Order Submission Strategies and Information: Empirical Evidence from the NYSE

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Abstract

We investigate the role of asymmetric information in affecting order submission strategies. Order aggressiveness depends on the state of the order book and on the asset dynamics. We find that the most important determinants are the depth on the same side of the book and a momentum indicator. When we focus on specific situations characterized by higher probability of information-based trading, we find that orders are less aggressive, suggesting strategic behavior of informed traders. This conjecture is supported by a different response to changes in the investor's information set and by a stronger price impact of less aggressive orders.

JEL classifications: C35; G14
Keywords: Order Aggressiveness, Informed Trading, Order Flow

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Executive Summary

This paper investigates how an investor would change the strategy of submission of an order on the stock market according to the information she has. Understanding how new information is incorporated into prices is a major focus of an extensive research in finance. In particular, market microstructure models provide a useful framework to analyze how prices become efficient through the interaction of both informed and uninformed traders, and often a market maker learning new information from the arrival and composition of trades. However, most theoretical models assume informed agents enter the market aggressively to exploit their private information.

In this paper, we argue that informed agents act strategically using limit orders. We address this issue empirically, analyzing an essential aspect of the trading process, the order submission. We examine order submission strategies on a sample of ten high transacted stocks on the NYSE. At the outset, we study the general relation between the changes in the investor's information set, defined by the characteristics of the asset and the characteristics of the market, and the decision to submit a more or less aggressive order. We then analyze how an investor modifies her order submission strategies in settings with a higher probability of information-based trading.

Our results show that order submission strategies depend in general both on microstructure variables, like the bid-ask spread and the order book, and market conditions. More specifically, we observe that the most important determinants are the quantity of shares on the same side of the book, which induces more aggressive orders, and a momentum indicator, which is positively related to buy order aggressiveness, but negatively related to sell order aggressiveness. We find weaker evidence that volatility affects order submission strategies.

When we examine situations with a higher probability of information-based trading, we observe an intriguing pattern. Informed traders are likely to use non-aggressive strategies.

More specifically, we find that before positive earnings announcements, they submit buy limit orders well below the bid price, in order to hide their information. Moreover, we detect a different interpretation of some of the conditioning information that is consistent with a possible attempt to disguise informed trades. This conjecture is supported by a relatively stronger impact on prices for less aggressive orders when they are likely to be submitted by informed agents.

Introduction

Understanding how new information is incorporated into prices is a major focus of an extensive research in finance. In particular, market microstructure models provide a useful framework to analyze how prices become efficient through the interaction of both informed and uninformed traders, and often a market maker learning new information from the arrival and composition of trades. However, both simple settings, such as Glosten and Milgrom (1985), and models of limit order books, like Glosten (1994), Rock (1996), and Seppi (1997), assume informed agents enter the market aggressively to exploit their private information.

In our paper, we argue that the order flow has information content beyond trades when informed agents act strategically using limit orders. We address this issue empirically, analyzing an essential aspect of the trading process, the order submission. Specifically, we try to answer the following questions. First, do order submission strategies change around periods where traders are likely to be asymmetrically informed? Second, are the observed order strategies consistent with informed traders using only market orders, or is there evidence consistent with informed traders using both market and limit orders?

We examine order submission strategies on a sample of ten high transacted stocks on the NYSE, using the three-month time-series in the TORQ (Trades, Orders, Revisions, and Quotes) database. At the outset, we study the general relation between the changes in the investor's information set, defined by the characteristics of the asset and the characteristics of the market, and the decision to submit a more or less aggressive order. We then analyze how an investor modifies her order submission strategies in settings with a higher probability of information-based trading.

Our analysis is important for a number of reasons. First, we are able to better understand how market conditions influence the trade-off between the order price and its probability of execution. Since this trade-off is reflecting investor's beliefs about both the underlying asset value and the probability of facing information-based trading, we can obtain useful insights on the role of market characteristics in shaping these beliefs. For instance, we find that higher momentum in the stock prices induces aggressive buy orders and passive sell orders. This result is consistent with investors assuming the existence of stock price trends. Second, our study provides some helpful indications in terms of security market design. Our evidence of a higher frequency of market orders submission on the NYSE, with respect to the Paris bourse (Biais et al., 1995), suggests that the role of the specialist in stopping and improving market orders and the presence of floor brokers could be a suitable incentive for a quicker revelation of information through more aggressive orders.[1] Moreover, the similarity of the order frequencies for the more passive categories between the NYSE and the Paris bourse is an indication that the open versus the closed book should not particularly affect order submission strategies. Finally, we can provide insights into informed traders' behavior and thus into the emergence of market liquidity and its information content.

