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Empirical evidence on the evolution of liquidity: Choice of market versus limit orders by informed and uninformed traders ☆

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Abstract

We empirically investigate the evolution of liquidity, as well as the changing strategies of informed traders, over the course of the trading day. In particular, we empirically examine the relative use of market versus limit orders by informed and liquidity traders early versus later in the trading day using detailed order and audit trail data from the NYSE. Our study complements experimental research that shows that informed traders tend to take liquidity earlier in the trading day while acting as liquidity suppliers later in the day. We find that informed (i.e., institutional) traders actually use market orders more often in the first half of the day than the second. We also find support for informed traders' use of limit orders. Limit orders placed by informed traders perform better than those placed by uninformed

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(i.e., individual) traders. Our findings serve to underscore the importance of developing new theoretical models to more accurately reflect the changing and complex trading milieu.

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1. Introduction

How do informed traders behave with regard to the choice of their strategies over the course of the trading day? How do the uninformed liquidity demanding traders respond with their own strategy choices over the same period? The answers to such questions hark back to the fundamental questions related to the source and availability of liquidity, which is a crucial determinant of the success of any modern exchange. In recent years, both the regional stock exchanges and electronic markets such as ECNs have emerged as viable trading alternatives for investors. These alternative trading systems have transformed the use of limit orders, and made the role of public limit orders as suppliers of liquidity particularly significant. Given this increased prominence of limit orders in today's environment, it behooves us to understand the evolution of informed trading, especially through traders' choice of market and limit orders, over the course of the trading day.

Unfortunately, this is easier said than done. Informed traders are not observable since they take pains to disguise themselves and their trading motives, and it is left to the creative resources of empirical researchers to come up with reasonable proxies of what comprises informed (and uninformed) trades. Our research builds on the important assumption that institutions are informed traders while individuals are uninformed.[1] Additionally, most publicly available intraday transactional databases do not provide details pertaining to orders behind each transaction, let alone on the counterparties to the trade, or a view of when limit orders are submitted, and the market conditions prevailing at the time of order submission. There is, however, one publicly available database which allows us to investigate the above questions. This is a well used (and well documented) audit trail of all orders and their execution details, over a well represented sample of NYSE stocks over a three month period, known as TORQ.

Using this data, we find that informed initiating trades (through market orders and marketable limit orders)[2] account for a higher cumulative price change in the first half of the day than the second. Thus, informed traders use market orders early on in the trading session. We also study the performance of institutional and

[1] Szewczyk et al. (1992), Alangar et al. (1999), and Dennis and Weston (2001) find corroborating evidence of institutions being better informed. Chakravarty (2001) finds that institutional medium-size orders have a significantly greater cumulative stock price impact than individual orders.

[2] A marketable limit order is one that is placed at or better than the opposite quote and hence is immediately executable.

individual limit orders after order submission and find that institutional limit orders perform better than individual limit orders. This result holds even after controlling for order and stock specific characteristics, indicating the use of information in placing limit orders and thereby demonstrating the role of limit orders in informed trading.

While the extant theoretical literature provides some guidance on the question of the evolution of liquidity over the trading period (see, for example, Angel (1994), Chakravarty and Holden (1995), Harris (1998), Parlour (1998), and Kaniel and Liu (2003)), these models are stylized (i.e., restrictive) enough to make it impossible to find in them the answers to the questions we ask above. So, absent a clear direction from the existing theoretical models, it is clear that any answer on the issue of evolution of trading strategies vis-à-vis the relative usage of market and limit orders by both the informed and the uninformed traders has to come from the data itself.

Bloomfield et al. (2005) (hereafter BOS) tackle this problem by experimentally modeling an electronic market to provide insight into the evolution of liquidity. BOS's experimental electronic market includes informed and large and small liquidity traders trading via market and limit orders in a continuous time setting. The emergent intuition from their study is that informed traders take liquidity earlier in the trading day with market orders so as to profit from their private information. In so doing, they push prices closer to their true values and then use their knowledge of the true price to act as dealers by switching to submitting limit orders and earning the bid-ask spread later in the trading day. Thus, toward the end of the trading period, informed traders, on average, trade more often with limit orders than do liquidity traders. The uninformed or liquidity traders tend to use limit orders early on but as the end of the trading day approaches they switch to market orders in order to meet their targets.

Counter to these predictions, however, is the prevailing intuition from the theoretical literature that informed traders are much more likely to be liquidity demanders than liquidity suppliers. Angel (1994) and Harris (1998) allow for the use of limit orders by informed traders, but argue that they are more likely to use market orders. Harris (1998) predicts that informed traders are more likely to use market orders if they believe their information to be short lived. Furthermore, as trading deadlines approach, the likelihood of market order use by informed traders increases. These studies set up our alternative hypothesis that limit orders will be used sparingly (or not at all) by informed traders.[3]

Our study contributes to this literature by providing empirical evidence on the market versus limit order choice of informed traders. In focusing on the evolution of

[3]Kaniel and Liu (2003) allow the expected time horizon of informed traders' private information to vary and show that when this expected time horizon is large, informed traders are likely to prefer limit orders over market orders and, when this probability is high enough, limit orders will convey more information than market orders. Therefore, studies like Chakravarty and Holden (1995), and Kaniel and Liu (2004), that argue for the use of limit orders by informed traders, serve to underscore the significance of the limit order book.

trading strategies of informed traders over a trading day, we also complement the experimental analysis of BOS.

Empirical studies in the area have focused on various dimensions of order choice. Lee et al. (2004), for example, find that different trader types on the Taiwan Stock Exchange act as de facto liquidity suppliers while also trading based on information. Their results suggest the changing order choice of individuals and institutional investors that we study in this paper. Harris and Hasbrouck (1996) study all limit orders placed through NYSE's SuperDOT system and find that limit orders placed at or better than the prevailing quote outperform market orders. Griffiths et al. (2000) also find that order aggressiveness plays an important role in the order's performance. Biais et al. (1995) examine the role of the limit order book in order choice on the Paris Bourse. Chung et al. (1999) examine the role of the limit order traders in setting the bid-ask spread on the NYSE. They find (p. 257) that "the majority of bid-ask quotes reflect the interest of limit-order traders."[4]

The plan for the remainder of the paper is as follows. In the next section we describe the data; Section 3 presents the methodology and the results. Section 4 concludes.

