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The other side of the trading story: Evidence from NYSE

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The Other Side of the Trading Story: Evidence from NYSE

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Abstract

We analyse the well-known TORQ dataset of trades on the NYSE over a 3-month period, breaking down transactions depending on whether the active or passive side was institutional or private. This allows us to compare the returns on the different trade categories. We find that, however we analyse the results, institutions are best informed, and earn highest returns when trading with individuals as counterparty. We also confirm the conclusions found elsewhere in the literature that informed traders often place limit orders, especially towards the end of the day (as predicted on the basis of laboratory experiments in Bloomfield, O'Hara, and Saar (2005)). Finally, we find that trading between institutions accounts for the bulk of trading volume, but carries little information and seems to be largely liquidity-driven.

JEL Classification: G14, G12

Keywords: liquidity trade, informed trades

1 Introduction

A large literature has appeared in recent years dealing with questions relating to the way information is disseminated in modern stock markets, which is hardly surprising given that the issues are of obvious importance for traders, investors and regulators. Are institutions informed – or at least better informed than individuals? Do informed traders place limit orders? Is there more information in early morning trades? Are spreads larger for informed trades? The microstructure literature has addressed questions like these empirically, sometimes theoretically, and in one important recent case, experimentally, yet they remain far from being resolved.

A possible starting point would be the question of how to distinguish informed from uninformed traders. A number of different approaches have been taken here. On the one hand, the question can be sidestepped by simply identifying institutions as informed traders and taking individuals as uninformed, an assumption which has been challenged on empirical grounds by Lee, Lin and Liu (1999). Alternatively, it has been traditionally argued that to be informed is to be active (e.g. Glosten (1994)). On this view, the relevant distinction involves no more than separating market orders from limit orders, an assertion which has been questioned on both theoretical and empirical grounds (Kaniel and Liu (2006), Bloomfield, O'Hara, and Saar (2005)). A more indirect, less arbitrary approach starts from a theoretical model and tries to estimate the probability that any given transaction is information-based or purely noise trade, using as an indicator a measure of order imbalance (e.g. Easley, Hvidkjaer and O'Hara (2002), Easley et al (2002)).

In an influential recent paper, Bloomfield, O'Hara, and Saar (2005) addressed these ques-

tions in an experimental setting, finding that informed traders do not, as previously assumed, always take liquidity off the market. Instead, they start the day by using their informational advantage to pick off mispriced limit orders while they are available, thereby driving the market towards the true price and progressively eroding the value of their information. Towards the end of the day, they switch increasingly to limit orders, presumably because the value of their information has diminished to the point where it is outweighed by the prospect of avoiding the bid-ask spread.

However, the acid test of informativeness is whether it makes money in actual market conditions. In other words, if informed traders are those who rationally make the best possible use of available information, then by definition they must on average make excess returns in dealing with the uninformed. It follows that, wherever the data makes it possible to track subsequent returns, we can measure information directly and, moreover, use the results as a check on the accuracy of other, more indirect measures, like the probability of information-based trade (henceforth: PIN) mentioned earlier, and of the other assumptions made in the literature.¹

In this paper, we get to the heart of the matter by examining the well-known TORQ dataset in detail. Specifically, we take the approach of Anand, Chakravarty and Martell (2005) a stage further. Whereas they analyse the data by whether trades are initiated by institutions or individuals, we do the same on the active and passive sides. In other words, we break down the set of all transactions into subsets, depending on whether the traders are institutional or individual², whether they are active or passive, and whether they are buys

¹ Our use of returns is closely related to Hasbrouck's (1991a, 1991b) measure of trade informativeness by price impact via a vector autoregressive model of trades and mid-quote returns.

² Strictly, as a result of the clustering of deals, it is impossible completely to unscramble institutional

or sells. Thus, we have eight classes: institution-initiated buys from (sales to) passive individuals, denoted $B(i-u)$ and $S(i-u)$ respectively, institution-initiated buys from (sales to) passive institutions, $B(i-i)$ and $S(i-i)$, and similarly, individual-initiated buys from (sales to) passive individuals, $B(u-u)$ and $S(u-u)$, and individual-initiated buys from (sales to) passive institutions, $B(u-i)$ and $S(u-i)$. The motivation for following this route is that, if informed traders sometimes choose to place limit orders, as suggested by Kaniel and Liu (2006) in the context of a model of optimal trade strategy and by Bloomfield, O'Hara, and Saar (2005) in an experimental setting, looking only at the active side of trades may be seriously misleading.

