from empirical microstructure research that is based on aggregate data.

Our analysis is closely related to Chordia and Subrahmanyam (2004) and Griffin, Harris, and Topaloglu (2003). Chordia and Subrahmanyam develop a simple two-period trading model where a competitive discretionary liquidity trader can split orders between two periods. In addition, a nondiscretionary liquidity trader and a competitive informed trader, who receives a noisy signal before trading, submit orders in the second period. A competitive market maker picks up the imbalance resulting in each trading period. Chordia and Subrahmanyam show that it is optimal for the discretionary liquidity trader to split orders, so that order imbalances are positively autocorrelated over time. Moreover, because market makers can partially predict the second-period order imbalance, the model implies a positive relationship between returns and lagged imbalances. Using a sample of (on average) 1322 NYSE-listed stocks between 1988 and 1998, Chordia and Subrahmanyam estimate security-specific time series regressions and find evidence consistent with these predictions.[3]

Griffin, Harris, and Topaloglu observe the identity of brokerage firms in Nasdaq 100 stocks for each trade over 210 trading days from May 2000. They classify brokers according to their main clientele, and in this way

---

[2] Program and index arbitrage program trades are institutional trades but we differentiate these from regular institutional trades. First, the NYSE defines program trades as simultaneous trades in 15 or more stocks worth at least $1 million. In contrast, the typical trade size on the NYSE is about $20,000. Second, trading motives differ. Index arbitrage program trading attempts to profit from the temporary discrepancies between derivative and cash markets, whereas regular program trading can be associated with other specific trading strategies. Third, regulatory treatment differs across these order types. Both types of program trade must be reported to the exchange, and NYSE Rule 80A suspends some type of index arbitrage program trades on volatile trading days.

[3] Chordia, Roll and Subrahmanyam (2002) use a similar approach to study daily order imbalances aggregated across stocks. They document that aggregate imbalances are highly persistent and positively related to contemporaneous market returns. They also find that, in the aggregate, traders exhibit contrarian behavior on daily basis.

obtain an approximate classification into institutional and retail for most of the trades. They document that institutional imbalances are persistent over several days. Moreover, institutions are more likely to buy after positive returns on the previous day and their imbalance has a positive contemporaneous relation to returns.

Our proprietary data set allows additional inferences that complement the results in Chordia and Subrahmanyam and Griffin, Harris, and Topaloglu. In contrast to Chordia and Subrahmanyam's analysis of order flow aggregated across all traders, we do not have to infer trade direction and, implicitly, market maker trades using the Lee and Ready (1991) algorithm. Rather, we directly observe buys and sells for each trader type and market-maker trades. Griffin, Harris, and Topaloglu's sample allows a distinction between institutional and retail trades, but is limited to the 100 most liquid Nasdaq stocks over a short period. One important advantage of Griffin, Harris, and Topaloglu's data is that it provides trade-by-trade information, which they exploit to look at the cause of institutional imbalances. They find results consistent with previous evidence that institutions are positive-feedback traders and the intraday information allows Griffin, Harris, and Topaloglu to disentangle the direction of causality between returns and institutional trading decisions. In contrast, our panel is much larger both in the cross-section and over time and provides a finer trader-type classification that does not depend on classifying brokerage firms. Moreover, our NYSE data is not limited to the most liquid stocks. While we provide some results on the determinants of order imbalances, our main focus is on their consequences for contemporaneous and future prices and on measures of market liquidity. Furthermore, we analyze how these consequences differ across trader types going beyond a retail-institutional dichotomy.

First, we find that, during our sample period, institutions trade as contrarians with respect to prior-day returns. This is consistent with Lipson and Puckett (2005) and aggregate evidence in Chordia, Roll, and Subrahmanyam (2002), but contrary to the Nasdaq evidence in Griffin, Harris, and Topaloglu (2003). We further show that, for the largest size quartile, institutions are momentum traders with respect to market movements on the previous day. We argue that the countervailing effects of idiosyncratic and market returns could explain the differences between our results and those in Griffin et al., whose sample is limited to a period of substantial negative returns.

Second, we find that institutional imbalances are positively related to contemporaneous returns, controlling for market movements and persistence in imbalances. This suggests that institutional trading is associated with positive price impacts, as predicted by theory, and is consistent with a prevalence of information-based trading. While our daily data limits inferences about information content, we show that the institutional price impact coefficient is positively related to cross-sectional proxies for information asymmetry. In particular, institutional imbalances have a greater effect on contemporaneous returns in stocks with high effective spreads, controlling for firm size. This could indicate that information is an important driver of the effect that institutional imbalances have on prices, but it is also consistent with an inventory effect: if market makers hold undesirable inventory levels, liquidity would be limited, causing high spreads and larger effects of trading on returns. To disentangle these two explanations, we decompose effective spreads into a temporary price impact (likely associated with inventory effects) and a permanent component (likely associated with information in order flow). We find that institutional order imbalances have a greater effect on returns when permanent price impacts are large, even when controlling for inventory effects. Therefore, information appears to play a more prominent role than inventory effects in explaining how institutional trading affects prices.

Third, institutional imbalances have explanatory power for next-day returns. This also suggests that institutional trading is, at least in part, information based. We note that this predictive ability cannot be exploited to generate abnormal trading profits, because information on trader groups is confidential and not even disclosed ex post. No trader (including specialists) can observe the trader type and base his own trading on specific types' order flow.

About one quarter of institutional trading is in form of program trades, and we document that this order type plays a special role during our sample period. Institutions choose endogenously between a regular order and a program trade. Our priors are that program trades are unlikely to be motivated by firm-specific private information, and that their relationship to prices differs from the one we find for regular institutional imbalances. This is strongly supported by the evidence. While program-trade imbalances also tend to be contrarian, they have a negative relationship to contemporaneous returns. This suggests that institutions use program trades when they have little information, and provide liquidity to other traders in the course of looking for the best price by trading passively.

Consistent with Kaniel, Saar, and Titman (2004), we show that individuals also trade as contrarians. Kaniel et al. infer that individuals provide liquidity to institutions and we provide evidence consistent with this claim. Specifically, we show that individual order imbalances have a negative effect on contemporaneous returns, consistent with liquidity provision. While individuals buy and sell at different times than institutions, their imbalances also have predictive power for next-day returns. But individuals provide only 5% of trading volume, so that they alone cannot satisfy the imbalances of informed institutional traders. Our results suggest that the remaining imbalance is filled by other institutional traders, who tend to be uninformed and use program trades (which account for about 20% of trading volume). The remaining imbalance is then filled by market makers.

Our analysis is related to several studies that also address differences between trader types. Lee (1992) examines order imbalances around earnings announcements to see if institutional investors react differently from individual investors to the same earnings news using trade sizes as proxies for institutions and individuals. Lee et al. (2004) examine marketable order imbalances from various investor categories on the Taiwan Stock Exchange. Grinblatt and Keloharju (2000) investigate the trading behavior of Finnish investors. Griffin, Harris, and Topaloglu (2005) study aggregate trading behavior around the "tech bubble." Choe, Kho and Stulz (1999) analyze order imbalances to investigate if foreign investors contribute to the Korean stock market crisis in 1997.

The rest of this paper is organized as follows. We describe the data, sample selection, and variables in Section I. Section II contains the main empirical tests and Section III concludes.

I. Data and sample construction

We use proprietary data from the New York Stock Exchange that allows us to separately observe buy and sell transactions for different trader types. These data cover all securities traded on the NYSE between January 2000 and April 2004 and are based on the NYSE's Consolidated Audit Trail Data (CAUD), which provide information on nearly all trades executed at the NYSE. CAUD are the result of matching trade reports to the underlying order data; they show for each trade the individual buy and sell orders executed against each other (or market maker interest). Each component is identified by an account-type variable that gives some information on trader identity. Providing the account type classification is mandatory for brokers (although it is not audited by the NYSE on a regular basis). Different regulatory requirements include obligations to indicate orders that are part of program trades, index arbitrage program trades, specialist trades, and orders from other market makers in the stock. Each of these categories is further divided into proprietary member trades, trades by retail customers, and agency trades.

The data set available for this study aggregates buy and sell volume separately for each day and security for certain combinations of account types, using the number of trades, share volume, and dollar volume. We exclude trades that are cancelled or later corrected, trades with special settlement conditions, and trades outside regular market hours. We can distinguish the following six account-type categories: individuals, institutions, institutional regular program trades, institutional index arbitrage program trades, non-NYSE market maker proprietary trades, and specialists. NYSE account types have been used in a handful of other papers. For example, using the same data set Kaniel, Saar, and Titman (2004) investigate retail trading and Boehmer and Kelley (2005) look at the relationship between informational efficiency and institutional trading. Boehmer, Jones, and Zhang (2005) analyze differences in the informativeness of short selling across account types.