2. Data

The TORQ database contains transactions, quotes, order data and audit trail data for a sample of 144 NYSE stocks for the months of November 1990–January 1991. The sample selection criteria for picking the 144 stocks ensure that the firms are representative of the universe of stocks trading on the NYSE.[5] The level of detail in TORQ makes it unique and is the primary reason that it continues to be widely used in academic studies.[6] In particular, all of the analyses in the current paper are conducted using two particular files within TORQ: the audit trail (CD) files and the system order data base (SOD).

We restrict our sample to those stocks where there are likely to be significant informational effects. Specifically, we pick the stocks which experienced a 5% increase

[4]A few recent studies [see, for example, Hasbrouck and Saar (2002), and Biais et al. (2002)] have used detailed data from the Island ECN in their analysis of market quality on such electronic systems. Island data, however, is not appropriate for the current analysis for two reasons. First, it does not provide details on the identity of the order submitter. Thus, we cannot differentiate between institutional/professional and individual orders. Second, Island is part of a fragmented marketplace where traders have a wide choice of market centers. This factor could complicate any such analysis, as informed and liquidity traders can choose among different venues, and can easily switch from one market to the other at different times of the day. The NYSE, on the other hand, is a far more consolidated market. This is true even more of our sample period (November 1990–January 1991). Thus, in our study, we empirically test the predictions coming out of BOS and extend them to a different, albeit arguably the most important, market structure in U.S. equity trading.

[5]Hasbrouck (1992) provides a detailed description of the database as well the sample selection criteria. Hasbrouck et al. (1993) describe NYSE systems and procedures.

[6]See, for example, Hasbrouck (1996), Sias and Starks (1997), Koski and Scruggs (1998), Angel (1998), Chung et al. (1999), Ready (1999), and Chakravarty (2001).

in prices over the sample period. This gives us a sample of 97 stocks.[7] The average price increase in these stocks is 28%, which is significantly higher than the 12% for the 144 TORQ stocks over the sample period. However, for robustness, wherever appropriate, we also replicate our analysis using all 144 stocks in the data base.

The TORQ data includes orders submitted through the NYSE's SuperDOT system, OARS (the opening automated reporting system) and ITS (the Intermarket Trading System). Thus, orders that are handled manually are not included in this database. For the orders entered into one of the computerized systems, the database contains information on the price and time of order entry, price and time of order execution/cancellation, other details of the order such as whether it is a market or a limit order, special conditions attached to the order, etc.

More important for the current analysis is the account type indicator which identifies whether the particular order was placed by an Individual (account type I), whether the order came from a member firm trading on its own account (account type P)[8] or from a member firm trading on behalf of a customer or possibly another member firm (account type A). For the current analysis, we combine the account types ***P*** and ***A*** into trades from institutions, under the assumption that almost all exchange members are, arguably, institutions. More importantly, the specialists do not have direct access to this account type information. And in order to attribute the price response to an order with certain characteristics, we need to establish that such orders are, at least partially, identified by the specialist. In our case, these characteristics involve the identification of whether an order originated from an individual investor or an institutional client.

Aside from the basic features of an order necessary for its proper execution, such as ticker symbol, buy/sell, market/limit, size, and price (if limit), the specialist knows, or can deduce, further information about incoming orders, especially if an order is from an institutional or a retail (individual) investor, as they flash on his computer screen. Thus, for example, the size of an order itself can sometimes provide important clues. Larger orders are more likely to be from institutions than individuals. If a specialist is curious about the origin of an order, he can go to a special screen on his monitor that provides him with certain mnemonics through which he may determine the submitting broker's identity. Over time, specialists claim they can recognize patterns in trades associated with certain mnemonics and, in turn, deduce the trader type behind an order.[9] In sum, all evidence points to the probability that specialists are able to deduce the trader type submitting the order.[10] In addition, Hasbrouck (1996) assumes that market participants are able to

[7]This was a period of rising prices. There are only 14 stocks that experienced a decline of 5% or more. Moreover, these are all thinly traded stocks, thereby making it impossible to perform separate estimations with any degree of power.

[8]Trades from specialists are not identified in the database.

[9]We thank Joel Hasbrouck for providing these insights in private conversations.

[10]A very pragmatic reason behind why market makers would like to keep tabs on who is behind a given order is the simple fact that trades of certain investors (or investor-groups) are followed and mimicked by other investors. This is known as "follow-on trading" and has been discussed by many researchers (see, for example, Barclay and Dunbar (1996), Chakravarty and McConnell (1997, 1999), and Chakravarty and Sarkar (2002)).

distinguish between program and non-program trades within the context of the TORQ data, while Sias and Starks (1997, p. 109) use the TORQ data to test if institutional holdings can effectively proxy for institutional trading under the assumption that the specialist is able to distinguish between individual and institutional trades.

The two issues we need to resolve with the data are as follows. First, the transactions data in TORQ do not have a one-to-one correspondence with the orders that make up the transaction.[11] And second, the audit file in TORQ does not identify whether the buyer or the seller in a transaction was the trade initiator. Since the specialist has the freedom to report a transaction in multiple ways, absent a direct mapping between a trade and its underlying orders, it is unreliable to use transactions data directly to measure the effect of trade size on stock prices. The audit file of the TORQ data set, however, identifies the traders (and their order sizes) on either side of a transaction.