This paper contributes to the extant literature in two main directions. First, we expand the conditioning information set to adequately describe the complexity of an order submission strategy. Several studies have empirically investigated specific determinants of order aggressiveness. In particular, Biais et al. (1995) show that, on the Paris bourse, limit orders are more frequently placed when the bid-ask spread is wide or the order book is thin, while the opposite is true for market orders.[2] Harris and Hasbrouck (1996) analyze the ex-post performance of different order submission strategies on the NYSE, using the TORQ data, without considering conditioning variables. Recent concurrent work by Ellul et al. (2003) analyzes a broader set of conditioning information, but does not separate the decision to buy and to sell from the decision to submit a more or less aggressive order. As shown in Keim and Madhavan (1995), the motivation for the trade decision is not symmetric for buys and sells. In our paper, we explicitly analyze the problem of the order submission

[1]The model of Ready (1999) shows that allowing the specialist to stop orders provides greater benefits to liquidity traders. His analysis thus indicates that policymakers interested in attracting liquidity to the market might want to allow the specialist to stop orders.

[2]Griffiths et al. (2000) and Ranaldo (2003) provide similar results for the Toronto Stock Exchange and for the Swiss stock market, respectively.

strategy, taking the decision to buy or to sell as given. Our methodology allows us to best concentrate on the strategic choice of the order submission. Furthermore, our econometric specification provides indications about the relative importance of each single determinant in affecting the aggressiveness of an order.

Our second line of contribution is to examine changes in order submission strategies when the probability of information-based trading is higher. A similar approach is adopted in Kavajecz (1999), who investigates liquidity provision around the time of earnings announcements to analyze situations in which some market participants could have more information. The microstructure literature has traditionally assumed that informed traders exploit their advantage right away using market orders (e.g., Glosten, 1994). However, there is recent evidence that this may not be the case in practice. Kaniel and Liu (2002) model the conditions under which informed traders may want to submit limit orders and empirically show that limit orders are more informative. Bloomfield et al. (2003), using an experimental market setting, find that informed traders use more limit orders than do liquidity traders. Cao et al. (2003) show that the limit order book on the Australian Stock Exchange contains valuable information to determine the true value of a stock. In this paper, we obtain the conditional order submission strategies for specific settings characterized by a higher probability of information-based trading. We then focus on the differences between conditional and actual order submission strategies, thus inferring the behavior of informed traders. Furthermore, we can control for whether the relation between the order submission strategy and conditioning information changes.

Our results show that order submission strategies depend in general both on microstructure variables and market conditions. In most cases, the relations we find are consistent with the literature for other market structures and for simpler approaches. More interestingly, we observe that the most important determinants are the depth on the same side of the book, which induces more aggressive orders, and a momentum indicator, which is positively related to buy order aggressiveness, but negatively related to sell order aggressiveness. We find weaker evidence that volatility affects order submission strategies. When we examine situations with a higher probability of information-based trading, we observe an intriguing pattern. Informed traders are likely to use non-aggressive strategies. More specifically, we find that before positive earnings announcements, they submit buy limit orders well below the bid price, in order to hide their information. Moreover, we detect a different interpretation of some of the conditioning information that is consistent with a possible attempt to disguise informed trades. This conjecture is supported by a relatively stronger impact on prices for less aggressive orders when they are likely to be submitted by informed agents.

The remainder of the article is organized as follows. In Section 1 we describe the data. In Section 2 we illustrate our description of the investor's information set. In Section 3 we briefly explain the econometric model. Section 4 presents the empirical results for the general case. Section 5 illustrates the analysis of specific situations with higher probability of information-based trading. Section 6 concludes.