We match the NYSE data to the security information from the Center for Research in Security Prices (CRSP) and obtain daily returns, market capitalization, and consolidated trading volume. Our sample includes only domestic, single-class common stocks. Once a security is delisted or its monthly average price falls below $1 or rises above $999, it is subsequently dropped from the sample. Next, we obtain all primary market prices and quotes from TAQ that satisfy certain criteria.[4] For each stock, we aggregate all trades during the same second that execute at the same price and retain only the last quote for every second if multiple quotes were issued. We require that the monthly average number of daily transactions for a stock be greater than 20. In addition, a stock

---

[4] We use trades and quotes only during regular market hours. For trades, we require that TAQ's CORR field is equal to zero, and the COND field is either blank or equal to *, B, E, J, or K. We eliminate trades with non-positive prices or sizes. We also exclude a trade if its price is greater than 150% or less than 50% of the price of the previous trade. We include only quotes that have positive depth for which TAQ's MODE field is equal to 1, 2, 3, 6, 10, or 12. We exclude quotes with non-positive ask or bid prices, or where the bid price is higher than the ask price. We require that the difference between bid and ask be less than 25% of the quote midpoint.

has to have at least 100 consecutive trading days to be included in the empirical time-series analysis. This procedure leaves 1,300 different firms over the sample period.

For each security, we compute daily equally-weighted relative effective spreads as proxies for information asymmetry. Effective spreads are computed as twice the absolute difference between the execution price and the quote midpoint prevailing when the trade was reported (see Bessembinder, 2003).

I.1 Measuring order imbalances

Following Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004), we compute three measures of order imbalance for each trader group-stock-day observation: the number of buy transactions less the number of sell transactions of a trader group scaled by the total number of trades, the number of shares bought less the number of shares sold by a trader group scaled by total share volume, and a trader group's dollar volume of buys minus sells scaled by total dollar volume. Scaling the order imbalances by total trading activity standardizes the imbalance measures across stocks. We use a volume-based normalization (rather than shares outstanding) for two reasons. First, we believe it is preferable to standardize a flow measure by a flow measure. Second, we wish to abstract from volume effects in order imbalances to better focus on the relative imbalances across different trader groups.

Our measures of order imbalances are similar to those used in Griffin, Harris, and Topaloglu (2003), but differ in important ways from the TAQ-based measures used in Chordia, Roll, and Subrahmanyam (2002) and Chordia and Subrahmanyam (2004). TAQ provides information on executed trades, so by construction there is precisely one share bought for every share sold. Therefore, a direct measure of imbalances between demand and supply is not available – shares bought always equal shares sold. Researchers get around this issue by defining order imbalances in terms of order aggressiveness. TAQ does not provide information on trade direction – it has to be inferred from approximate algorithms such as Lee and Ready (1991). Based on this algorithm, a trade executed at a price higher (lower) than the prevailing quote midpoint is classified as a buyer- (seller-) initiated. If the transaction price equals the quote midpoint, it is classified as buyer- (seller-) initiated if the transaction price is above (below) the previous transaction price. This procedure seeks to identify the active side of the trade, that is, the side who is less patient and therefore pays the spread to the passive side. In practice, the active side is likely to be a trader using a marketable order; the passive side could be a limit-order trader or a market maker. Order imbalances based on only the initiating side then provide a measure of the relative impatience of buyers and sellers. This makes economic sense, because one can imagine a latent pool of liquidity that becomes available when the premium offered by an impatient trader becomes sufficiently large. An impatient trader can access this latent liquidity by offering better prices than currently available.

Defining imbalances in terms of trader aggressiveness has two disadvantages. First, the Lee and Ready (1991) algorithm is known to be somewhat inaccurate. Lee and Radhakrishna (2000) show that 40% of NYSE trades cannot be classified at all, and 7% of the remaining trades are not classified correctly. Second, we need to assume that all traders who intend to achieve a certain portfolio position use marketable orders. While this assumption is relatively innocuous on a trade-by-trade basis, it becomes problematic when traders have longer-term horizons and use different order types to achieve their trading targets. Evidence suggests that traders do indeed use complex strategies to achieve trading objectives. In an experimental study, Bloomfield, O'Hara and Saar (2005) find that traders switch among order types based on the value of their information. Kaniel and Liu (2005) show that informed traders may prefer to use limit orders depending on the horizon of their information. Order switching affects inferences from TAQ-based imbalances. To illustrate this point, suppose a portfolio manager sets a trading target for the day of 100,000 IBM shares and no other active traders are in the market. To achieve this position, his strategy need not be limited to marketable orders. For example, he might initially try to obtain the position at low cost by placing passive limit orders, which may attract some sellers. But if execution rates are low, he may resort to marketable orders towards the end of the trading day. Another example is the prevalence of VWAP trading, where traders aim at achieving an average execution price that equals the volume-weighted price (VWAP) over the same period. In both cases, the true order imbalance is 100,000 shares, but the TAQ-based imbalance could be very different, depending on the fraction of trades using marketable orders. As these simple examples illustrate, TAQ-based imbalances may not capture true imbalances when traders use complex strategies.

In this paper, we use a different approach that is not sensitive to order choice or to misclassification associated with trade-signing algorithms. While our data is also trade-based, so aggregate demand equals aggregate supply, this is not true within individual trader types. For each trading day and each security, we observe imbalances that reflect the entire buying and selling activity for each trader type, including the specialist. For example, suppose retail buyers purchase *N* shares from institutions; in this case, the aggregate imbalance is zero, but we would observe a retail imbalance of *N* and an institutional imbalance of -*N*. Consistent with the evidence in Kaniel and Liu (2005), our approach implicitly assumes that market and limit orders can both affect price.

I.2 Characteristics of order imbalances

We summarize the trading activity and order imbalances for our sample in Table 1. We compute cross-sectional averages of time-series means separately for each trader type. Panel A shows that institutions account for the bulk of the trading: regular institutional share volume averages 56% of total volume, and program/index arbitrage program trading account for 19% and 1.6%, respectively. Retail traders account for 5% of volume, other market makers for 0.7%, and specialists for about 18%. These averages are similar in terms of dollar trading volume. Comparing to the percentages of trades, we see that institutional trades tend to be larger-sized than the average, while program trades are somewhat smaller. Consistent with Madhavan and Sofianos (1998), we note that specialists do not always take the opposite side of externally initiated trades, which would imply a participation rate of 50%. This implies that a substantial fraction of trading is among market participants.

Panel B of Table 1 reports mean levels of order imbalances for each trader type. Institutions are net buyers over the sample period, whether using regular or program trades (the negative imbalance in terms of transactions indicates that institutions tend to use larger trades). The three remaining groups are net sellers. Panel C of Table 1 presents mean order imbalance scaled by the corresponding measure of total trading volume. Again, we observe that institutions are net buyers in terms of share and dollar volume, regardless of order type. One difference to the levels in Panel B is that specialists are net buyers based on scaled order imbalances. This could be due to relatively high buying activity from specialists for less actively traded stocks. If the public tries to sell these less liquid stocks, specialists are more likely to step in to provide liquidity by buying from an outside trader. Consistent with a policy that seeks to minimize inventory, we note that specialists' average imbalance is small relative to those of other traders.

I.3 Cross correlations of order imbalances among trader groups

Table 2 shows the correlations across trader groups. We compute the time-series correlation for each stock and then average across stocks. The three different imbalance measures generally provide comparable results, and we make a couple of interesting observations. First, with the exception of index arbitrage trades, specialists' imbalances are negatively correlated with those of each other group. This is what we would expect if their trading is mainly passive, that is, specialists engage in market making activity and provide liquidity when orders arrive. Second, institutions trade in the opposite direction as individuals. This is consistent with the Kaniel, Saar, and Titman's (2004) interpretation that individuals provide liquidity to institutions, although the simple correlations do not reveal whether institutions or retail are the more active side. Third, institutions appear to decrease their regular trading when they use program trades. This suggests that program trades serve a specific purpose – we will return to this issue later on.

The table also shows the correlation between imbalances and contemporaneous returns. Consistently across different measures, specialist imbalances are negatively correlated with returns. This is again an expected consequence of market making – as other traders buy, for example, they drive up price and specialists sell in the course of liquidity provision. Again consistent with Kaniel, Saar, and Titman's interpretation, individuals also seem to provide liquidity in that their imbalances are negatively correlated with returns. Most interesting are the three institutional types. Focusing on one of the volume measures in Panel B or C, regular institutional trades and index arbitrage trades are moving with the market. In contrast, program trades are moving against the market. This suggests that institutions use regular orders when they are trading actively. Index arbitrage trades attempt to exploit potentially short-lived price discrepancies between the derivative and cash markets; therefore, they are also active trades that move price in the direction of trading. In contrast, institutions appear to use program trades primarily when they are trading passively and therefore program trades seem to provide liquidity. Of course, the correlation evidence presented here is only suggestive and we address each of these issues more rigorously below.