Even with this correspondence between orders and transactions, the initiating order side may have multiple parties involved in the trade. For example, a 10,000-share buyer-initiated transaction may be comprised of an individual buyer for 2,000 shares and an institutional buyer for 8,000 shares, matched with an institutional seller for 10,000 shares. This would make the task of identifying whose trades impacted the price change difficult, if not impossible. We overcome this problem by eliminating all transactions where the active (or initiating) side has less than 100% participation in any single trader type. Thus, if the initiating buy side of a 20,000-share trade has 4 traders each with a 5,000-share order, and if all 4 are institutional buyers, the observation is included in our data. Using this filter, we are left with 151,367 (a little over 60% of the initial) observations in the audit file in the 97 chosen stocks. This is the sample used in the current study. The data includes 151,367 initiating orders representing a total of 389,943,500 shares traded. A majority of this volume (87%) is initiated by institutional traders. Buyer initiated trades are more frequent than seller initiated trades for both individuals and institutions and account for a higher proportion of volume (51% of volume for institutional buyer initiated trades versus 36% for seller initiated, and 6% of volume for individual buyer initiated trades versus 7% of volume for sell trades initiated by individuals). Individual trades account for approximately 38% of the sample, suggesting that individual transactions tend to be smaller than institutional, which is, in fact, the case. The average individual trade is for 917 shares while the average institutional trade is for 3,253 shares.

Extant theories of market microstructure, modeling the impact of trades on prices and other observables, are based on the trade initiator (see O'Hara (1995) for a survey). It is therefore important to infer the initiator of a trade (buyer or seller)

[11] This is an important distinction because transactions data do not always have a one-to-one mapping with individual orders in the TORQ database. Thus, an 800-share transaction reported in the data could represent a pairing of a market buy order for 800 shares with two market sell orders for 400 shares each. The specialist could report this trade either as a single transaction of 800 shares (a medium-size trade) or as two transactions of 400 shares each (small-size trades). This introduces noise in the system when trying to determine the effect of trade size on price change.

Table 1
Summary of the limit orders sample. All limit orders submitted over the November 1990–January 1991 period. To isolate informed orders we only use buy orders for upward trending stocks and sell orders in downward trending stocks. Results are presented separately for limit orders at or better than standing quotes (but excluding marketable orders), and for those behind standing quotes. Panel A presents summary statistics for the 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990–January 31, 1991). Panel B presents statistics for the entire TORQ universe of 144 stocks.

Account type	Aggressiveness	Average order size	Average order size ($)	Number of orders	Proportion of orders (%)
Panel A: 97 stocks					
Individual	At or better	919.9	17089.4	17259	53
Individual	Behind the quote	608.3	15470.0	15048	47
Institutional	At or better	1383.9	48279.9	32340	78
Institutional	Behind the quote	1334.5	56409.6	9265	22
Panel B: 144 stocks					
Individual	At or better	920.6	18559.6	26058	57
Individual	Behind the quote	646.0	16641.2	19583	43
Institutional	At or better	1404.8	49312.6	43480	79
Institutional	Behind the quote	1371.0	56243.8	11786	21

because the validity of all economic studies, based on such theories, also hinges critically on the *accurate* classification of trades as buyer or seller initiated. To do so, we use the Lee and Ready (1991) algorithm, to classify trades as buyer or seller initiated. Thus, if a trade occurs at the prevailing bid (ask) price or anywhere between the bid (ask) and the midpoint of the prevailing bid ask spread, it is considered a seller-initiated (buyer-initiated) trade. For trades occurring at the prevailing spread midpoint, the tick test rule is applied to determine the trade initiator, whereby a trade is buyer-initiated (seller-initiated) if the price move from the previous transaction price is upwards (downwards). Also, the prevailing spread is assumed to be at least five seconds old. Otherwise, the previous quote is used to compute the prevailing spread.

While the above sample focuses on market orders, we also study non-marketable limit orders for some of the analysis.[12] For this analysis, we use information from the SOD file in the TORQ data. The use of the SOD file is necessary because non-marketable limit orders do not immediately execute, and often don't execute or are cancelled. Thus, any analysis of such orders needs information on when the order was submitted, and the market conditions prevailing at the time of order submission. Table 1 provides information on our non-marketable limit order sample. There are

[12]A non-marketable limit order is one that is not immediately executable. Hence, limit orders to buy (sell) at a price lower (higher) than the ask (bid) price are not marketable and have to wait for execution.

32,307 individual and 41,605 institutional limit orders. Institutions tend to be more aggressive, placing 78% of their orders at or better than the same side quote. Individuals, on the other hand, place 53% of their non-marketable limit orders at or better than the standing quotes and 47% behind the quotes. Not surprisingly, institutional limit orders tend to be bigger than individual limit orders, both in number of shares each order represents and in their dollar value. Order size is likely to be related to price impact and, thus, needs to be carefully considered in the analysis. We also present similar statistics for our robustness sample of all 144 stocks. The sample is qualitatively similar in that institutional orders are more aggressive and of larger size.

3. Results

We begin our analysis by testing the null hypotheses based on the experimental analysis of BOS. The BOS findings would indicate a differential use of market and limit orders by informed traders at different times during the day. However, theoretical studies of information-based trading such as Glosten (1994) and Kyle (1985) assume that informed traders trade with market orders, while the research of Angel (1994) and Harris (1998) either assumes, or predicts, that informed traders are more likely to use market orders, and limit orders are more likely to come from liquidity traders. These studies confirm the conventional wisdom that informed traders are unlikely to use limit orders, and provide the underpinnings of our alternative hypothesis: there is no difference in the performance of limit orders placed by individuals and institutions.

3.1. Use of limit orders by informed traders

In this subsection, we test for the use, and the consequent performance, of limit orders placed by informed traders. In so doing, we test the assumption underlying the analysis of Chakravarty and Holden (1995) and of Bloomfield et al. (2005) that informed traders would include limit orders in their trading strategies. Specifically, we perform a cross sectional analysis of the limit order performance following their *submission* by individual and institutional investors where limit order performance is measured as the midquote prevailing 5 min (or 60 min) after order submission less the midquote at the time of order submission for buy orders. For sell orders, limit order performance is measured as the prevailing midquote at the time of order submission less the midquote 5 min (or 60 min) after order submission. For the current analysis, we examine limit buy orders only for upward trending stocks and limit sell orders only for downward trending stocks under the assumption that such orders are more likely to be informed. Further, if institutional orders are more informed than individual orders, we should see better performance associated with institutional limit orders than with individual limit orders.[13]

[13]We examine price reversal on the basis of limit order submission, rather than limit order execution, because limit order execution depends on market conditions after the order is submitted, which may not be under the control of the trader who submitted the order.