1 Data and Preliminaries

In this Section, we describe the filtering criteria used to obtain our sample from the TORQ database. We then illustrate the results of an unconditional analysis of aggressiveness.

1.1 Sample

The data used in this study come from TORQ. The data set contains detailed histories for orders, transactions and quotes on 144 NYSE stocks for the period covering November 1990 through January 1991. A thorough description of the TORQ database is provided in Hasbrouck (1992).

The TORQ data do not account for the reductions in the tick size that took place in 1997 and 2000. However, the empirical results provided in Goldstein and Kavajecz (2000) and Bacidore et al. (2003) show that the different tick size causes a reduction in quoted and effective spreads, a reduction in quoted depths, smaller limit order sizes, but no major changes in order submission strategies or in execution quality. Furthermore, the work in the decimal pricing environment by Ellul et al. (2003) obtains some results that are consistent with our evidence.

We study the ten stocks that showed the highest average value of transacted volume during the whole three-month sample. The high liquidity of these stocks allows a timely relation between order submission strategies and the variables of the investor's information set. This is a crucial feature for our methodological design, since we want to investigate the decision on the aggressiveness of an order at a high frequency. More specifically, we study the behavior of a buyer or seller that is indifferent about the time of the day of the actual trade, but that is not willing to wait a few days to get an order execution. In this framework, we can better disentangle the determinants of the order submission strategy from the determinants of the decision to buy or to sell. This kind of analysis is not feasible for stocks with a few submitted orders per day. For the most traded stock in our sample, International Business Machines (IBM), we register an average of 3.5 buy orders and 5.7 sell orders in a five-minute interval, whereas for the least traded stock in our sample, Colgate-Palmolive (CL), there is an average of 0.7 and 0.6 buy and sell orders in a five-minute interval.[3] Furthermore, restricting the analysis to ten stocks allows us to consider the whole sample in the time-series dimension. Some other microstructure studies using large data sets have analyzed more stocks, but at the same time have investigated substantially shorter time spans. The drawback of our methodological choice is that empirical estimates based on the analysis of ten stocks can be influenced by one or two stocks. In the empirical section of the paper, we perform robustness checks to make sure that our results are not driven by outliers. Finally, sampling large stocks limits the influence of the unmodelled specialist behavior on our results, since the specialist

[3]The average number of orders per time interval is just the total number of standard market and limit orders in our sample divided by trading time. These statistics show that a high frequency analysis of order submission strategies in our sample cannot consider infrequently traded stocks. For example, even the median stock for trading volume in the TORQ database has an average of just 0.8 orders per hour.

has moderate participation for these stocks (Kavajecz, 1999). This last aspect is especially important for our sample period when the specialist had considerable discretion in posting quotes (see McInish and Wood, 1995).

Table 1 presents summary statistics for the sample stocks. We obtain the market capitalization at the beginning of November 1990 and the average transacted volume during the sample period from the Center for Research on Security Prices (CRSP). The orders data come from the System Order Database (SOD) file of the TORQ database. Although we consider the ten most transacted stocks, there is still substantial cross-sectional variation in market capitalizations and volume. Notice that Exxon (XON) is more than 20 times larger than Glaxo (GLX), and IBM's average transaction volume is about 15 times higher than CL. The composition of the order flow also exhibits considerable cross-sectional variation: submission of limit or market orders represents a highly variable proportion of the total order submission. For example, market orders for XON are almost twice as much as limit orders, while the opposite is true for Federal National Mortgage Association (FNM).

We apply a set of filter rules to the data to exclude obvious errors and misreported information. The first criteria takes into account the daily operating structure of the market. The NYSE opens with a call auction market and operates as a continuous market for the remainder of the trading day. To avoid mixing different trading structures, we ignore overnight price and quote changes. We also exclude orders submitted during the opening auction. We start considering order placement just after the opening quotes have been posted and we eliminate any order with a time stamp after the market has closed.