I.4 Persistence of order imbalances

Chordia and Subrahmanyam (2004) report that TAQ-based order imbalances are highly persistent on a daily basis. They suggest that this is because traders split order to minimize price impact. Order splitting is typically attributed to large traders, such as institutions (Keim and Madhavan, 1995; Chan and Lakonishok, 1995). Table 3 shows evidence consistent with this claim: regular institutional trades and program trades are highly persistent. Individual trades, however, show even stronger persistence, consistent with the Nasdaq evidence in Griffin, Harris, and Topaloglu (2003). We measure the weakest persistence for index arbitrage trades; this makes sense if these traders' motives are short-lived. Specialists are the only trader type with negatively autocorrelated (volume-based) imbalances. This is consistent with inventory management – when specialists accumulate a long inventory position, for example, they are more likely to sell on the subsequent day.

II. The relationship between order imbalances and returns

Microstructure theory suggests that informed traders impact stock prices (Kyle, 1985; Glosten and Milgrom, 1985). We also know from previous analysis that different market participants are differentially informed and have different trading motives, and therefore their orders are likely to have a different relationship to price changes. While several studies examine institutional influence on returns (see, for example, Keim and Madhavan, 1995; Chan and Lakonishok, 1995; Griffin, Harris, and Topaloglu, 2003; Boehmer and Kelley, 2005), few studies examine the influence of retail trading (see Jones and Lipson, 2004; Kaniel, Saar, and Titman, 2004), and little is known about how program trading and specialist activity are related to returns. In this section, we analyze the dynamic relationship between imbalances and returns for the different trader types in three different ways. First, we test how past price changes affect imbalances. These tests allow inferences on the determinants of order imbalances. Second, we estimate the price impact of imbalances. By regressing returns on contemporaneous imbalances, we can make inferences about which traders demand and which traders supply liquidity. Third, we estimate simple predictive regressions that relate returns to imbalances on the previous day. These tests allow inferences on the information of traders in the different groups.

Following Chordia and Subrahmanyam (2004), we estimate time-series regressions for each stock and conduct inferences on the cross-section of estimated coefficients. For each security-specific regression, we require at least 100 valid observations. In contrast to Chordia and Subrahmanyam, we conduct this analysis separately for each trader type. The Fama-MacBeth approach alleviates problems with autocorrelated errors in the time-series regressions, but cross-sectional correlation could affect the standard errors we use to construct test statistics. Although the cross sectional correlations in most regression specifications turn out to be quite small, we correct for the cross-sectional correlations following the procedure in Chordia and Subrahmanyam (2004).

From here on, we report only results based on share-volume imbalances, which we believe best capture the essence of the argument based on Kyle (1985) and Glosten and Milgrom (1985) that order imbalances are related to returns. We have repeated all regressions using scaled imbalances defined in terms of transactions and dollar volume. Our results do not qualitatively change across measures and we note differences where applicable.

II.1 Determinants of order imbalances

To determine how order imbalances on day *t* depend on past returns, we estimate the following time-series regression for each trader type:

$$OIB_{it} = \alpha_i + \sum_{k=1}^{5} \beta_{ik} R^*_{i,t-k} + \sum_{k=1}^{5} \gamma_{ik} R_{m,t-k} + \sum_{k=1}^{5} \delta_{ik} OIB_{i,t-k} + \varepsilon_{it} \tag{1}$$

where *OIB* is the trader-type specific share imbalance scaled by total share volume, R_m is the equally-weighted close-to-close midpoint return across all sample stocks, and R_i^* is the residual from a time-series regression of R_i, the close-to-close midpoint returns for stock *i*, on R_m. We employ close-to-close midpoint returns to mitigate the effect of bid-ask bounce on returns, although we obtain qualitatively identical results using returns based on closing prices from CRSP. Decomposing returns into market and idiosyncratic returns allows us to assess separately each component's effect on order imbalances.

We first estimate a restricted variant of Equation (1) that replaces the R_i^* and R_m by the respective weekly returns preceding day *t*. Panel A of Table 4 presents cross-sectional mean and median coefficients for the restricted model and Panel B presents the unrestricted model. Consistent with Table 2, both regressions show that specialists' order imbalances tend to be negatively autocorrelated, and those of all other trader types are positively autocorrelated.

We show that institutions trade as contrarians relative to past returns. In fact, comparing the magnitude of coefficients, institutions show the strongest contrarian response among all trader types when using regular trades.

Contrarian behavior with respect to security-specific past returns is less pronounced when institutions use program trades, and it is not visible when they engage in index arbitrage. Our results contrast to Griffin, Harris, and Topaloglu's (2003) findings, who argue that institutions are trend chasers on a daily basis. But our results are consistent with Lipson and Puckett (2005), who study imbalances of pension fund on volatile days and find that pension funds are contrarian traders. They are also consistent with the evidence presented in Chordia, Roll and Subrahmanyam (2002), who find that aggregate order imbalances are contrarian. In Panel B, we show that the contrarian behavior is primarily driven by returns on the previous two days.

Consistent with Kaniel, Saar, and Titman (2004), we find that individuals trade as contrarians relative to a stock's returns during the previous week. Only specialists trade in the direction of previous-week returns, apparently in response to the contrarian demand by the other trader types.

While regular institutional and individual imbalances are not sensitive to market returns, we find that institutional program and index arbitrage imbalances are also contrarian with respect to market returns. In fact, these imbalances are more sensitive to market returns than to idiosyncratic returns. This is a notable result, because it suggests that institutions use program trades to respond to market movements.

Panel C demonstrates that the return effects are present in each size quartile (size quartiles are based on the time-series average market value of equity). Only quartile 4 (the largest firms) shows somewhat different coefficients on market returns. In this quartile, institutions and individuals are still contrarian with respect to idiosyncratic returns, but they are momentum traders with respect to market returns. The counteracting influences of market and security returns in the top size quartile could potentially explain the differences between our results and those in Griffin, Harris, and Topaloglu, because they do not allow market returns to affect order imbalances.[5] Their sample consists of all Nasdaq 100 stocks between May 1, 2000 and February 28, 2001. During this period, the Nasdaq 100 index declined by 50.7%. If institutional trading decisions depend on market returns, this

[5] Griffin, Harris, and Topaloglu control for market movements by regressing order imbalances on excess returns, defined as security returns net of market returns. When we repeat this approach on our data, the coefficient on excess returns are very similar to those reported in Table 4. In particular, institutional imbalances are still significantly negatively related to past (excess) returns. Therefore, allowing the coefficient on market returns to vary does not cause the different results. We also obtain similar results when we include unadjusted security returns (and omit market returns).

pronounced decline should prompt large negative institutional imbalances. If the Nasdaq decline affected most securities in a similar (negative) way, we would expect a positive correlation between security returns and imbalances during this period. Therefore, it is possible that the momentum behavior documented in Griffin, Harris, and Topaloglu is driven by selling due to these pronounced market-wide price moves, rather than a response to security-specific returns.

Finally, we note that our results are not inconsistent with cross-sectional institutional momentum patterns documented at the quarterly horizon (see Grinblatt, Titman, and Wermers, 1995, or the review in Sias, 2005), because their decisions about long-term holdings could differ from their decisions about daily trading strategies. This is an important distinction, because information on institutional holdings is only available with quarterly frequency. Our findings illustrate that more detailed information is necessary to obtain a more accurate picture on institutional trading decisions.

II.2 Price impact: order imbalances and contemporaneous stock returns

In this section, we ask how daily order imbalances affect contemporaneous returns. This analysis allows inferences about potential differences in informedness and liquidity provision across trader types. The two concepts are closely related but work in opposing directions. In general, traders with short-lived information need to trade actively so their orders execute before their information gets impounded into prices. Impatient, active trades tend to move prices in the direction of the order. For example, a market buy order should lead to a price increase. In contrast, patient traders can afford to trade passively. For example, a limit buy order only gets executed once prices decline sufficiently. Upon execution, the active part of this trade (the sell order) should generally exert downward pressure on price. In this case, the buyer provides liquidity to the market. As a result, we expect a stronger positive relationship between imbalances and returns for trader types who, on average during a trading day, are more informed; we expect a negative relationship for trader types who, on average, supply liquidity to the market.

We estimate the following regression model:

$$R_{it} = \alpha_i + \beta_i R_{mt} + \sum_{k=0}^{4} \gamma_{ik} OIB_{i,t-k} + \varepsilon_{it} \qquad (2)$$

where the variables are as defined in Equation (1). We believe it is important to control for market returns, because we would like to capture return movements that are idiosyncratic to the order imbalances we examine. A potential problem with this specification is that market returns are correlated with imbalances, as shown in Table 4, so model (2) is subject to multicollinearity. As a robustness check, we estimate a regression without market adjustment and another regression of excess returns (over R_m) on current and lagged order imbalances and obtain qualitatively identical results in both cases. Therefore, we present results from (2) and do not impose the restriction that the coefficient on R_m equal one. We also repeat the estimation with a different risk adjustment and use the three Fama-French factors instead of market returns alone. The results are qualitatively identical and therefore not reported.