Examining returns (as well as other market variables such as volume and spread) disaggregated in this way, we are able to answer a number of the questions in the literature. First, we show that institutions are indeed better informed than individuals, an advantage they are able to exploit to earn higher returns, through actively initiating trades (Chakravarty (2001), Wong and Girardin (2007)). Second, we are able to track the changing situation over the six and a half hours in the trading day, to show that the informativeness of trade drops steadily over the day and, moreover, that informed traders tend to submit limit buy orders towards the end of the day's trading, both of which results confirm the findings of Bloomfield, O'Hara, and Saar (2005) in their experiment-based research. We are also able to show that the bulk of trading throughout the day is between institutions. As such, it carries little information and seems to be largely motivated by liquidity considerations. This conclusion may provide some justification for the insistence by Duarte and Young (2007) and individual deals. We initially apply the 50% rule here: if more than half of the active side of a trade is institutional, we classify it accordingly. Later, we examine the robustness of our results to changes in this criterion.

on decomposing PIN into its liquidity and information components. It may also be seen as supporting the association of high trade volume with differences in the way information is interpreted, which (Kandel and Pearson (1995) and Bamber, Barron and Stober (1999)) offer as an explanation of the fact that high levels of activity often result in only small movement in prices.³

We start with a brief discussion of our dataset. We then go on to examine the evidence from the disaggregation of trades on whether or not institutions appear to be informed traders able to earn excess returns. The evidence from gross returns data for periods that are sometimes overlapping turns out to be largely confirmed by formal regressions. We go on in the succeeding section to consider the pattern of trading over the day, before finishing with a few concluding comments.

2 The TORQ Dataset

The TORQ database of transactions, quotes, orders and audit trail data for the 3 months November 1990 to January 1991 has been widely used in the published literature and is well-known enough not to need detailed description.⁴ In this paper, only 8 firms with fewer than 100 lines of quotes and with spreads larger than 50% are excluded from the study, so that our findings are free from the effects of outliers. We thus have 136 NYSE stocks as our sample. The descriptive statistics given in Table 1 show the sample size broken down by transaction type. Out of a total dataset comprising nearly half a million buy and sell trades, institutions were the active side (i.e placed market orders) in about

³ See also the market-sidedness interpretation in Sarkar and Schwartz (2007).

⁴ See Hasbrouck (1992) for more details.

two out of every three cases which could be classified. In volume terms, the institutional predominance is even more marked, as their trades are on average over three times as great as those of individuals.⁵ We are concerned here with measuring the information in share dealing, as indicated by the post-trade return, defined as the log difference in the mid-quote price in the hour following a transaction. Average and median returns were significantly⁶ positive for buy trades, but negative on average (median zero) for sells. The net effect was positive, since the market rose somewhat over this three-month period. In addition to the (best) bid-ask spreads, the Table also gives two indicators related to market depth. The sum of the number of shares on offer at the lowest selling price and the number being bid for at the highest buying price represents a measure of liquidity. The difference between the two could be regarded as a reflection of information asymmetry (e.g. Rinaldo (2004), Harris and Panchapagesan (2005)), a proposition which is consistent with the sign pattern: a positive (negative) bid minus ask depth implies that investors are impatient to buy (sell), which in turn forecasts an upward (downward) movement in price.

3 Are institutions informed?

The top section of Table 2 contains an analysis of the dataset by type of transaction. In the top half, we give the results for buy trades where both sides were individuals (u-u), where the active side was an institution while the passive was a private individual (i-u), the opposite

⁵ Interestingly, for both institutions and individuals, as far as average trade size is concerned it seems to make little difference whether they are active or passive.

⁶ Note that significance tests are not strictly warranted in this case, because many of the returns are for overlapping periods, a problem we address later.

case (u-i), and where both parties were institutions (i-i). The lower half of the table gives the same analysis for sells. In both cases, the last two lines cover cases where one or the other party was unclassified (labelled “other”).

The most notable results in the table are in the i-u and u-i lines. From the returns column, it can be seen that institutions buying shares offered by individual traders earned an average return of just under 0.5%. On the other hand, when the roles were reversed, individuals earned only 0.16%, with the other two categories generating returns in between these two extremes. Looking at the sell trades, the same pattern is repeated, with the return in the aftermath of institutional sales to individuals averaging -0.35%, while the reverse deals were followed only by a share price fall of 0.07%.⁷ The obvious interpretation of these results is that, judged by the most direct criterion, institutions are better informed than individuals, so they make significantly higher returns when they initiate trades with individuals than with other institutions. At the same time, some individual traders are apparently well-informed enough to profit from deals with other individuals, as evidenced by the return of 0.31% from u-u buys and -0.27% from u-u sells. Note that when individuals buy shares from sales offers posted by institutions, they earn only 0.16%, and when selling to institutions, the subsequent price fall is only 0.04%.

The advantages enjoyed by the institutions is also apparent from the spread, which is about 0.7% on i-i deals, but averages 1.8% on buys between individuals and over 2.5% on

⁷ Note that most of the hour returns are overlapping. But the differences between i-u and u-i categories are significant, as can be seen from the regression analyses later in the section. For all other variables, most of the differences are significant based on the Newey-West robustness correction. Results are available from authors upon request.

sell trades. The lower spreads on all-institution deals is likely to be explained to a great extent by the fact that they tend to be around 3 to 7 times as large as trades between individuals. However, the literature relates the spread to two other variables. On the one hand, the more information asymmetry in the market (or believed to be in the market), the wider spreads have to be in order to protect traders submitting limit orders from the peril of adverse selection bias. On the other hand, the more liquid the market for a stock, the lower the spread, other things being equal. In the present case, the fact that the spread on all-institution trades is so small (roughly 0.7%) means that the difference in returns between u-u and i-u has to be attributable to information asymmetry.