We consider only New York's quotes because they are the most representative of prevailing consolidated prices (see Hasbrouck, 1991 and 1995; Blume and Goldstein, 1992 and 1997). We filter out the anomalous data.[4] In particular, we carefully avoid to take into account second copies of orders already considered. This may happen when an order is executed in

[4]For instance, we discard all the transactions and quotes that occurred on November 23, 1990, because they reflect a very peculiar trading day pattern. The NYSE internal information computerized system was down for several hours that day and it was the day after Thanksgiving.

parts over the course of the trading session, or when an order is executed in a different day with respect to the original submission. We also eliminate from the original file tick-sensitive market and limit orders, and stop orders, because they are likely to be submitted for different motivations compared with standard orders.

1.2 Order Aggressiveness

Given the decision to buy or sell a stock, the investor's order submission strategy is not just a choice between a market and a limit order. In fact, she can submit very different limit orders, trading off probabilities of execution with transaction costs. Moreover, the order placement is a joint decision of price and quantity: large orders can be split in smaller ones, again to influence probabilities of execution and transaction costs. We thus define an aggressive order submission as the investor's preference for an immediate and certain execution, coupled with her indifference for the transaction cost component.

We categorize an investor's order choice in six levels of aggressiveness for each side of the market, following a classification scheme similar in logic to Biais et al. (1995) or Griffiths et al. (2000). We use both the price of the limit order and its size with respect to the depth at the best quotes to define the appropriate category.[5]

Category 1 is composed of the most aggressive orders. Specifically, either buy (sell) market orders and buy (sell) limit orders for a price greater (less) than or equal to the best ask (bid), both submitted for a quantity of shares larger than the correspondent quoted depth. Category 2 comprises buy (sell) market orders and buy (sell) limit orders for a price greater (less) than or equal to the best ask (bid), but for a size smaller than the quoted depth.[6]

[5] In our sample period an investor could have information about the depths at the best quotes, whereas the remainder of the order book was restricted. Only recently the NYSE has adopted an open book.

[6] Marketable limit orders have the same trading priority as market orders because the NYSE prioritizes orders on price. The only difference between a market order and a marketable limit order is that the limit order has an execution price bounded by the limit price (Peterson and Sirri, 2002).

Buy (sell) limit orders in category 3 have a price that lies between the bid and the ask. Buy (sell) limit orders in category 4 have a price equal to the bid (ask). The limit orders in category 5 and 6 are the least aggressive, with prices below (above) the bid (ask): up to four ticks from the prevailing relevant best quote for orders in category 5, more than four ticks for the orders in category 6.

Table 2 presents the number of orders for each category of aggressiveness in our sample. The most frequent order type is category 2: market orders and marketable limit orders are the 60.48% and the 61.34% of the total buy and sell orders, respectively. Interestingly, there is a high number of orders placed at the best quote (category 4). This is consistent with the evidence of a good average performance for these orders (Harris and Hasbrouck, 1996). The number of limit orders whose price lies within the quotes is about half of the number of buy (sell) limit orders placed below (above) the bid (ask). We notice higher aggressiveness for sell orders with respect to buy orders, stemming especially from the different frequency in the most passive category. This last finding is consistent with previous evidence (e.g., Keim and Madhavan, 1995), and may occur because the risks of failing to sell in declining markets are perceived to be greater than the risks of failing to buy in rising markets.

The comparison of our results to the findings for the Paris bourse limit-order book (Biais et al., 1995), and for the Toronto Stock Exchange hybrid specialist/limit order system (Griffiths et al., 2000), reveals a number of insights. First, NYSE market orders are more frequent. This may happen because of the role of the NYSE specialist in improving the execution of market orders by stopping orders (see Harris and Hasbrouck, 1996). Second, NYSE limit orders are less frequently placed within the quotes. This could be the result of the previously mentioned incentive in placing market orders, or just the effect of a narrower bid-ask spread for the stocks in our sample. Third, the most aggressive NYSE orders (category 1, in our classification) are less frequent than in other markets. This result is possibly due to the low representativeness of the SuperDOT system order flow for orders of large size (see Harris and Hasbrouck, 1996). Finally, the frequency of orders in the least aggressive categories is very similar to other markets featuring an open book. We thus argue that pre-trade transparency does not seem to affect order submission strategies to a great extent.

