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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 questions 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 individual[2], 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)

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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 significantly[6] 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. Ranaldo (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 intrainstitution 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

		Active			Passive		
	Total	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

		Active			Passive		
	Total	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 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 nt	Institution trade size	Inst + Indi + uncl nt	Inst + Indi + uncl 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 nt	Institution trade size	Inst + Indi + uncl nt	Inst + Indi + uncl 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 Coefficient	t-stat	R-sq = 0.0128 Coefficient	t-stat	R-sq = 0.0230 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 Coefficient	t-stat	R-sq = 0.0073 Coefficient	t-stat	R-sq = 0.0142 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						
	#Observations = 16270					
	R-sq = 0.0027		R-sq = 0.0132		R-sq = 0.0249	
Variables	**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						
	#Observations = 16272					
	R-sq = 0.0007		R-sq = 0.0070		R-sq = 0.0146	
Variables	**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 differnce from zero; for the first and last hour time intervals, significance is with respect to difference from the 10.30-15.00 time interval.