There are two possible objections to these results. The first is that they are based on an arbitrary classification criterion: if more than 50% of the buying (selling) side is institutional, the buyer (seller) is treated as an institution in Table 2. Otherwise, it is treated as a private trade. However, to ensure the results are not distorted by the application of this criterion, Table 3 compares the results of using three different cut-off points: 25%, 50% and 75%. We also take the opportunity to analyse the results for small, medium and large firms.

Looking at the final column of the table first, it is evident that, as expected, the return ranking is preserved across trade-types. It remains the case that i-u trades earn the highest returns for all three classification criteria, while u-i still earn the lowest, confirming our conclusions regarding the informational disadvantage faced by private traders. The conclusion is reinforced insofar as returns tend to be higher the greater the proportion of institutional trade, and lower the more “private” is a trade.

The analysis by firm size also conforms to expectations. Although small firms generate higher returns than large other things being equal, it remains true that within each size

category, the highest returns are earned when institutions hit individuals' limit orders.

Insofar as they relate to partially overlapping periods, these results suffer from another possible shortcoming. In order to remedy this problem and to allow more rigorous hypothesis testing, we present regressions on non-overlapping returns in Tables 4 and 5, for 50% and 75% volume criteria respectively. (Note that the number of observations is reduced to just over 16000 for both buy and sell trades, as a result of eliminating overlaps.) In the first instance, the constant is associated with u-i and the other independent variables are simply four indicator dummies taking the value 1 when the trade is u-u (i-u, i-i and other), zero otherwise. Doing so gives an easy reading as to whether the returns of other trade categories are significantly larger than that of u-i. The results here are striking. As can be seen from the second and third columns of the table, the key finding is that institutions make significant returns from deals they initiate with individuals, whether they buy or sell, whereas individuals tend to lose when they hit limit orders posted by institutions. Moreover, this conclusion is quite robust to the introduction of more conventional explanatory variables. Both beta and (log of) market value enter the equation with the correct sign, the latter highly significant, but neither causes the signs on the four trade-type dummies to change. In the last two columns of the table, we introduce variables which figure largely in the microstructure literature: (log of) trade size (Hasbrouck (1991b)), bid-ask spread, total depth and net depth. Again the trade-type dummies point to the same conclusion. Noticeably, beta remains insignificant, while market value remains significant and correctly signed i.e. larger stocks provide lower returns to stock buyers and larger returns to sellers. On the other hand, trade size has a positive effect on returns, as in Hasbrouck (1996). The final three variables in Tables 4 and 5 relate to the level of information asymmetry. The spread is believed to be

positively related to information asymmetry, a point reflected in the fact that it is associated with significantly higher returns to both buy and sell trades. The same applies to the net depth (D-depth in the table). On the other hand, greater liquidity, as measured by total depth on both buy and sell sides, attracts a lower return since it implies less risk, other things being equal. Not surprisingly, our conclusions emerge even more sharply when the 75% criterion is applied (Table 5) than with the 50% cutoff (Table 4).

4 Intraday Trading Patterns

In their experiment-based research, Bloomfield, O'Hara, and Saar (2005) found that informed traders choose to place market orders in the morning, so as to maximise their advantage before their private information can leak into the public domain. Towards the close of business, as the price is driven towards its fair value, in the process eroding their trading advantage, they switch to limit orders. On the other hand, uninformed liquidity traders submit limit orders at first, then market orders as the end of trading approaches, in order to achieve their trading objectives by the close of business. While Anand, Chakravarty and Martell (2005) provide some evidence in support of these experimental findings, their approach is indirect insofar as they show only that the informativeness of limit orders declines in the second half of trading. Our intraday analysis of the disaggregated data, on the other hand, provides direct evidence of an increase in the number of informed, passive limit orders as market closing approaches.

Table 6 summarises the intraday data.

First, our previous analyses have established that institutions are better informed than

individuals. As such, the passive sell orders by institutions in the B(u-i) category suggest that the stocks concerned would underperform the market. This knowledge is likely to be shared by other equally informed institutions and this leaves the relatively uninformed retail investors to actively buy these stocks. Now if we consider the volume data in the top segment of the table, we see in broad terms the familiar U-shape replicated. Closer observation on the first and last hour of trading, however, reveals a surge of 40% more passive sell limit orders (1,978,000 shares) placed by institutions in the B(u-i) category at the close of market, which is in sharp contrast with other categories in which the volume of final hour trading remains about the same or even less. We take this as evidence supporting the claim that informed traders switch to limit orders when the price is near its fair value towards the close of market. Though no such evidence is found for the S(u-i) case, we offer a possible reason. We first note that the TORQ sample experienced a general increase in stock prices over the period studied. As our analysis is only based on realised trades, it is possible that the buy limit orders by the more informed institutions were not taken up in an upward moving market.⁸