Table 2
The table summarizes changes in bid-ask midpoint 5 and 60 min after limit order submission. For buy orders, price change is measured as the midquote prevailing 5 min (or 60 min) after submission less the midquote at the time of order submission. For sell orders, price change is measured as the midquote at the time of order submission less the midquote 5 min (or 60 min) after order submission. Panel A presents results for the 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991). Panel B presents results for the entire TORQ universe of 144 stocks. Buy limit orders are used for upward trending stocks and sell orders for downward trending. Results are separated by the aggressiveness of the order.

Aggressiveness		Institutional	Individual	Institutional–Individual
Panel A: 97 stocks				
At or better	5 min after order placement	0.021	0.012	0.009*[,a]
At or better	60 min after order placement	0.040	0.024	0.016*[,a]
Behind the quote	5 min after order placement	0.001	0.002	−0.001[b]
Behind the quote	60 min after order placement	0.025	0.021	0.003
Panel B: 144 stocks				
At or better	5 min after order placement	0.020	0.011	0.009*[,a]
At or better	60 min after order placement	0.035	0.020	0.016*[,a]
Behind the quote	5 min after order placement	0.001	0.002	−0.001[a]
Behind the quote	60 min after order placement	0.020	0.018	0.002

*t-test significant at 1%.
[a]Non-parametric linear rank sum z-statistic significant at 1%.
[b]Non-parametric linear rank sum z-statistic significant at 5%.

Accordingly, Table 2 presents the aggregate performance of institutional and individual limit orders at two points in time discussed above—5 and 60 min—after the order is submitted. We also partition the limit orders based on orders placed at, or better than, the prevailing quotes at the time of limit order submission (more aggressive limit orders) and those placed behind the prevailing quotes (less aggressive limit orders). We find that for limit orders placed at or better than the prevailing quotes, institutional limit orders show significantly better performance (significant at the 1% level) compared to individual limit orders at both 5 and 60 min after order submission. For the less aggressive limit orders, however, there appear to be no statistical differences in performance across limit orders submitted by institutions and individuals. We further find that the pattern of results as reported above obtains for all 144 stocks in the TORQ data set (Panel B).

3.2. Robustness related to the differences between institutional and individual limit orders

We also conduct multivariate regressions to test whether differences in institutional and individual limit orders exist after controlling for order and stock specific characteristics. Griffiths et al. (2000) describe a trader's decision variables as order direction, order aggressiveness and order size. They find that buy orders convey more information and that more aggressive orders tend to be more informative. Order size can also convey information. Easley and O'Hara (1987), for example, show that the profit maximizing behavior of informed traders, combined with the appropriate inference by the market makers, will lead to the informed traders optimally choosing large orders over small orders. Chakravarty (2001) also relates order size to price impact and finds that medium sized trades account for a majority of the cumulative price change in the stocks in his sample.

Given the above, we run the following regression:

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Aggressiveness + \beta_3 Inst. + D_1 + \cdots + D_{n-1} + \varepsilon, \quad (1)$$

where $Diff_t$ is the difference between the quote midpoint at time $t+n$, (where t is the time of order submission) and the quote midpoint current at the time of order submission for buy orders. For sell orders, $Diff_t$ is the difference between the quote midpoint current at order submission and the quote midpoint at time $t+n$, *Size* is the number of shares in the particular order divided by the mean daily volume of shares traded in the particular stock over the sample period (November 1990–January 1991, where the mean daily volume is calculated using CRSP data.) *Aggressiveness* is a dummy variable that equals 1 for orders placed at, or better, than the standing quotes, and 0 for orders placed behind the quotes, *Inst.* is a dummy variable which takes the value 1 for institutional orders and 0 for individual orders, and D_1 to D_{n-1} are stock specific dummies associated with the particular stock that was traded. We include stock specific dummies to ensure that the difference in the performance stems from not just which stocks institutions trade but when these stocks are traded. This, in essence, is a very strong test of informational use of limit orders. These regressions are run for differences that exist 5 and 60 min after limit order submissions. Table 3 provides the results. Panel A provides the results for the 97 stocks while Panel B provides the results for all 144 stocks in the TORQ data set.

The institutional dummy (Table 3, Panel A) measures whether institutions have an informational advantage over individuals after controlling for order characteristics. For the two regressions (5 and 60 min after order submission), we see a significant positive coefficient indicating that institutional orders show superior performance due to reasons other than such discretionary variables as order direction, order size and order aggressiveness. We attribute this to "informed" limit order trading by institutional investors. As a further check of robustness, we also run these tests for all 144 stocks in the TORQ universe and find results very similar to the ones described here (Table 3, Panel B).

It is also important to relate the above results to the literature on stealth trading and the implications flowing from there. Information plays a key role in the trading process and, among other things, in setting the bid-ask spread. Market makers are concerned about trading with an informed trader and the adverse selection component of the spread is their compensation for bearing this risk. Informed traders, on the other hand, are concerned about managing their information and may trade in ways that minimize the impact of their trades. Thus, Barclay and

Table 3
This table summarizes the results of robustness regressions testing for a difference in the performance of institutional and individual orders. The regression equation controls for stock selection by institutional and individual traders

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Aggressiveness + \beta_3 Inst. + D_1 + \cdots + D_{n-1} + \varepsilon, \tag{1}$$

where $Diff_t$ is the difference between bid-ask midpoint at time $t+n$, where t is the time of order submission and n equals 5 and 60 min and the bid ask midpoint prevailing at time t for buy orders. For sell orders $Diff_t$ is the difference between the quote midpoint at time t and the quote midpoint 5 and 60 min after order submission. *Size* is the number of shares in the particular order divided by the mean daily volume of shares traded in the particular stock over the sample period (November 1990–January 1991). For buy orders *Aggressiveness* is a dummy which takes the value 1 if the order is placed at or better than the standing quote and zero otherwise. *Inst.* is a dummy variable, which takes the value 1 for institutional orders and 0 for individual orders. D_1 to D_{n-1} are stock specific dummies associated with the particular stock that was traded.