Next, we examine the relationship between different trader groups' imbalances and contemporaneous price changes. Table 5 reports cross-sectional averages of the time-series coefficients for each security. Controlling for persistence in order imbalances, the coefficient on contemporaneous institutional imbalances is positive. This implies that institutional buying is associated with a greater price increase than implied by the simple market-model adjustment, and institutional selling is associated with a greater price decline. This result is consistent with institutions having information that affects prices when they trade. The distribution of coefficients is somewhat skewed, however, because the median coefficient is not distinguishable from zero using a Wilcoxon test. Unfortunately, we do not have information on trader identity beyond the account types and cannot differentiate between institutions likely to have private information (perhaps hedge funds and other active traders) and others (such as index funds). For example, Keim and Madhavan (1995) document considerable heterogeneity in trading styles based on past price movements. Some institutions pursue trend-chasing strategies while others tend to adopt contrarian strategies; thus, the overall effect of institutional trading strategies on contemporaneous prices could also differ substantially. This naturally makes it difficult to isolate information-based trading by looking at institutions as a group.

The mean effect of regular institutional trading is positive, however, indicating that the average institutional trader appears to move prices. But this only holds for regular institutional trades – program trade imbalances have a negative contemporaneous relationship to prices, and index arbitrage imbalances have no effect at all. These observations are consistent with two economic explanations. First, it is unlikely that program trades of either type are motivated by private information about individual securities, because they involve simultaneous orders in several different stocks. Second, institutions may use program trades for passive strategies. For example, when institutions experience inflows or outflows, they could be indifferent between trading several specific stocks and prefer to change their holdings of those where they obtain the best price. This could be achieved by a passive trading strategy that places a set of limit orders for a range of stocks (which, for sufficient size and at least 15 stocks, would be classified as a program strategy). Depending on which orders execute, the institutions can then cancel the remaining orders and/or resubmit new ones to remain close to its desired target portfolio. Such a strategy would supply liquidity to the market, consistent with a negative price impact for program trades.

Individuals, specialists, and other market makers' imbalances have a significantly negative association with contemporaneous returns. These trader types appear to provide liquidity to active institutional traders. The negative price impact for specialists and other market makers is what we expect from bona fide market making activities. The negative price impact for individuals is consistent with Kaniel, Saar and Titman (2004), who suggest that individuals provide liquidity to institutions. It is important that the negative contemporaneous relationship with returns does not imply that individuals and market makers lose, on average. If the price pressure generated by institutional traders is temporary, individuals and market makers can reverse their positions when it subsides and earn the spread on their trades.

Panel B of Table 5 shows average price impact coefficients for the same model, but computed separately for each size quartile. Coefficients for individuals and market makers are largely consistent with those in Panel A, but the disaggregation provides a partial explanation for the large dispersion of institutional price impacts. Panel B shows that institutional price impacts differ significantly across size quartiles. Positive impacts are strongest in the smallest quartile. In fact, institutional imbalances cause price moves in small firms whether they arise from regular or program trades. In the largest quartile, we again observe similar skewness in coefficients as in the full sample. It is well known that institutions tend to invest more in larger firms, so institutional trading in the small quartile could be dominated by information-based active traders. In the large quartile, information-based traders are likely to co-exist with passive institutional traders, so the overall price impact coefficient is more ambiguous.

We have no good explanation for why institutional price impacts are zero (with negative median) in the middle quartiles. Overall, we note that only individuals and market makers consistently do *not* move prices in the direction of their imbalances.

A better way to address the heterogeneity among institutions is to relate firm-specific price impact coefficients to cross-sectional characteristics of the securities. If the positive coefficients arise because of information-based trading, we would expect them to be larger for firms that are characterized by greater information asymmetry. Following Llorente et al. (2002), we regress the price impact coefficients (the coefficient on *OIB (t)* in Panel A of Table 5) on proxies for information asymmetry. Higher information asymmetry is typically associated with greater relative effective spreads. However, effective spreads also increase for other reasons that affect prices in the short term. We attempt to separate these two effects by decomposing effective spreads into a temporary component (realized spreads) and a permanent component (the trade-to-trade price impact). Realized spreads are typically associated with inventory effects and are measured as the price change from the trade price to the quote midpoint five minutes after the trade (multiplied by -1 for sell-signed trades). Trade-by-trade price impacts provide an estimate of the degree of informed trading in a security and are defined as the change in quote midpoints from just before a trade to five minutes afterwards. Using TAQ, we compute daily equally-weighted averages of these variables, and use their time-series averages as regressors. If information asymmetries are driving institutional price impact coefficients, we expect that it is positively related to the permanent component of spreads in the cross-section of stocks.

The estimates in Table 6 are broadly consistent with the information-based explanation for institutional price impact coefficients. Controlling for firm size, coefficients on effective spreads are positive. This suggests that institutional imbalances are associated with greater price impacts in stocks with greater information asymmetry. When we decompose spreads into temporary and permanent components, only the permanent component is related to institutional price impacts. Therefore, institutional price impacts are greater in stocks that are characterized by more informed trading activity.

II.3 Predictability: order imbalances and future stock returns

A more direct way to evaluate the average information advantage of particular trader groups is to estimate return movements on the day following an order imbalance. Chordia and Subrahmanyam (2004) show that trade-based order imbalances predict next-day returns. In this section, we investigate which trader types are driving this predictability. There is some prior evidence of such predictive ability for certain traders. Guun and Gaun (2003) find that, in Australian markets, limit order imbalances have some predictability for returns. For the U.S., Boehmer, Jones and Zhang (2005) show that institutional shorting activity is most informative among different trader types.

A positive relationship between current imbalances and future returns could also arise if traders split their order across days and the resulting autocorrelation in imbalances is not immediately reflected in prices. Evidence in Chordia, Roll, and Subrahmanyam (2005) shows, however, that at least for large stocks this is not the case – this type of information is rapidly impounded into prices. Despite predictability in imbalances over several days, they find little evidence of predictability in returns for intervals longer than about 30 minutes. Therefore, it is unlikely that order splitting alone could drive a positive relationship between imbalances and subsequent returns. We also note that any apparent predictability based on trader-group specific imbalances could not be exploited by market participants, because information on group-specific order flow is not publicly disclosed.[6]

We estimate the following model:

$$R_{i,t} = \alpha_i + \beta_i R_{mt} + \sum_{k=1}^{5} \gamma_{ik} OIB_{i,t-k} + \varepsilon_{it} \qquad (3)$$

where the variables are as defined in Equation (1). Similar to the forecast regression specifications used in Chordia and Subrahmanyam (2004), we regress a stock's return on five lags of a trader type's imbalances and the market return. We obtain qualitatively similar results when we add lagged security returns as explanatory variables, or when we use excess returns over market as the dependent variables (and omit market return on the right hand side).

---

[6] The specialist can observe whether an order is part of a program trade, but cannot distinguish any of the other account types.

Table 7 reports the results. Inconsistent with Griffin, Harris, and Topaloglu (2003), who find no predictability on Nasdaq, institutional imbalances resulting from regular trades have some predictive ability in our data. This suggests that institutions have some information about future returns on NYSE-listed stocks. Although we use a share-based measure of imbalances, our estimates are of similar magnitude as those reported in Chordia and Subrahmanyam (2004). But as implied by the evidence in Table 5, institutional imbalances only contain information when they result from regular trades. When institutions decide to use program trades, their imbalances are not informative. This corroborates our argument that institutions use program trades primarily for liquidity-motivated trading.[7]

Consistent with Kaniel, Saar and Titman (2004), Table 7 also shows that individuals have predictive ability. Their imbalances are, on average, informative about returns during the next few days, although the much smaller median suggests that their information is particularly large in specific stocks. Specialists do not appear to have private information (or cannot trade to exploit it) – their market making function implies that they buy in declining markets and sell in rising markets to satisfy the trading demand of other market participants. As a result, their imbalances are negatively related to next-day returns. In Panel B, we compute separate coefficients for each size quartile and find largely similar results. In particular, institutional and individual imbalances tend to predict next-day returns, while program and specialist imbalances do not.

III. Conclusions

Microstructure theory predicts that order flow affects prices (Kyle, 1985; Glosten and Milgrom, 1985). While this prediction is well documented empirically, we know little about which traders drive this relationship.

[7] Our result that program trades are negatively related to contemporaneous and future predict returns contrasts with earlier findings by Harris, Sofianos, and Shapiro (1994) and Hasbrouck (1996), who both argue that program trades contain information. The differences could be due to different samples and different periods. The former study uses aggregate information on program trades from 1989 to 1990, and the latter study uses program trades on a small sample of firms over three months from November 1990. It is likely that trading strategies have changed since then, especially the use of limit-order strategies. During the 1989 and 1990 sample periods, specialists had no obligation to display limit orders immediately, which probably discouraged their large-scale use by traders. But without limit order usage a main argument for the liquidity-supplying nature of today's program trades does not apply. During our 2000-2004 sample period, limit orders are the dominant order type and their use has increased after the NYSE started to display its order book publicly (see Boehmer, Saar, and Yu, 2005).