Throughout the day, the overwhelming majority of trades involve institutions on both sides. Moreover, the return earned on this type of trade is relatively low – less than half that on trades between institutions and individuals, confirming that most are motivated more by liquidity requirements than by information. We can relate this evidence to the conclusion of Duarte and Young (2007), who find that Easley, Hvidkjaer and O’Hara (2002)’s PIN

⁸ We remark that Chakravarty (2001) and Anand, Chakravarty and Martell (2005), which use the same TORQ database, consider only buy trades in their analysis of informativeness of institutions’ trades and limit orders.

predominantly reflects trading driven by liquidity requirements rather than by information, and may also shed some light on why PIN is found by Vega (2006) to be insignificant in explaining the price reaction to public and private information.

As far as returns are concerned, the decreasing pattern over the day is broadly consistent with the Hasbrouck (1991b) price impact measure based on a vector autoregressive model for trades and returns. In fact, institutions buying from individuals make average returns of 0.66% in the first hour, 0.52% in the middle of the day and still a substantial 0.4% in the final hour's trade. Moreover, as passive sellers to individuals, they earn more in the final hour than in the rest of the day, suggesting that they do indeed switch to limit orders in late afternoon, confirming the findings of Anand, Chakravarty and Martell (2005) and Bloomfield, O'Hara, and Saar (2005).

5 Conclusions

This paper has presented results based on a novel disaggregation of the well-known TORQ dataset by private versus institutional trader on both active and passive sides, to allow for the fact that in the light of work by Bloomfield, O'Hara, and Saar (2005), Kaniel and Liu (2006) and Anand, Chakravarty and Martell (2005), we can no longer assume that informed traders always use market orders. On the whole, our findings confirm the results from the theoretical models, without the need to make the same simplifying assumptions needed to rule out strategic behaviour by informed agents. More generally, while volume is indicative of information flow (e.g. Clark (1973), Tauchen and Pitts (1983) and Lamoureux and Lastrapes (1990), Lamoureux and Lastrapes (1994)), we find the bulk of trade is generated by the intra-

institution category, which has all the characteristics of liquidity trading (low information content, low return and the narrowest spread).

The approach followed here opens up a number of different avenues for exploration. It would, for example, be interesting to know whether the Easley, Hvidkjaer and O’Hara (2002) PIN is robust enough to survive as a measure of information content in the context of the type of disaggregation used here.

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Table 1: DESCRIPTIVE STATISTICS

| Buy trades | | | | | | | |
|--|----------------|--------------------|-------------------|---------------------|--------------------|-------------------|---------------------|
| | Total | Active | | | Passive | | |
| | | Institution | Individual | Unclassified | Institution | Individual | Unclassified |
| #buy trades (thousands) | 256 | 108 | 49 | 99 | 111 | 40 | 106 |
| Total volume (million shares) | 393 | 237 | 31 | 125 | 211 | 25 | 157 |
| Average volume per trade (shares) | 1532 | 2189 | 630 | 1266 | 1900 | 629 | 1484 |
| #best buy quotes = 83018 | | | | | | | |
| | Average | Std error | Min | Q1 | Median | Q3 | Max |
| Mid-quote price 1 hr log-return (%) | 0.249 | 0.006 | -87.821 | -0.164 | 0.050 | 0.534 | 117.401 |
| Spread (%) | 0.997 | 0.005 | 0.098 | 0.283 | 0.580 | 1.183 | 30.769 |
| Bid plus ask depth (shares) | 204.7 | 0.900 | 2 | 53 | 115 | 250 | 1998 |
| Bid minus ask depth (shares) | 18.6 | 0.584 | -993 | -30 | 0 | 50 | 998 |
| Sell trades | | | | | | | |
| | Total | Active | | | Passive | | |
| | | Institution | Individual | Unclassified | Institution | Individual | Unclassified |
| #sell trades (thousands) | 215 | 90 | 48 | 77 | 93 | 35 | 87 |
| Total volume (million shares) | 321 | 200 | 31 | 91 | 177 | 20 | 124 |
| Average volume per trade (shares) | 1494 | 2221 | 638 | 1177 | 1899 | 577 | 1427 |
| #best sell quotes = 73811 | | | | | | | |
| | Average | Std error | Min | Q1 | Median | Q3 | Max |
| Mid-quote price 1 hr log-return (%) | -0.119 | 0.007 | -87.821 | -0.409 | 0.000 | 0.241 | 139.216 |
| Spread (%) | 1.098 | 0.006 | 0.098 | 0.257 | 0.576 | 1.250 | 31.579 |
| Bid plus ask depth (shares) | 220.8 | 0.999 | 2 | 55 | 120 | 270 | 1998 |
| Ask minus bid depth (shares) | 56.6 | 0.674 | -995 | -10 | 10 | 90 | 998 |

Only NYSE quotes and trades are used in our analyses. To remove potential outliers from our sample, firms with less than 100 quotes or with spread larger than 50% are removed. After applying the filter rules, we are left with 136 firms in the sample. Each trade's direction (buy or sell) is determined using the method given by Lee and Ready (1991). For buyer (seller) initiated trades, the buy (sell) shares are described as active whereas the sell (buy) shares are passive, with classification based on the TORQ audit trail. The 1 hour mid-quote log return is the log of mid-quote at $(t + 1 \text{ hour})$ less the log of mid-quote at t , where t is the time the trade takes place. Spread is the quoted spread divided by the mid-quote. The depth refers to the size (in number of shares) at the best bid and ask being quoted.