	Intercept order	Size order	Aggressiveness dummy	Institutional dummy
Panel A: 97 stocks				
5 min after order placement	0.005	0.010*	0.016*	0.004*
60 min after order placement	0.020**	0.020*	0.012*	0.006*
Panel B: 144 stocks				
5 min after order placement	0.006	0.012*	0.014*	0.004*
60 min after order placement	0.021**	0.023*	0.012*	0.004*

**t*-test significant at 1%; ***t*-test significant at 5%.

Warner (1993) find support for the stealth trading hypothesis that informed investors tend to trade in sizes that are neither too big nor too small. Chakravarty (2001) finds that institutional investors use medium sized trades to "stealthily" fulfill their demands. However, the ability of the specialist at the NYSE to (imperfectly) infer the trader group behind an order leads to an unusually large price impact for such trades. But Chakravarty (2001) focuses only on initiating trades, which are primarily market orders.

Stealth trading, however, can be carried out through other means as well. If informed traders use limit orders to strategically trade with incoming market orders, and if these informed traders can be shown to perform better than uninformed limit orders, then such informed limit order trading can be argued to be another expression of stealth trading. That is precisely what we find in the current analysis: institutional limit orders perform better than individual limit orders.

We also conduct this analysis of limit order performance by comparing the limit price of the order with a subsequent quote midpoint—5 min or 60 min after order submission. Table 4 presents the results. We find that the institutional limit orders placed at or better than the standing quotes tend to be more informed than individual limit orders in that prices move in the direction of these orders (up for buy orders, and down for sell orders) after placement. The results for orders placed

Table 4
The table summarizes changes in bid-ask midpoint (relative to limit price) 5 and 60 min after limit order submission. For buy orders, price change is measured as the midquote prevailing 5 min (or 60 min) after submission less the limit price. For sell orders, price change is measured as the limit price less the midquote 5 min (or 60 min) after order submission. Panel A presents results for buy orders for the 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990 to January 31, 1991). Panel B presents results for the entire TORQ universe of 144 stocks. Buy limit orders are used for upward trending stocks and sell orders for downward trending. Results are separated by the aggressiveness of the order.

Aggressiveness	Variable	Institutional	Individual	Institutional–Individual
Panel A: 97 stocks				
At or better	5 min after order placement	0.078	0.061	0.017*[,a]
At or better	60 min after order placement	0.097	0.073	0.024*[,a]
Behind the quote	5 min after order placement	1.885	2.479	−0.594*[,a]
Behind the quote	60 min after order placement	1.909	2.498	−0.589*[,a]
Panel B: 144 stocks				
At or better	5 min after order placement	0.078	0.061	0.017*[,a]
At or better	60 min after order placement	0.094	0.069	0.024*[,a]
Behind the quote	5 min after order placement	1.712	2.237	−0.524*[,a]
Behind the quote	60 min after order placement	1.730	2.252	−0.521*[,a]

*t-test significant at 1%.
[a]Non-parametric linear rank sum z-statistic significant at 1%.

behind the quotes are opposite—individual limit orders seem to be better placed. However, it should be remembered that these are submitted orders. As can be seen from the price difference of these ‘‘behind the quote’’ orders, they tend to be placed far behind the standing quotes and, as such, are less likely to execute and be relevant from an informational, or a liquidity provision, standpoint. Then, the price movement captured here (as say, the quote midpoint 5 min after order submission less the limit price for buy orders) is more a reflection of how far behind the quote these orders are, than of their information content.[14] Thus, for our discussion, we concentrate on the more aggressive limit orders ‘‘at or better’’ than the standing quotes in the market. Table 5 presents the results of cross sectional regressions, similar to equation (1), for the more aggressive limit orders only (the aggressiveness dummy is thus not included in the regression). The results show that the difference in institutional and individual limit order performance after submission is highly significant after controlling for order size and the specific stock that the order is

[14]We did not face this problem in our earlier analysis (i.e., in Table 3) as we used the midpoint at a subsequent time less the quote midpoint at order submission as the performance measure. The limit price of the order was not a part of the analysis.

Table 5
This table summarizes the results of robustness regressions testing for a difference in the performance of institutional and individual orders. The regression equation controls for stock selection by institutional and individual traders

$$Diff_t = \beta_0 + \beta_1 Size + \beta_2 Inst. + D_1 + \cdots + D_{n-1} + \varepsilon, \quad (1)$$

where $Diff_t$ is the difference between bid-ask midpoint at time $t+n$, where t is the time of order submission and n equals 5 and 60 min and the limit price. For sell orders $Diff_t$ is the difference between the limit price and the quote midpoint 5 and 60 min after order submission. *Size* is the number of shares in the particular order divided by the mean daily volume of shares traded in the particular stock over the sample period (November 1990 –January 1991). *Inst.* is a dummy variable, which takes the value 1 for institutional orders and 0 for individual orders. D_1 to D_{n-1} are stock specific dummies associated with the particular stock that was traded. We estimate these regressions for aggressive limit orders (at the best quotes or better) only, because of the big differences between the limit prices and prevailing prices for orders behind the quotes. These orders are clearly not informed.

	Intercept	Order size	Institutional dummy
Panel A: 97 stocks			
5 min after order placement	0.064*	0.023*	0.015*
60 min after order placement	0.073*	0.038*	0.018*
Panel B: 144 stocks			
5 min after order placement	0.064*	0.030*	0.015*
60 min after order placement	0.074*	0.046*	0.017*

*t-test significant at 1%.

placed for. Tables 4 and 5 also show similar results for the sample of all 144 stocks in the TORQ universe.