Trading strategies and information differ across traders and, therefore, we also expect that the relationship between order flow and prices differs across traders. We provide new evidence on this issue using a proprietary NYSE data set that allows us to observe daily order imbalances for different trader groups. For all common stocks between 2000 and April 2004, we observe buys and sells for institutions, individuals, and market makers, and can further distinguish regular institutional trades from institutional program and index-arbitrage program trades. Institutional trading accounts for 77% of total share volume during this period, individuals account for 5%, and specialists for about 18%. Thus, institutions clearly are the most important trader group.

First, we document that institutions are contrarians with respect to returns on the previous day. This finding contrasts to evidence based on quarterly holdings, which suggests that institutions are momentum traders at longer horizons (see Sias, 2005). These results are not necessarily inconsistent; but because momentum trading would arguably be most destabilizing at shorter horizons, our results appear to alleviate such concerns. We further show that individuals are contrarians as well, consistent with Kaniel, Saar, and Titman (2004). In fact, only specialists trade as if they are momentum traders on a daily basis – but this is a plausible result of bona fide market making activity. A positive-return day is typically characterized by positive order imbalances and market makers may short to satisfy this demand. When returns reverse on the next day, they can purchase shares to rebalance their inventory.

Second, we document that order imbalances from different trader types play distinctly different roles in price formation. While institutions and individuals are both contrarians, they differ in the effect their order imbalances have on contemporaneous returns. Institutional imbalances are positively related to contemporaneous returns, and we provide cross-sectional evidence that this relationship is likely to be the result of firm-specific information institutions have. In contrast, the imbalances of individuals, specialists, and institutional program traders are negatively related to contemporaneous returns. This suggests that these trader types provide liquidity to the actively trading institutions. Moreover, this result suggests a special role for institutional program trades. Institutions appear to choose regular trades when they have firm-specific information, but they choose program trades when they do not and can, therefore, afford to trade passively. As a result, program trades provide liquidity to the market.

Third, both institutional non-program and individual imbalances (information which is not available to market participants) have predictive power for next-day quote-midpoint excess returns. In contrast, specialist and program trade imbalances are negatively related to next-day returns. This does not imply that profitable trading strategies exist, because trader-type information is not publicly (and not even privately) disseminated. It does suggest, however, that institutions often have private information when their trading results in order imbalances. But because their imbalances also move prices contemporaneously, their trading profits appear to be bounded. This scenario is consistent with prior evidence that institutions have some stock-picking ability (see, for example, Daniel et al. (1997) and that institutions improve the informational efficiency of share prices (see Boehmer and Kelley, 2005). Moreover, our results also suggest that institutions use program trades when they do not have private information. This makes intuitive sense, because by packaging orders into baskets institutional traders can signal to the market that they are uninformed, which should result in lower execution costs.

During our sample period, institutions generate 56% of share volume in the average stock. Our results imply that this portion of trading activity tends to be more informed than other trades. Therefore, institutional trading appears to drive the generally positive relationship between order flow and prices. Individuals provide 5% of volume and, on average, also tend to be informed. But the price impact results reveal that institutions trade more aggressively than individuals. Thus, consistent with Kaniel, Saar, and Titman’s (2004) interpretation, individuals appear to provide liquidity to institutions. Their order volume is far too small, however, to satisfy institutional imbalances. Our results imply that the remainder of these imbalances is filled by market makers and, in particular, by other institutions who are apparently not privately informed and use program trades.

References

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

Amihud, Yakov and Haim Mendelson, 1980. Dealership market: Market making with inventory, Journal of Financial Economics 8, 31-53.

Back, Kerry, and Shmuel Baruch, 2005. Working orders in limit-order markets and floor exchanges, Working paper, Texas A&M University.

Baker, Malcolm and Jeremy Stein, 2004. Market liquidity as a sentiment indicator, Journal of Financial Markets 7, 271-299.

Bessembinder, H., 2003. Issues in assessing trade execution costs, Journal of Financial Markets 6, 233-257.

Bloomfield, Robert, Maureen O'Hara and Gideon Saar, 2005. The "make or take" decision in an electronic market: evidence on the evolution of liquidity, Journal of Financial Economics 75, 165-199.

Boehmer, Ekkehart, Charles Jones and Xiaoyan Zhang, 2005. Which shorts are informed? Working paper, Texas A&M University.

Boehmer, Ekkehart and Eric Kelley, 2005. Institutional investors and market efficiency, working paper, Texas A&M University.

Boehmer, E., G. Saar, and L. Yu, 2005. Lifting the veil: An analysis of pre-trade transparency at the NYSE, Journal of Finance 60, 783-815.

Campbell, John, Sanford Grossman and Jiang Wang, 1993. Trading volume and serial correlation in stock returns, Quarterly Journal of Economics 108, 905-939.

Chan, Louis K.C. and Josef Lakonishok, 1995. The behavior of stock prices around institutional trades, Journal of Finance 50, 1147-1174.

Choe, Hyuk, Bong-chan Kho, and Rene Stulz, 1999. Do foreign investors destabilize stock markets? The Korean experience in 1997, Journal of Financial Economics 54, 227-264.

Chordia, Tarun, Sahn-wook Huh, and Avanidhar Subrahmanyam, 2004. The cross-section of expected trading activity, Working paper, UCLA.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2001. Market liquidity and trading activity, Journal of Finance 56, 501-530.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002. Order imbalance, liquidity and market returns, Journal of Financial Economics 65, 111-130.

Chordia, Tarun and Avanidhar Subrahmanyam, 2004. Order imbalance and individual stock returns: Theory and evidence, Journal of Financial Economics 72, 485–518.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2005. Evidence on the speed of convergence to market efficiency, Journal of Financial Economics, forthcoming.

Daniel, Kent, Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997. Measuring mutual fund performance with characteristic-based benchmarks, Journal of Finance 52, 1035-1058.

Easley, D. and M. O'Hara, 1987. Price, trade size, and information in securities markets, Journal of Financial Economics 19, 69-90.

French, K. and R. Roll, 1986. Stock return variances: The arrival of information and the reaction of traders, Journal of Financial Economics 17, 5-26.

Garman, M., 1976. Market microstructure, Journal of Financial Economics 3, 257-275.

Glosten, L. and P. Milgrom, 1985. Bid, ask, and transaction prices in a specialist market with heterogeneously informed traders, Journal of Financial Economics 13, 71-100.

Griffin, John, Jeffery Harris and Selim Topaloglu, 2003. The dynamics of institutional and individual trading, Journal of Finance 58, 2285-2320.

Griffin, John, Jeffery Harris and Selim Topaloglu, 2005. Who drove and bust the tech bubble? Working paper, University of Texas at Austin.

Grinblatt, Mark, and Matti Keloharju, 2000. The investment behavior and performance of various investor types: a study of Finland's unique data set, Journal of Financial Economics 55, 43-67

Grinblatt, Mark, Sheridan Titman, and Russ Wermers, 1995. Momentum investment strategies, portfolio performance, and herding: A study of mutual fund behavior, American Economic Review 85, 1088-1105.

Guun, Andrew and Clive Gaun, 2003. Limit order imbalances and return predictability, Working paper, University of Queensland.

Harris, Lawrene, Goerge Sofianos, and James Shapiro, 1994. Program trading and intraday volatility, Review of Financial Studies 7, 653-685.

Hasbrouck, Joel, 1988. Trades, quotes, inventory, and information, Journal of Financial Economics 22, 229-252.

Hasbrouck, Joel, 1991a. Measuring the information content of stock trades, Journal of Finance 46, 178-208.

Hasbrouck, Joel, 1991b. The summary informativeness of stock trades: An econometric analysis, Review of Financial Studies 4, 571-595.

Hasbrouck, Joel, 1996. Order characteristics and stock price evolution: an application to program trading, Journal of Financial Economics 41, 129-149.

Ho, T. and R. Macris, 1984. Dealer bid-ask quotes and transaction prices: An empirical study of some AMEX options, Journal of Finance 39, 23-45.

Ho, T. and H. R. Stoll, 1981. Optimal dealer pricing under transactions and return uncertainty, Journal of Financial Economics 9, 47-73.

Holden, C. W. and A. Subrahmanyam, 1992. Long-lived private information and imperfect competition, Journal of Finance 47, 247-270.

Jones, Charles and Marc Lipson, 2004. Are retail orders different? Working paper, Columbia University.

Kaniel, Ron and Hong Liu, 2005. So what orders do informed traders use? Journal of Business, forthcoming.

Kaniel, Ron, Gideon Saar and Sheridan Titman, 2004. Individual investor sentiment and stock returns, working paper, Duke University.

Karpoff, Jonathan, 1987. The relation between price changes and trading volume: A survey, Journal of Financial and Quantitative Analysis 22, 109-126.