Table 2: RETURNS AND TRADE CATEGORIES

| BUY TRADES | | | | | | | | |
|-------------------|-----------|---------------|---------------|--------------|--------------------|-------------------|---------------------------|-------------------|
| | nq | return | Spread | Depth | Institution | | Inst + Indi + uncl | |
| | | | | | nt | trade size | nt | trade size |
| u-u | 2991 | 0.315 | 1.835 | 185 | 219 | 412 | 5019 | 506 |
| i-u | 2886 | 0.474 | 1.375 | 194 | 4957 | 1216 | 6874 | 957 |
| u-i | 6720 | 0.161 | 1.275 | 226 | 10671 | 872 | 13692 | 805 |
| i-i | 19409 | 0.218 | 0.689 | 234 | 51681 | 2833 | 74048 | 2229 |
| other | 53751 | 0.268 | 1.063 | 189 | 52299 | 1674 | 163684 | 1315 |

| SELL TRADES | | | | | | | | |
|--------------------|-----------|---------------|---------------|--------------|--------------------|-------------------|---------------------------|-------------------|
| | nq | return | Spread | Depth | Institution | | Inst + Indi + uncl | |
| | | | | | nt | trade size | nt | trade size |
| u-u | 3395 | -0.274 | 2.535 | 201 | 299 | 371 | 6156 | 517 |
| i-u | 2555 | -0.348 | 1.740 | 210 | 4358 | 1131 | 6107 | 884 |
| u-i | 7292 | -0.041 | 1.407 | 251 | 11491 | 841 | 14790 | 767 |
| i-i | 17147 | -0.072 | 0.738 | 253 | 42301 | 3042 | 61055 | 2333 |
| other | 46312 | -0.145 | 1.150 | 200 | 43967 | 1575 | 133700 | 1242 |

u and i are used to denote trades where individuals and institutions respectively account for more than 50% of shares traded. There are 8 categories of buy and sell trades to be considered. For example, an i-u buy trade means institutions account for more than 50% of the trade-initiating (active) buy shares whereas individuals account for more than 50% of the liquidity-providing (passive) sell shares. nq and nt are the number of quotes and trades respectively. Return is the 1-hr mid-quote log-return, spread is quoted spread divided by mid-quote, depth is the bid-plus-ask depth, and trade size is the average number of shares traded in each trade. Figures that are bold and italic denote significantly different from zero at 1% level.

Table 3: FIRM SIZE AND VOLUME BREAKDOWN

| BUY TRADES | | | | | | | | | | | | | | |
|------------|---------|-------------|-------|-------|------|--------------|-------|-------|------|-------------|-------|-------|------|-----------|
| | | Small firms | | | | Medium firms | | | | Large firms | | | | ALL FIRMS |
| | | n | ret | spr | vol | n | ret | spr | vol | n | ret | spr | vol | ret |
| u-u | 75% < r | 684 | 0.500 | 3.680 | 776 | 1089 | 0.344 | 1.509 | 599 | 752 | 0.140 | 0.618 | 347 | 0.326 |
| | 50% < r | 777 | 0.483 | 3.773 | 1074 | 1275 | 0.343 | 1.548 | 946 | 939 | 0.137 | 0.622 | 548 | 0.315 |
| | 25% < r | 964 | 0.556 | 4.041 | 1270 | 1692 | 0.336 | 1.630 | 919 | 1649 | 0.108 | 0.607 | 500 | 0.298 |
| | All | 6143 | 0.751 | 4.377 | 1001 | 17821 | 0.385 | 1.590 | 733 | 61793 | 0.171 | 0.539 | 559 | 0.257 |
| i-u | 75% < r | 331 | 1.316 | 3.796 | 1073 | 653 | 0.522 | 1.599 | 1341 | 1049 | 0.233 | 0.546 | 1029 | 0.502 |
| | 50% < r | 416 | 1.265 | 3.953 | 1446 | 892 | 0.540 | 1.630 | 1458 | 1578 | 0.229 | 0.552 | 1250 | 0.474 |
| | 25% < r | 559 | 1.205 | 4.107 | 1927 | 1359 | 0.551 | 1.670 | 1609 | 3364 | 0.192 | 0.518 | 1270 | 0.391 |
| | All | 6143 | 0.751 | 4.377 | 2018 | 17821 | 0.385 | 1.590 | 2449 | 61793 | 0.171 | 0.539 | 2278 | 0.257 |
| u-i | 75% < r | 635 | 0.355 | 4.453 | 934 | 1655 | 0.074 | 1.517 | 793 | 3090 | 0.078 | 0.502 | 742 | 0.109 |
| | 50% < r | 767 | 0.396 | 4.585 | 1089 | 1950 | 0.117 | 1.548 | 1038 | 4003 | 0.137 | 0.509 | 1094 | 0.161 |
| | 25% < r | 981 | 0.475 | 4.726 | 1097 | 2573 | 0.163 | 1.583 | 844 | 6167 | 0.130 | 0.517 | 966 | 0.174 |
| | All | 6143 | 0.751 | 4.377 | 1750 | 17821 | 0.385 | 1.590 | 2243 | 61793 | 0.171 | 0.539 | 2071 | 0.257 |
| i-i | 75% < r | 393 | 0.648 | 4.186 | 2894 | 1704 | 0.485 | 1.537 | 3863 | 10892 | 0.167 | 0.463 | 3190 | 0.224 |
| | 50% < r | 514 | 0.641 | 4.154 | 2446 | 2299 | 0.480 | 1.560 | 2711 | 16596 | 0.168 | 0.461 | 2303 | 0.218 |
| | 25% < r | 712 | 0.616 | 4.152 | 1812 | 3208 | 0.496 | 1.586 | 1833 | 23215 | 0.169 | 0.463 | 1780 | 0.219 |
| | All | 6143 | 0.751 | 4.377 | 1490 | 17821 | 0.385 | 1.590 | 1606 | 61793 | 0.171 | 0.539 | 1490 | 0.257 |