We now turn our attention to the evolution of informed trading using limit orders over the course of the trading day. In their experimental market, BOS find that informed traders become liquidity suppliers towards the end of the trading period and earn the bid-ask spread by trading around the true value. If limit orders are placed more for information-related reasons in the morning and for reasons related to liquidity supply in the second half of the day then we should see better performance for limit orders by institutions in the first half vis-à-vis the second.[15] We measure limit order performance as the midquote prevailing 5 min (or 60 min) after submission less the midquote at the time of order submission. For sell orders, price change is measured as the prevailing midquote at the time of order submission less the midquote 5 min (or 60 min) after order submission. This is similar to the analysis

[15]Strictly speaking, informed traders use the information both in the morning and in the afternoon to place limit orders. However, their information is worth more in the morning and that is why they use market orders. In the afternoon, their information is worth less and they may not be able to profitably trade using market orders but can still efficiently provide liquidity (due to their better assessment of the value of the stock) using limit orders. We thank the anonymous referee for suggesting this line of investigation.

in Section 3.1, except now we calculate limit order performance separately for the first and second halves of the day. From Table 6 we find that, consistent with BOS, institutional limit orders perform better in the first half than the second. This indicates that limit orders are more likely to be information motivated in the first half, and supply liquidity in the second. However, individual limit orders also display a similar trend implying that all limit orders tend to display this pattern rather than just institutional limit orders.

3.3. Use of market orders by informed traders

In the BOS framework, informed traders start the trading day by taking liquidity and trading through market orders, but once prices reach their true value, informed traders profit by earning the spread by supplying liquidity as dealers. Thus, informed traders are more likely to use market orders in the beginning of the day and limit orders towards the end of the day. Liquidity traders tend to behave in the opposite manner. These uninformed traders start the trading period using limit orders but switch to market orders as they approach the end of trading and need to fill their quotas. These patterns identified by BOS are clearly testable and we look for them in our data.

Further, extant studies have found that institutional orders are more likely to be informed than individual orders. It would then seem straightforward to test for the proportion of limit and market orders (from institutions and individuals) at different times of the day. However, it must be noted that not all orders originating from institutions are informed, as institutions do frequently trade for liquidity (or, non-information related) reasons. Such confounding factors make it difficult to simply test for the number of limit and market orders submitted at different times of the day, since the motivations (information or liquidity) behind those submissions are not known. Therefore, we need a measure which allows us to focus on informed trading without getting unduly diluted by confounding factors.

The Barclay and Warner (1993) measure fulfils this requirement as it cumulates the price impact of all trades in a given stock.[16] Thus, any price movements associated with liquidity motivated trades tend to cancel each other out while the price movements caused by informed trades consistently add up (since they are all in the same direction). Further, the combined results from Barclay and Warner (1993) and Chakravarty (2001) imply that institutional medium sized orders tend to be the most informed. We use this intuition in the current analysis. Specifically, we study the cumulative price impact of institutional and individual initiating trades (our sample consists of market and marketable limit orders) by size, and time of day when the order executes. If informed traders are more likely to use market orders in the first half of the day, and these informed trades tend to be institutional medium sized

[16]Specifically, the Barclay and Warner measure attributes a price change to a specific trade, i.e., the difference between the price of the current trade and the previous trade is associated with the current trade. These price changes are then cumulated across classes of trades that are of interest and divided by the total price change in the stock to measure the proportion of total price change caused by that class of trades.

Table 6
The table summarizes the differences in price movement after limit order submission, by the time period in which the limit order is submitted. Specifically, we divide the sample into two halves of the trading day. The first half comprises all non-marketable limit orders submitted from 9.30 to 12.45, and the second non-marketable limit orders submitted between 12.45 and 4.00. For buy orders, price change is measured as the midquote prevailing 5 min (or 60 min) after submission less the midquote at the time of order submission. For sell orders, price change is measured as the midquote at the time of order submission less the midquote 5 min (or 60 min) after order submission. Panel A presents results for the 97 NYSE firms in the TORQ database that experienced a significant price increase in the sample period (November 1, 1990–January 31, 1991). Panel B presents results for the entire TORQ universe of 144 stocks. Buy limit orders are used for upward trending stocks and sell orders for downward trending. Results are separated by the aggressiveness of the order.

Account type	Aggressiveness	Variable	First half	Second half	First–second
Panel A: 97 stocks					
Individual	At or better	5 min after order placement	0.014	0.010	0.004*,[a]
Individual	At or better	60 min after order placement	0.033	0.012	0.021*,[a]
Individual	Behind the quote	5 min after order placement	0.002	0.001	0.001
Individual	Behind the quote	60 min after order placement	0.025	0.016	0.009**,[a]
Institutional	At or better	5 min after order placement	0.023	0.019	0.003*,[a]
Institutional	At or better	60 min after order placement	0.051	0.026	0.025*,[a]
Institutional	Behind the quote	5 min after order placement	0.003	−0.003	0.007*,[a]
Institutional	Behind the quote	60 min after order placement	0.037	0.005	0.032*,[a]
Panel B: 144 stocks					
Individual	At or better	5 min after order placement	0.012	0.009	0.003*,[a]
Individual	At or better	60 min after order placement	0.026	0.011	0.015*,[a]
Individual	Behind the quote	5 min after order placement	0.002	0.001	0.001
Individual	Behind the quote	60 min after order placement	0.022	0.013	0.009**,[a]
Institutional	At or better	5 min after order placement	0.021	0.018	0.003*,[a]
Institutional	At or better	60 min after order placement	0.045	0.023	0.022*,[a]
Institutional	Behind the quote	5 min after order placement	0.003	−0.003	0.006*,[a]
Institutional	Behind the quote	60 min after order placement	0.030	0.004	0.026*,[a]

**t*-test significant at 1%; ***t*-test significant at 5%.
[a]Non-parametric linear rank sum *z*-statistic significant at 1%.

trades, then we should expect a higher cumulative price impact associated with these trades in the first half vis-à-vis the second half of the day.[17]

Table 7 reports that institutional medium size trades are associated with 49.4% of the cumulative price change in a stock in the first half of the trading day versus

[17]We should underscore that even if the usage of market orders is the same by informed traders in the first half and second half of the day, the information content of market orders (hence their price impact) will be smaller in the second half simply due to the Bayesian learning of the market makers about the private information during the first half of the day (and assuming that an information event occurs once a day prior to the opening of trading).