Keim, Donald and Ananth Madhavan, 1995. Anatomy of the trading process: Empirical evidence on the behavior of institutional traders, Journal of Financial Economics 37, 371-398.

Kyle, Albert, 1985. Continuous auctions and insider trading, Econometrica 53, 1315-1336.

Lee, Charles, 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, Journal of Financial Markets 3, 83-111.

Lee, Charles and Marc Ready, 1991. Inferring trade direction from intraday data, Journal of Finance 46, 733-746.

Lee, Yi-Tsung, Yu-Jane Liu, Richard Roll and Avanidhar Subrahmanyam, 2004. Order imbalances and market efficiency: Evidence from the Taiwan Stock Exchange, Journal of Financial and Quantitative Analysis 39, 327-341.

Lipson, Marc and Andy Puckett, 2005. Volatile markets and pension fund trading, working paper, University of Georgia.

Llorente, Guillermo, Roni Michaely, Gideon Saar and Jiang Wang, Dynamic Volume-Return Relation of Individual Stocks, Review of Financial Studies 15, 1005-1047.

Madhavan, Ananth and George Sofianos, 1998. An empirical analysis of NYSE specialist trading, Journal of Financial Economics 48, 189-210.

Sias, R., 2005. Reconcilable differences: Momentum trading by institutions, Working paper, Washington State University.

Spiegel, M. and A. Subrahmanyam, 1992. Informed speculation and hedging in a noncompetitive securities market, Review of Financial Studies 5, 307-330.

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

Table 1. Summary statistics.

We present cross-sectional averages of time-series means for 1300 NYSE common stocks from January 2000 to April 2004. Panel A shows the fraction of trading volume of each trader type. Panel B presents the level of order imbalances by trader types. Panel C presents each trader type's imbalances scaled by the total trading activity of each stock each day.

Means	Institutions	Regular program trades (institutional)	Index arbitrage program trades (institutional)	Individuals	Specialists	Other market makers
Panel A: Relative trading volume of each trader type						
% of transactions	45.3%	27.0%	3.5%	5.3%	18.0%	0.9%
% of share volume	56.0%	18.8%	1.6%	5.0%	17.9%	0.7%
% of dollar volume	56.0%	18.8%	1.6%	5.0%	17.9%	0.7%
Panel B: Level of order imbalances by trader types						
Order imbalances in number of transactions	-12	9	4	-5	-5	-1
Order imbalances in shares	3,032	5,007	1,034	-4,696	-311	-538
Order imbalances in dollar volume	150,686	190,623	43,317	-205,093	-10,543	-40,025
Panel C: Scaled order imbalances by trader types						
Scaled order imbalances in transactions / number of trades	-1.3%	1.0%	0.4%	-1.5%	-0.2%	-0.2%
Scaled order imbalances in shares / share volume	0.7%	0.8%	0.1%	-1.5%	0.1%	-0.2%
Scaled order imbalances in dollars / dollar volume	0.7%	0.8%	0.1%	-1.5%	0.1%	-0.2%

Table 2. Cross correlations across trader types.
We report cross-sectional averages of time-series correlations. The sample includes 1300 NYSE common stocks from January 2000 to April 2004.

	Institutions	Regular program trades (institutional)	Index arbitrage program trades (institutional)	Individuals	Specialists	Other market makers	Return
Panel A: Order imbalances measured in transactions standardized by the total number of transactions							
Institutions	1.00	-0.20	-0.12	-0.08	-0.27	-0.02	-0.02
Regular program trades (institutional)		1.00	0.13	-0.11	-0.43	-0.05	-0.03
Index arbitrage program trades (institutional)			1.00	-0.06	-0.21	-0.05	0.11
Individuals				1.00	-0.10	0.19	-0.05
Specialists					1.00	-0.04	-0.17
Other market makers						1.00	-0.10
Return							1.00
Panel B: Order imbalances measures in shares standardized by total share volume.							
Institutions	1.00	-0.24	-0.08	-0.13	-0.21	-0.05	0.01
Regular program trades (institutional)		1.00	0.07	-0.06	-0.05	-0.03	-0.02
Index arbitrage program trades (institutional)			1.00	-0.03	0.00	-0.02	0.09
Individuals				1.00	-0.04	0.10	-0.06
Specialists					1.00	0.02	-0.25
Other market makers						1.00	-0.08
Return							1.00
Panel C: Order imbalances measures in dollars standardized by total dollar volume.							
Institutions	1.00	-0.24	-0.08	-0.13	-0.21	-0.05	0.01
Regular program trades (institutional)		1.00	0.07	-0.06	-0.05	-0.03	-0.02
Index arbitrage program trades (institutional)			1.00	-0.03	0.01	-0.02	0.08
Individuals				1.00	-0.04	0.10	-0.06
Specialists					1.00	0.02	-0.25
Other market makers						1.00	-0.08
Return							1.00

Table 3. Persistance of order imbalances

We report cross-sectional averages of time-series autocorrelations. The sample includes 1300 NYSE common stocks from January 2000 to April 2004.

	Institutions	Regular program trades	Index arbitrage program trades	Individuals	Specialists	Other market makers
Panel A: Order imbalances measured in transactions standardized by the total number of transactions						
lag1	0.26	0.32	0.09	0.45	0.17	0.21
lag2	0.15	0.20	0.07	0.37	0.10	0.17
lag3	0.11	0.15	0.08	0.33	0.08	0.15
lag4	0.08	0.12	0.06	0.31	0.07	0.14
lag5	0.06	0.08	0.01	0.29	0.04	0.13
Panel B: Order imbalances measured in shares standardized by total share volume.						
lag1	0.21	0.29	0.04	0.27	-0.14	0.14
lag2	0.12	0.18	0.04	0.20	-0.03	0.11
lag3	0.09	0.13	0.05	0.18	-0.01	0.09
lag4	0.07	0.11	0.02	0.16	0.00	0.09
lag5	0.05	0.08	0.01	0.14	0.00	0.08
Panel C: Order imbalances measured in dollars standardized by total dollar volume.						
lag1	0.21	0.29	0.04	0.27	-0.14	0.14
lag2	0.12	0.18	0.04	0.20	-0.03	0.11
lag3	0.09	0.13	0.05	0.18	-0.01	0.09
lag4	0.07	0.11	0.02	0.16	0.00	0.09
lag5	0.05	0.08	0.01	0.14	0.00	0.08

Table 4. Determinants of order imbalances

For each security, we regress order imbalance in shares, scaled by total share volume, OIB (t), on a stock's lagged residual returns, lagged market return, Rm (t-k), and trader-type specific lagged order imbalances, OIB (t-k). Residual returns are security-specific market-model residuals. Security-specific returns are computed based on closing-price midpoint, and market returns are computed as the equally-weighted average of these returns across all sample stocks. We report cross-sectional averages of the time-series regression coefficients.The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel A uses holding-period returns over the previous week, while Panel B uses daily returns over the previous week. Panel C uses the same model as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). Numbers in boldface indicate that the mean coefficient (using a t-test corrected for cross-sectional correlations as in Chordia and Subrahmanyam, 2004) or the median coefficient (using a Wilcoxon test) are significant at the 5% level.