| SELL TRADES | | | | | | | | | | | | | | |
|-------------|---------|-------------|--------|-------|------|--------------|--------|-------|------|-------------|--------|-------|------|-----------|
| | | Small firms | | | | Medium firms | | | | Large firms | | | | ALL FIRMS |
| | | n | ret | spr | vol | n | ret | spr | vol | n | ret | spr | vol | ret |
| u-u | 75% < r | 1059 | -0.345 | 4.905 | 702 | 996 | -0.426 | 1.669 | 605 | 772 | -0.036 | 0.612 | 576 | -0.289 |
| | 50% < r | 1214 | -0.361 | 4.931 | 1085 | 1181 | -0.395 | 1.686 | 852 | 1000 | -0.025 | 0.628 | 581 | -0.274 |
| | 25% < r | 1463 | -0.423 | 4.943 | 996 | 1613 | -0.387 | 1.721 | 917 | 1769 | -0.031 | 0.619 | 454 | -0.268 |
| | All | 7378 | -0.543 | 4.877 | 843 | 15521 | -0.252 | 1.627 | 855 | 53802 | -0.040 | 0.521 | 554 | -0.131 |
| i-u | 75% < r | 381 | -0.750 | 4.884 | 984 | 557 | -0.502 | 1.618 | 1210 | 904 | -0.083 | 0.579 | 940 | -0.348 |
| | 50% < r | 491 | -0.880 | 4.984 | 1481 | 723 | -0.454 | 1.679 | 1344 | 1341 | -0.096 | 0.585 | 1178 | -0.348 |
| | 25% < r | 686 | -0.874 | 5.147 | 1572 | 1126 | -0.494 | 1.747 | 1398 | 2770 | -0.082 | 0.570 | 1332 | -0.302 |
| | All | 7378 | -0.543 | 4.877 | 1839 | 15521 | -0.252 | 1.627 | 2357 | 53802 | -0.040 | 0.521 | 2340 | -0.131 |
| u-i | 75% < r | 841 | -0.238 | 5.132 | 793 | 1653 | -0.068 | 1.581 | 928 | 3324 | 0.012 | 0.476 | 709 | -0.047 |
| | 50% < r | 980 | -0.277 | 5.098 | 897 | 1986 | -0.087 | 1.600 | 1242 | 4326 | 0.033 | 0.482 | 925 | -0.041 |
| | 25% < r | 1210 | -0.264 | 5.030 | 659 | 2603 | -0.108 | 1.616 | 801 | 6753 | 0.003 | 0.487 | 788 | -0.055 |
| | All | 7378 | -0.543 | 4.877 | 1733 | 15521 | -0.252 | 1.627 | 2364 | 53802 | -0.040 | 0.521 | 2140 | -0.131 |
| i-i | 75% < r | 423 | -0.532 | 4.384 | 2536 | 1642 | -0.216 | 1.600 | 3764 | 9679 | -0.050 | 0.459 | 3528 | -0.091 |
| | 50% < r | 529 | -0.500 | 4.500 | 2930 | 2301 | -0.258 | 1.601 | 2469 | 14317 | -0.027 | 0.461 | 2350 | -0.072 |
| | 25% < r | 708 | -0.559 | 4.564 | 1697 | 3098 | -0.279 | 1.617 | 1741 | 19974 | -0.023 | 0.462 | 1711 | -0.072 |
| | All | 7378 | -0.543 | 4.877 | 1274 | 15521 | -0.252 | 1.627 | 1368 | 53802 | -0.040 | 0.521 | 1404 | -0.131 |

r is the proportion of shares traded that are attributable to institutions or individuals e.g. a buy i-u category with r > 75% means that both the institutional active buy shares and the individual passive sell shares account for at least 75% of shares traded. n, ret, spr and vol are the number of quotes, mid-quote 1-hr log return, spread and trade size respectively. Firms are divided into small, medium and large depending on whether their market value is in the top, middle or bottom third.