Table 7
Price impact of initiating orders by time of day. This table summarizes the price impact of initiating trades by the time of execution, for our sample of 97 stocks that experienced a significant price increase. Specifically, we divide the sample into two halves of the trading day. The first half comprises all trades executed from 9.30 to 12.45, and the second trades executed between 12.45 and 4.00. According to Bloomfield et al. (2005), we should expect informed traders to trade using market orders in the beginning of the day, thus we should see higher cumulative price impact for initiating trades at the beginning of the day compared to the end of the day.

Trade size	% of cumulative price change			% of trades		% of volume	
	First half	Second half	First–second	First half	Second half	First half	Second half
Trades initiated by individuals							
Small (100–499 shares)	7.8	−0.5	8.3	10.4	9.7	1.5	1.4
Medium (500–9,999 shares)	−0.7	−1.4	0.7	6.6	6.0	5.1	4.3
Large (10,000 + shares)	1.9	−0.1	2.0	0.3	0.2	2.0	1.8
Trades initiated by institutions							
Small (100–499 shares)	1.9	−10.2	12.1**	7.7	7.5	1.1	1.1
Medium (500–9,999 shares)	49.4	27.9	21.5**,[a]	17.8	14.7	19.8	16.1
Large (10,000 + shares)	16.4	8.3	8.1	2.9	2.3	20.4	17.7

**t-test significant at 5%.
[a]Non-parametric linear rank sum z-statistic significant at 5%.

27.9% in the second half. The difference is statistically and economically significant, and cannot be accounted for by a difference in volume or the number of trades during the two halves of the trading day. The median stock has an approximately 19 percentage point higher cumulative price impact in the first half relative to the second. Individual medium size trades do not display the same pattern. These results therefore support the BOS prediction that informed traders prefer market orders in the beginning of the trading period. It could also be that the weak result of a lower price impact for individual trades is driven by the Bayesian learning of market makers, whereas the institutional results are driven by a combination of this Bayesian learning and the stronger effects of institutions switching from using market to limit orders.

We now explicitly test whether the results reported above are driven by a larger amount of information in the market in the morning, rather than a preference for market orders by informed traders. To control for differences in information environment in the morning versus the afternoon, we regress the cumulative price impact in the time period on a dummy variable which equals 0 for the first half of the day and 1 for the second, and the percentage quoted spread (time weighted) in the time period. The percentage spread proxies for the level of information asymmetry in the market and allows us to isolate the market order choice of informed orders.[18]

[18]The exact form of the regression is as follows: $Cumpi_{t,s} = \beta_0 + \beta_1 Timedum + \beta_2 Perspread_{t,s} + \varepsilon$, where $Cumpi_{t,s}$ is the cumulative price impact of the trade size category in time period t (morning or afternoon)

Table 8
In this table, the results of regressions of cumulative price impact of trades are presented, on a time dummy which equals 0 for the first half of the day and 1 for the second, and the time weighted percentage quoted spread during the time period. The first half of the trading day comprises all trades executed from 9.30 to 12.45, and the second trades executed between 12.45 and 4.00. The time weighted percentage spread controls for differences in information asymmetry (and thus, the amount of information) at different time periods during the trading day.

Initiating account	Size	Intercept	Time dummy	Percentage spread
Individual	Small	0.099	−0.084	−1.631
Individual	Medium	−0.153*	−0.002	11.405*
Individual	Large	0.041	−0.019	−2.145
Institutional	Small	−0.014	−0.120	2.564
Institutional	Medium	0.586*	−0.219**	−7.148
Institutional	Large	0.267*	−0.086	−8.501*

*t-test significant at 1%; **t-test significant at 5%.

Consistent with our earlier results, we find that the time dummy for institutional medium size trades is negative and statistically significant (see Table 8).

We also perform Barclay and Warner (1993) style cross sectional regressions for our sample. The dependent variable is alternatively the cumulative price change associated with individual orders and that associated with institutional orders—estimated over the first half of the trading day and over the second half of the day. The independent variables are dummy variables for small, medium and large size trades as well as either the proportion of trades of small, medium and large trade size classes or the proportion of volume of the same three trade sizes.[19] Consistent with the stealth trading hypothesis, the coefficient on the medium size trade dummy is positive and significant for institutional trades (Table 9), after controlling for the proportion of trades (Panel A) and the proportion of volume (Panel B) associated with a particular trade size category.

We also check for these results in the overall TORQ universe of 144 stocks. Table 10 shows that, although medium size institutional trades have a higher price

(*footnote continued*)
for stock s, *Timedum* takes on the value 0 for the first half of the day and 1 for the second half. $Perspread_{t,s}$ is the average percentage spread (time weighted) of stock s in the first and second half of the day. The regression is run separately for small, medium and large institutional and individual trades.

[19]This regression equation looks as follows: $Cumpi_{i,s} = \beta_0 Small + \beta_1 Medium + \beta_2 Large + \beta_3 Proptrds_{i,s} + \varepsilon$, where $Cumpi_{i,s}$ is the cumulative price impact of the trade size category i (small, medium or large) for stock s, *Small*, *Medium and Large* are dummy variables for small, medium and large trade size categories. $Proptrds_{i,s}$ is the proportion of trades of total associated with trade size category i in stock s. We also estimate a similar regression controlling for proportion of volume instead of the proportion of trades. The regressions are run separately for the first and second halves of the day for institutional and individual trades.