	Institutions			Regular program trades			Index arbitrage program trades			Individuals			Specialists			Other market makers		
	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t
Panel A: Order imbalances and previous-week holding-period returns																		
Intercept	**0.0047**	**0.0035**	8.20	**0.0049**	**0.0050**	15.33	**0.0007**	**0.0007**	14.65	**-0.0077**	**-0.0056**	-16.30	**0.0013**	**0.0004**	5.82	**-0.0008**	**-0.0005**	-9.77
Residual Ret (t-5, t-1)	**-0.1584**	**-0.1114**	-14.25	**-0.0948**	**-0.0655**	-15.95	-0.0012	-0.0005	-1.03	**-0.0821**	**-0.0517**	-23.71	**0.1584**	**0.0913**	23.04	**-0.0065**	**-0.0041**	-4.22
Rm (t-5,t-1)	-0.0014	0.0129	-0.10	**-0.1368**	**-0.1344**	-15.30	**-0.0281**	**-0.0279**	-14.83	-0.0080	0.0051	-1.11	**0.0992**	**0.0784**	12.07	0.0017	**0.0017**	1.23
OIB (t-1)	**0.1789**	**0.1849**	97.92	**0.2479**	**0.2559**	112.78	**0.0350**	**0.0343**	10.54	**0.1911**	**0.1923**	82.35	**-0.1645**	**-0.1727**	-57.23	**0.1046**	**0.0954**	31.79
OIB (t-2)	**0.0589**	**0.0615**	38.14	**0.0768**	**0.0784**	48.01	**0.0262**	**0.0273**	13.41	**0.0898**	**0.0914**	50.12	**-0.0719**	**-0.0734**	-32.20	**0.0466**	**0.0416**	19.90
OIB (t-3)	**0.0385**	**0.0397**	27.39	**0.0442**	**0.0451**	29.15	**0.0456**	**0.0516**	25.46	**0.0696**	**0.0711**	40.80	**-0.0258**	**-0.0243**	-13.97	**0.0415**	**0.0353**	21.16
OIB (t-4)	**0.0236**	**0.0236**	16.46	**0.0332**	**0.0345**	21.54	**0.0188**	**0.0202**	10.83	**0.0562**	**0.0560**	33.70	**-0.0057**	**-0.0043**	-3.28	**0.0355**	**0.0301**	18.62
OIB (t-5)	**0.0220**	**0.0230**	14.91	**0.0234**	**0.0235**	15.87	**0.0068**	**0.0059**	3.95	**0.0587**	**0.0594**	38.02	**0.0119**	**0.0150**	7.11	**0.0347**	**0.0273**	20.21
Panel B: Order imbalances and previous-week daily returns																		
Intercept	**0.0046**	**0.0035**	8.18	**0.0048**	**0.0049**	14.40	**0.0007**	**0.0007**	9.48	**-0.0076**	**-0.0055**	-16.66	**0.0012**	**0.0004**	5.67	**-0.0008**	**-0.0005**	-9.79
Residual Ret (t_1)	**-0.6090**	**-0.5294**	-28.67	**-0.6034**	**-0.5268**	-36.65	-0.0012	0.0000	-0.36	**-0.1176**	**-0.0690**	-16.50	**0.3400**	**0.2205**	24.66	**-0.0061**	**-0.0020**	-4.23
Residual Ret (t_2)	**-0.1970**	**-0.1434**	-10.15	**-0.0751**	**-0.0285**	-6.08	0.0052	**0.0001**	1.59	**-0.0895**	**-0.0584**	-12.07	**0.2010**	**0.1063**	19.24	-0.0045	**-0.0040**	-1.21
Residual Ret (t_3)	0.0075	**0.0343**	0.43	**0.0419**	**0.0434**	3.90	-0.0022	-0.0006	-0.75	**-0.0747**	**-0.0509**	-9.30	**0.1034**	**0.0421**	9.70	**-0.0071**	**-0.0041**	-2.88
Residual Ret (t_4)	0.0128	**0.0204**	0.85	**0.0869**	**0.0607**	6.99	-0.0018	0.0000	-0.50	**-0.0629**	**-0.0376**	-8.95	**0.0751**	**0.0308**	8.77	**-0.0085**	**-0.0034**	-6.18
Residual Ret (t_5)	**0.0252**	**0.0256**	1.96	**0.1130**	**0.0991**	10.47	-0.0057	**-0.0023**	-1.46	**-0.0549**	**-0.0278**	-8.21	**0.0526**	**0.0189**	6.26	**-0.0056**	**-0.0023**	-2.61
Rm (t_1)	0.0564	**0.0551**	1.64	**-0.5169**	**-0.5136**	-22.38	**-0.1360**	**-0.1231**	-11.96	0.0226	**0.0170**	1.37	**0.2151**	**0.1465**	10.30	0.0033	**0.0031**	0.99
Rm (t_2)	**-0.0801**	**-0.1211**	-2.60	**-0.1581**	**-0.1038**	-7.37	-0.0065	0.0029	-0.99	-0.0187	0.0013	-1.20	**0.1545**	**0.0910**	8.80	**0.0117**	**0.0002**	3.28
Rm (t_3)	**-0.0788**	**-0.0573**	-2.47	**0.0485**	**0.0311**	2.39	**0.0622**	**0.0435**	10.45	**-0.0435**	**-0.0076**	-2.68	**0.0789**	**0.0621**	4.23	**-0.0086**	0.0000	-2.38
Rm (t_4)	0.0047	-0.0246	0.15	0.0217	-0.0026	1.06	**0.0310**	**0.0321**	5.00	0.0090	**0.0107**	0.59	-0.0013	**0.0438**	-0.08	-0.0010	0.0000	-0.29
Rm (t_5)	**0.0833**	**0.0986**	2.94	**-0.0965**	**-0.1053**	-4.80	**-0.0964**	**-0.0867**	-15.32	0.0008	**0.0112**	-0.05	**0.0461**	**0.0331**	2.73	0.0031	**0.0024**	0.85
OIB (t_1)	**0.1820**	**0.1873**	103.25	**0.2469**	**0.2545**	113.99	**0.0549**	**0.0497**	10.84	**0.1920**	**0.1922**	84.29	**-0.1439**	**-0.1520**	-47.84	**0.1065**	**0.0975**	32.73
OIB (t_2)	**0.0648**	**0.0658**	41.52	**0.0836**	**0.0844**	50.36	**0.0308**	**0.0303**	9.79	**0.0932**	**0.0947**	52.20	**-0.0558**	**-0.0579**	-24.13	**0.0490**	**0.0428**	20.96
OIB (t_3)	**0.0415**	**0.0426**	28.63	**0.0475**	**0.0497**	29.01	**0.0419**	**0.0461**	14.91	**0.0713**	**0.0725**	41.52	**-0.0205**	**-0.0193**	-10.38	**0.0420**	**0.0353**	21.67
OIB (t_4)	**0.0246**	**0.0250**	16.69	**0.0372**	**0.0375**	22.52	**0.0081**	**0.0099**	3.00	**0.0573**	**0.0579**	34.29	**-0.0078**	**-0.0057**	-4.22	**0.0359**	**0.0308**	18.69
OIB (t_5)	**0.0209**	**0.0214**	13.96	**0.0245**	**0.0255**	16.09	**0.0113**	**0.0108**	3.92	**0.0595**	**0.0597**	38.34	**0.0035**	**0.0070**	2.02	**0.0352**	**0.0269**	19.98

Panel C: Order imbalances and previous-week holding-period returns by size quartiles (using Panel A regression, only average return coefficients shown)

Size quartile 1 (smallest)																		
Residual Ret (t-5, t-1)	**-0.1690**	**-0.1376**	-8.65	**-0.1070**	**-0.0783**	-9.17	**-0.0051**	-0.0002	-2.18	**-0.1405**	**-0.1222**	-15.28	**0.2476**	**0.1600**	12.43	**-0.0083**	**-0.0020**	-5.11
Rm (t-5,t-1)	-0.0112	0.0199	-0.26	**-0.1268**	**-0.1963**	-4.97	0.0071	-0.0012	1.44	-0.0232	0.0159	-0.89	**0.0690**	**0.0974**	2.42	-0.0038	0.0000	-0.77
Size quartile 2																		
Residual Ret (t-5, t-1)	**-0.2324**	**-0.1508**	-6.44	**-0.1367**	**-0.1127**	-9.36	**-0.0086**	**-0.0050**	-2.58	**-0.0922**	**-0.0660**	-12.31	**0.2223**	**0.1471**	14.89	-0.0010	**-0.0019**	-0.17
Rm (t-5,t-1)	**-0.0544**	**-0.0699**	-2.14	**-0.2003**	**-0.2064**	-10.87	**-0.0168**	**-0.0187**	-5.73	-0.0165	-0.0057	-1.74	**0.1920**	**0.1774**	14.34	0.0009	0.0005	0.49
Size quartile 3																		
Residual Ret (t-5, t-1)	**-0.1465**	**-0.1174**	-10.62	**-0.1115**	**-0.0765**	-8.74	-0.0016	**-0.0021**	-1.05	**-0.0592**	**-0.0404**	-11.36	**0.1123**	**0.0745**	16.06	**-0.0075**	**-0.0046**	-7.76
Rm (t-5,t-1)	-0.0007	-0.0131	-0.04	**-0.1478**	**-0.1381**	-10.43	**-0.0290**	**-0.0260**	-15.60	0.0001	0.0025	0.01	**0.1007**	**0.0881**	15.82	0.0029	**0.0020**	1.83
Size quartile 4 (largest)																		
Residual Ret (t-5, t-1)	**-0.0856**	**-0.0540**	-10.35	**-0.0241**	**-0.0120**	-4.28	**0.0105**	**0.0057**	7.57	**-0.0364**	**-0.0289**	-16.60	**0.0516**	**0.0351**	17.74	**-0.0091**	**-0.0075**	-12.51
Rm (t-5,t-1)	**0.0608**	**0.0722**	5.03	**-0.0722**	**-0.0642**	-9.28	**-0.0736**	**-0.0688**	-23.67	**0.0078**	**0.0116**	2.41	**0.0352**	**0.0276**	10.87	**0.0069**	**0.0050**	6.86

Table 5. The price impact of order imbalances.

For each security, we regress daily close-to-close quote-midpoint returns, R (t), on contemporaneous market returns, Rm (t), and current and lagged order imbalances, OIB (t-k). Order imbalances are measured in shares and scaled by total share volume. Market returns are computed as the equally-weighted average of close-to-close midpoint returns across all sample stocks. The reported coefficients are cross-sectional averages of the time-series regression coefficients. The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel B uses the same mode as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). Numbers in boldface indicate that the mean coefficient (using a t-test corrected for cross-sectional correlations as in Chordia and Subrahmanyam, 2004) or the median coefficient (using a Wilcoxon test) are significant at the 5% level.