Table 4: Regression using 50% volume criterion

| BUY TRADES REGRESSION | | | | | | |
|------------------------------|---------------|--------|---------------|--------|---------------|--------|
| #Observations = 16270 | | | | | | |
| Variables | R-sq = 0.0027 | | R-sq = 0.0128 | | R-sq = 0.0230 | |
| | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| Constant(u-i) | 0.157 | 2.801 | 0.176 | 3.166 | 0.210 | 3.562 |
| Indicator(u-u) | 0.120 | 1.724 | 0.052 | 0.775 | 0.043 | 0.668 |
| Indicator(i-u) | 0.367 | 5.352 | 0.410 | 5.874 | 0.353 | 5.027 |
| Indicator(i-i) | 0.054 | 0.918 | 0.093 | 1.564 | 0.010 | 0.135 |
| Indicator(other) | 0.083 | 1.394 | 0.019 | 0.329 | -0.004 | -0.074 |
| beta | | | 0.049 | 1.664 | 0.011 | 0.358 |
| ln(MV) | | | -0.093 | -8.112 | -0.056 | -4.219 |
| ln(trade size) | | | | | 0.051 | 4.851 |
| spread | | | | | 0.057 | 2.242 |
| D-depth (x1000) | | | | | 0.968 | 9.110 |
| depth (x1000) | | | | | -0.164 | -4.015 |

| SELL TRADES REGRESSION | | | | | | |
|-------------------------------|---------------|--------|---------------|--------|---------------|--------|
| #Observations = 16272 | | | | | | |
| Variables | R-sq = 0.0013 | | R-sq = 0.0073 | | R-sq = 0.0142 | |
| | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| Constant(u-i) | -0.030 | -0.722 | -0.057 | -1.401 | -0.093 | -2.265 |
| Indicator(u-u) | -0.186 | -3.377 | -0.116 | -2.248 | -0.091 | -1.699 |
| Indicator(i-u) | -0.288 | -4.197 | -0.300 | -4.338 | -0.234 | -3.440 |
| Indicator(i-i) | -0.096 | -2.110 | -0.119 | -2.542 | -0.036 | -0.789 |
| Indicator(other) | -0.113 | -2.209 | -0.048 | -1.014 | -0.025 | -0.534 |
| beta | | | -0.054 | -1.905 | -0.040 | -1.397 |
| ln(MV) | | | 0.073 | 6.968 | 0.042 | 3.465 |
| ln(trade size) | | | | | -0.047 | -4.294 |
| spread | | | | | -0.051 | -3.023 |
| D-depth (x1000) | | | | | -0.852 | -9.576 |
| depth (x1000) | | | | | 0.255 | 5.960 |

Non-overlapping mid-quote log returns are used in the regressions. Beta is obtained using 36 monthly stock returns regressing on the equal-weighted return index. ln(MV), ln(trade size) are logs of firm size and trade size). Spread and depth are as defined in Table 2. For buy (sell) trades regression, D-depth is the bid-minus-ask (ask-minus-bid) depth. Except for the constant and indicator variables, all control variables are mean adjusted (to have zero means). The 50% criterion is used to define both u and i. The coefficient of the constant gives the mean return on u-i trades, whereas the other categories give the incremental returns over u-i. t-stat is calculated using White's (1980) method to correct for heteroscedasticity.

Table 5: Regression using 75% volume criterion

| BUY TRADES REGRESSION | | | | | | |
|------------------------------|---------------|--------|--|--------|---------------|--------|
| Variables | R-sq = 0.0027 | | #Observations = 16270 R-sq = 0.0132 | | R-sq = 0.0249 | |
| | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| Constant(u-i) | 0.104 | 2.659 | 0.127 | 3.189 | 0.162 | 3.916 |
| Indicator(u-u) | 0.181 | 3.098 | 0.107 | 1.807 | 0.099 | 1.702 |
| Indicator(i-u) | 0.418 | 7.465 | 0.450 | 8.151 | 0.400 | 7.354 |
| Indicator(i-i) | 0.161 | 2.732 | 0.206 | 3.620 | 0.127 | 1.984 |
| Other | 0.156 | 3.635 | 0.099 | 2.296 | 0.064 | 1.418 |
| beta | | | 0.058 | 2.079 | 0.017 | 0.562 |
| ln(MV) | | | -0.090 | -8.430 | -0.048 | -3.750 |
| ln(trade size) | | | | | 0.043 | 5.419 |
| spread | | | | | 0.067 | 2.604 |
| D-depth (x1000) | | | | | 0.991 | 11.531 |
| depth (x1000) | | | | | -0.158 | -4.048 |