Table 9
This table summarizes the results of regressions, similar to those in Barclay and Warner (1993), to test for stealth trading. The regressions are run with the cumulative price impact associated with a particular trade size class of a trader type as the dependent variable, and dummy variables for small, medium and large sized trades as the independent variable. Panel A controls for the proportion of trades associated with the trade size class of a trader type, and Panel B controls for the proportion of volume. To reduce heteroskedasticity in the dependent variable, we weight each observation by the absolute cumulative price change for that firm over the entire sample period.

Panel A: Barclay– Warner (1993) regressions controlling for proportion of trades

Initiating account		Small	Medium	Large	Proportion of trades
Individual	First half	−0.073	−0.077**	0.017	2.561*
Individual	Second half	−0.112**	−0.100*	−0.003	0.757
Institutional	First half	−0.073	0.264*	0.126*	3.749*
Institutional	Second half	−0.207**	0.141*	0.054	1.468

Panel B: Barclay– Warner (1993) regressions controlling for proportion of volume

Initiating account		Small	Medium	Large	Proportion of volume
Individual	First half	−0.021	−0.071	0.022	2.573**
Individual	Second half	−0.103	−0.116*	−0.005	1.115
Institutional	First half	−0.060	0.313*	0.126*	1.250
Institutional	Second half	0.313	0.126**	1.000	−0.060

*t-test significant at 1%; **t-test significant at 5%.

impact in the first half than the second, the difference is not statistically significant. Thus, even after controlling for the amount of private information in the market over the two time periods in the overall sample, we find (limited) support of informed traders preferring market orders in the first half of the trading period vis-à-vis the second.

4. Conclusion

There is a gap in the literature in examining the evolution of trading strategies of informed versus uninformed traders over the course of the trading day. Existing theoretical research is unable to answer questions related to the evolution of liquidity, either because they are single period models or because they are multiperiod models with no adverse selection effects. Bloomfield et al. (2005) are able to provide answers to the issue—but within an experimental context. The current study is an effort to provide empirical validation to the hypotheses that flow out of BOS, as well as to provide empirical tests of the use of limit orders by informed traders.

Table 10
This table summarizes the price impact of initiating trades by the time of execution for the entire TORQ universe of 144 stocks. Specifically, we divide the sample into two halves of the trading day. The first half comprises all trades executed from 9.30 to 12.45, and the second trades executed between 12.45 and 4.00. According to Bloomfield et al. (2005), we should expect informed traders to trade using market orders in the beginning of the day, thus we should see higher cumulative price impact for initiating trades at the beginning of the day compared to the end of the day.

	% of cumulative price change			% of trades		% of volume	
	First half	Second half	Second–first	First half	Second half	First half	Second half
Trades initiated by individuals							
Small (100–499 shares)	6.60	−9.15	−16	16.20	16.39	3.96	3.99
Medium (500–9,999 shares)	−1.18	−3.75	−3	11.49	10.28	14.12	11.63
Large (10,000 + shares)	1.81	0.66	−1	0.59	0.23	9.89	1.65
Trades initiated by institutions							
Small (100–499 shares)	12.11	4.76	−7	9.82	9.93	2.53	2.49
Medium (500–9,999 shares)	46.13	32.92	−13	12.76	10.68	17.04	14.87
Large (10,000 + shares)	8.19	0.90	−7	1.05	0.58	13.17	4.65

Using data that enable us to distinguish between institutional (informed) and individual (uninformed) orders on a representative sample of NYSE stocks, we find that institutional limit orders perform significantly better than the limit orders placed by individuals. This difference is significant after controlling for order and stock specific characteristics. These results suggest that institutions are better able to predict at least the flow of information and use this knowledge to submit limit orders.

We also find that, even after controlling for the amount of private information in the market in the first half versus the second half of the trading day, institutional medium sized trade initiating (market or marketable limit) orders contribute a significantly higher proportion of the total price change in the first half of the day vis-à-vis the second, which indicates that these orders are more likely to be informed in the first half than the second. This result is consistent with the BOS finding that informed traders use market orders in the beginning of the trading period.

Further, we find that, consistent with informed traders turning to market making in the later part of the trading period, limit orders perform better in the first half of the trading day compared to the second. This result is, however, not limited to institutional orders and seems to be a general trend across all limit orders. Present research uncovers the importance of the limit order book as a source of informed trading activity.

A potential criticism of the current research is that it is performed with data that is over ten years old. Much has changed in the NYSE and the overall markets in the intervening ten years—including a tremendous growth in trading volume, greater specialist participation and two separate tick size reductions. The question then is: are the findings reported in the current paper likely to hold up in the face of recent market data similar to TORQ? While there are no other publicly available databases available to answer the questions investigated here, it is worthwhile musing on whether our findings are relevant to the current environment of the NYSE. Thus, for example, in the early nineties, specialist intervention was lower (9.9% as a percent of twice the NYSE total volume in 1991, versus around 15% in 2001 and 2002).[20] This implies that less trading was directly intermediated which is closer in spirit to an order driven market. The other big change over the years has been the impact of technology and the speed with which traders can now access markets. However, it is not clear what the impact of these changes would be in our context. On the one hand, the ability to quickly place and cancel orders might make limit orders more attractive to informed traders. However, the flip side of this ability is that market orders can also now more quickly pick-off limit orders if new information arrives in the market. Hasbrouck et al. (1993) document that market orders placed through SuperDOT were required to have a turnaround time (time between receiving an order and sending an execution report) of less than two minutes during our sample period. This indicates that market order traders could also not react very quickly to market events, making limit orders safer. In the net, it is unclear as to whether today's environment would exacerbate or ameliorate the findings we uncover using TORQ data.

By the same token, however, the NYSE has recently proposed to enhance the electronic features of the market by providing more automated execution capabilities and, in general, moving the market toward resembling an electronic limit order book. Such changes are almost certain to make the patterns associated with the investors' choices between market and limit orders on the NYSE more pronounced in the future. Therefore our current examination (even if somewhat dated) might actually serve to provide an early glimpse of things to come.

Our findings also serve as an early callout for the need to develop theoretical models that consider more complex order strategies within a dynamic context by multiple informed traders with distinct information sets to more closely resemble the current (and future) trading milieu.

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