	Institutions			Regular program trades			Index arbitrage program trades			Individuals			Specialists			Other market makers		
	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t
Panel A: Price impact regression																		
Intercept	**-0.0001**	0.0001	-2.51	0.0001	**0.0002**	1.61	0.0000	**0.0001**	-0.65	-0.0001	0.0000	-1.94	0.0001	0.0002	1.52	**-0.0001**	0.0000	-2.67
Rm (t)	**0.9783**	**0.9400**	82.02	**0.9927**	**0.9600**	82.43	**0.9806**	**0.9473**	81.09	**0.9731**	**0.9365**	82.50	**0.9151**	**0.8778**	80.60	**0.9656**	**0.9360**	83.53
OIB (t)	**0.0028**	-0.0006	4.50	**-0.0189**	**-0.0162**	-19.68	0.0242	**-0.0075**	1.00	**-0.0608**	**-0.0266**	-20.44	**-0.1274**	**-0.0864**	-34.85	**-0.1790**	**-0.0822**	-13.19
OIB (t-1)	**0.0016**	**0.0017**	6.15	-0.0002	**0.0001**	-0.33	-0.0253	**-0.0107**	-1.00	**0.0211**	**0.0095**	16.47	**-0.0263**	**-0.0174**	-20.89	0.0513	**0.0188**	1.92
OIB (t-2)	-0.0003	**0.0004**	-1.32	**0.0012**	**0.0007**	2.53	0.0019	-0.0019	0.08	**0.0110**	**0.0056**	10.92	**-0.0076**	**-0.0064**	-6.59	-0.0437	**0.0151**	-0.60
OIB (t-3)	0.0001	0.0002	0.34	0.0007	**0.0009**	1.59	0.0125	0.0007	0.57	**0.0077**	**0.0049**	9.34	**-0.0037**	**-0.0044**	-3.64	-0.0078	**0.0070**	-0.25
OIB (t-4)	0.0000	0.0003	0.15	0.0006	-0.0001	1.16	0.0054	0.0000	0.50	**0.0078**	**0.0047**	8.36	-0.0001	**-0.0016**	-0.10	-0.0643	**0.0138**	-1.10
Panel B: Price impact by size quartile (using Panel A regression, only average coefficients of contemporaneous OIB shown)																		
Size quartile 1 (smallest)																		
OIB (t)	**0.0061**	**0.0030**	6.21	**0.0088**	**0.0084**	5.44	**0.1792**	**0.0113**	2.29	**-0.0101**	**-0.0070**	-6.97	**-0.0770**	**-0.0680**	-34.58	-0.0556	**-0.0231**	-1.38
Size quartile 2																		
OIB (t)	-0.0011	**-0.0015**	-1.50	**-0.0117**	**-0.0106**	-10.97	**-0.0242**	**-0.0108**	-4.20	**-0.0227**	**-0.0157**	-12.80	**-0.0877**	**-0.0724**	-28.34	**-0.0616**	**-0.0302**	-3.61
Size quartile 3																		
OIB (t)	-0.0008	**-0.0029**	-0.82	**-0.0286**	**-0.0254**	-17.17	-0.0234	**-0.0396**	-0.47	**-0.0508**	**-0.0330**	-14.31	**-0.1244**	**-0.0928**	-20.39	**-0.1658**	**-0.0975**	-10.03
Size quartile 4 (largest)																		
OIB (t)	**0.0071**	-0.0020	3.80	**-0.0439**	**-0.0412**	-23.71	-0.0349	0.0018	-1.44	**-0.1595**	**-0.1147**	-17.83	**-0.2205**	**-0.1560**	-19.99	**-0.4329**	**-0.3389**	-19.80

Table 6. Explaining the price impact of institutional order imbalances.

The sample includes 1300 NYSE common stocks from January 2000 to April 2004. We estimate cross-sectional regressions to explain the security-specific coefficient on insitutional share imbalances in a regression of returns on contemporaneous market returns, contemporaneous instituional share imbalances, and lagged institutional share imbalances (see Table 5). The independent variables are relative effective spreads (RES), their decomposition into temporary and permanent components, and firm size. Spreads are computed as time-series average of a stock's daily equally-weighted relative effective spreads over the sample period.

	Average coefficient	t	Average coefficient	t
Intercept	-0.003	-3.78	-0.005	5.02
RES	1.279	9.05		
Temporary component of RES			0.315	0.97
Permanent component of RES			5.745	5.73
Size	0.000	7.71	0.000	8.18
adjusted R^2	0.083		0.091	

Table 7. The predictive power of order imbalances for excess returns.

For each security, we regress daily close-to-close quote-midpoint returns, R (t), on contemporaneous market returns, Rm (t), and five lagged daily order imbalances, OIB (t-k). Market returns are computed as the equally-weighted average of close-to-close midpoint returns across all sample stocks. Order imbalances are measured in shares and scaled by total share volume. The reported coefficients are cross-sectional averages of the time-series regression coefficients. The sample includes 1300 NYSE common stocks from January 2000 to April 2004. Panel B uses the same model as Panel A, but provides separate average coefficients for each size quartile (using the time-series mean market value of equity for each firm). Numbers in boldface indicate that the mean coefficient (using a t-test corrected for cross-sectional correlations as in Chordia and Subrahmanyam, 2004) or the median coefficient (using a Wilcoxon test) are significant at the 5% level.

	Institutions			Regular program trades			Index arbitrage program trades			Individuals			Specialists			Other market makers		
	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t	Mean	Median	t
Panel A: Predictive regressions																		
Intercept	-0.0001	**0.0001**	-1.54	0.0000	**0.0002**	0.17	0.0000	**0.0001**	-0.66	0.0001	**0.0002**	1.79	-0.0001	**0.0001**	-0.98	0.0000	**0.0001**	-0.21
Rm (t)	**0.9792**	**0.9382**	81.69	**0.9807**	**0.9405**	82.66	**0.9785**	**0.9403**	82.32	**0.9791**	**0.9398**	81.85	**0.9789**	**0.9373**	82.46	**0.9784**	**0.9402**	82.26
OIB (t-1)	**0.0018**	**0.0013**	7.04	**-0.0059**	**-0.0046**	-10.82	-0.0263	**-0.0108**	-1.04	**0.0075**	**0.0030**	7.97	**-0.0057**	**-0.0024**	-5.38	0.0197	**0.0004**	0.74
OIB (t-2)	-0.0002	0.0002	-0.67	-0.0002	**-0.0004**	-0.36	-0.0009	**-0.0023**	-0.04	**0.0044**	**0.0025**	4.70	-0.0002	-0.0001	-0.14	-0.0634	**0.0046**	-0.88
OIB (t-3)	0.0002	0.0001	0.96	0.0000	0.0001	0.03	0.0119	0.0000	0.56	**0.0028**	**0.0025**	3.38	-0.0015	**-0.0017**	-1.39	-0.0167	0.0000	-0.55
OIB (t-4)	0.0001	**0.0003**	0.55	0.0002	-0.0004	0.29	-0.0009	0.0000	-0.08	**0.0033**	**0.0018**	3.51	0.0006	-0.0001	0.55	-0.0732	**0.0049**	-1.25
OIB (t-5)	0.0000	0.0001	0.01	-0.0008	**-0.0008**	-1.69	-0.0401	-0.0012	-1.24	0.0008	**0.0011**	1.06	-0.0004	0.0002	-0.37	0.0005	0.0025	0.02
Panel B: Predictive regressions by size quartile (using Panel A regression, only average coefficients of OIB (t-1) shown)																		
Size quartile 1 (smallest)																		
OIB (t-1)	**0.0010**	**0.0008**	2.04	**-0.0080**	**-0.0057**	-4.81	**-0.1561**	-0.0014	-2.06	**0.0028**	**0.0017**	3.18	**-0.0038**	**-0.0028**	-3.53	-0.0600	**-0.0055**	-0.94
Size quartile 2																		
OIB (t-1)	0.0007	**0.0005**	1.88	**-0.0054**	**-0.0045**	-9.80	-0.0075	**-0.0163**	-0.82	**0.0043**	**0.0012**	2.62	-0.0023	0.0005	-1.88	0.0976	0.0012	1.16
Size quartile 3																		
OIB (t-1)	**0.0013**	**0.0013**	2.46	**-0.0049**	**-0.0029**	-4.56	0.0460	-0.0040	0.69	**0.0057**	**0.0027**	3.03	**-0.0045**	**-0.0024**	-2.50	0.0122	0.0026	1.10
Size quartile 4 (largest)																		
OIB (t-1)	**0.0042**	**0.0036**	7.10	**-0.0052**	**-0.0050**	-7.25	0.0122	**-0.0149**	1.07	**0.0172**	**0.0133**	6.61	**-0.0125**	**-0.0120**	-3.55	**0.0290**	**0.0192**	3.85