| SELL TRADES REGRESSION | | | | | | |
|-------------------------------|---------------|--------|--|--------|---------------|--------|
| Variables | R-sq = 0.0007 | | #Observations = 16272 R-sq = 0.0070 | | R-sq = 0.0146 | |
| | Coefficient | t-stat | Coefficient | t-stat | Coefficient | t-stat |
| Constant(u-i) | -0.034 | -0.742 | -0.061 | -1.368 | -0.099 | -2.215 |
| Indicator(u-u) | -0.171 | -2.832 | -0.098 | -1.737 | -0.072 | -1.242 |
| Indicator(i-u) | -0.235 | -3.338 | -0.243 | -3.437 | -0.187 | -2.657 |
| Indicator(i-i) | -0.095 | -1.890 | -0.126 | -2.437 | -0.041 | -0.796 |
| Other | -0.132 | -2.536 | -0.078 | -1.602 | -0.043 | -0.896 |
| beta | | | -0.064 | -2.284 | -0.046 | -1.609 |
| ln(MV) | | | 0.072 | 6.993 | 0.036 | 3.053 |
| ln(trade size) | | | | | -0.047 | -4.540 |
| spread | | | | | -0.058 | -3.468 |
| D-depth (x1000) | | | | | -0.850 | -9.206 |
| depth (x1000) | | | | | 0.224 | 5.224 |

Non-overlapping mid-quote log returns are used in the regressions. Beta is obtained using 36 monthly stock returns regressing on the equal-weighted return index. ln(MV), ln(trade size) are logs of firm size and trade size). Spread and depth are as defined in Table 2. For buy (sell) trades regression, D-depth is the bid-minus-ask (ask-minus-bid) depth. Except for the constant and indicator variables, all control variables are mean adjusted (to have zero means). The 75% criterion is used to define both u and i. The coefficient of the constant gives the mean return on u-i trades, whereas the other categories give the incremental returns over u-i. t-stat is calculated using White's (1980) method to correct for heteroscedasticity.

Table 6: INTRADAY ANALYSIS

| | | BUYS per hour | | | SELLS per hour | | |
|----------------------------|-------|---------------|--------------|--------------|----------------|---------------|---------------|
| | | 0930-1030 | 1030-1500 | 1500-1600 | 0930-1030 | 1030-1500 | 1500-1600 |
| Volume (1000 shares) | u-u | 14 | 13 | 19 | 18 | 17 | 16 |
| | i-u | 955 | 907 | 990 | 1070 | 655 | 914 |
| | u-i | 1414 | 1315 | 1978 | 2031 | 1336 | 1623 |
| | i-i | 30515 | 20016 | 25801 | 28325 | 17599 | 21162 |
| | other | 17498 | 12072 | 15727 | 15375 | 9196 | 12490 |
| Return | u-u | 0.319 | 0.283 | 0.212 | -0.424 | -0.177 | -0.182 |
| | i-u | 0.664 | 0.518 | 0.409 | -0.396 | -0.353 | -0.135 |
| | u-i | 0.163 | 0.151 | 0.178 | -0.105 | -0.078 | 0.224 |
| | i-i | 0.280 | 0.199 | 0.188 | -0.179 | -0.134 | -0.042 |
| | other | 0.242 | 0.249 | 0.212 | -0.271 | -0.144 | -0.034 |
| Spread | u-u | 1.657 | 1.850 | 1.937 | 2.616 | 2.512 | 2.548 |
| | i-u | 1.528 | 1.350 | 1.328 | 1.627 | 1.762 | 1.777 |
| | u-i | 1.306 | 1.268 | 1.276 | 1.521 | 1.362 | 1.455 |
| | i-i | 0.675 | 0.688 | 0.708 | 0.699 | 0.752 | 0.736 |
| | other | 1.044 | 1.056 | 1.101 | 1.113 | 1.133 | 1.241 |
| Depth | u-u | 165 | 188 | 189 | 215 | 202 | 185 |
| | i-u | 175 | 198 | 198 | 232 | 203 | 213 |
| | u-i | 214 | 231 | 214 | 276 | 249 | 230 |
| | i-i | 228 | 239 | 221 | 268 | 253 | 237 |
| | other | 180 | 195 | 175 | 193 | 206 | 187 |

Various statistics are provided for 0930-1030, 1030-1500 and 1500-1600 time intervals. Volume is the total number of institutional shares on the active side for u-u, i-u, i-i and 'other' categories; for u-i, number of passive institutional shares is calculated. For the 1030-1500, volumes are divided by 4.5 so that the reported figures are representative of an hour's volume in the time interval. Non-overlapping mid-quote log returns are used to calculate the average returns. Spread is the quoted spread divided by mid-quote and depth is the bid-plus-ask depth. Figures in bold (italic bold) are significant at the 5% (1%) level. For the 10.30-15.00 time-interval, significance is with respect to difference from zero; for the first and last hour time intervals, significance is with respect to difference from the 10.30-15.00 time interval.