We extend the analysis of the order flow composition by examining its evolution during the day. We divide the trading day into nine subperiods: one for the orders submitted in the first 30 minutes following the market opening, then one for every hour of the day until 3:00pm, and finally three other intervals for the last hour (30 minutes plus two 15 minutes subperiods). For each subperiod, we determine the number of orders for different categories. In Table 2 we observe that aggressive orders in category 2 are placed with increasing frequency during the day, on both the buy and the sell side, while limit orders become generally less frequent. Given that most of the orders in our sample are day-orders, we infer that traders perceive the gradual reduction in the probability of execution of limit orders while approaching the end of the trading day, consistent with a deadline effect.[7] This effect is similar to the 'magnet effect' suggested by Subrahmanyam (1994) and documented by Goldstein and Kavajecz (2004), whereby market participants accelerate the timing of their trades before a potential market-wide circuit breaker. We notice also an interesting pattern in the last half hour of trading: all categories of orders are decreasing in frequency, except market orders and limit orders in category 5. We deduce that, at that point of the day, the trade-off between probability of execution and transaction costs converges to a binomial choice, where orders of categories 3 and 4 are not offering enough in terms of price improvement to compensate the loss of probability and orders of category 6 are just very unlikely to be executed.

[7] This is an unconditional analysis and the gradual increase in order aggressiveness could be the result of an omitted variables problem. We address this issue by estimating a conditional model in the empirical analysis of Section 4.

2 Investor's Information Set

In this Section, we describe the variables used to characterize the investor's information set. We distinguish market microstructure-related variables, stock price-related variables and asymmetric information-related variables.

2.1 Microstructure-Related Variables

The state of the book, described by the bid-ask spread and the number of shares offered and demanded at the quotes, affects the order submission strategies of an investor.

More specifically, we relate the aggressiveness of an order to the bid-ask spread, computed as a proportion of the bid-ask midquote, prevailing just before the submission. We expect traders to provide liquidity when the price of liquidity is high, consistent with the results of Biais et al. (1995), Chung et al. (1999) and Griffiths et al. (2000). We thus predict order aggressiveness to be decreasing in the bid-ask spread width.

The probability of execution of a limit order, however, depends also on the orders standing on the book and on the aggressiveness of orders arriving over the remainder of the trading day. We measure the depth as the number of shares prevailing on the same and on the opposite side of an order that is being submitted. An investor submitting an order knows the quoted depth at the bid and at the ask prices. She does not know the depth on all the order book, at least in our sample period. We therefore consider only the number of shares prevailing at the best prices in describing the investor's information set. The dynamic model of the limit order book of Parlour (1998) distinguishes between a direct *competition* effect and a potential *strategic* effect on order submission strategies. Consider the submission of a buy limit order in a situation where there is a thick book at the bid. The long queue on the buy-side has two effects. First, the buy limit order has a lower time priority, and would therefore require the arrival of many sell market orders to be executed (*competition* effect). Likewise, sellers rationally anticipate the crowding out effect of buy limit orders and are thus better off submitting less aggressive sell orders (*strategic* effect). Both of these effects reduce the incentive to submit a buy limit order when there is higher depth at the bid. Furthermore, the combined effects of a thicker book at the bid on the aggressiveness of buy orders is greater than the effect induced by the expected variation in the aggressiveness of sell orders, given a longer queue at the ask.

In summary, we expect that a thicker quoted depth on the same (opposite) side will induce more aggressive (passive) orders and that the effect of the same side depth will be greater than the effect of the opposite side depth.[8]

2.2 Stock Price-Related Variables

A second group of variables defining the investor's information set describes the evolution of the stock price. We consider an indicator of momentum, volatility, volume and frequency of transactions. At the outset, we compute a time-homogeneous series for the stock price. Using the transaction prices reported in the Consolidated Transaction (CT) file of the TORQ database, we build a five-minute returns time-series by linearly interpolating between the stock price immediately preceding and immediately following the five-minute interval. Time-homogeneous five-minute returns allow to reduce market microstructure effects, such as the bid-ask bounce or the effect of multiple executions, and have been used extensively in the literature (e.g., Andersen and Bollerslev, 1997). We consider transaction prices more informative than bid-ask midpoints, because they represent actual trades and because actual trade prices are often better than the posted quotes (e.g., price improvement).

Momentum

A basic feature of a stock price evolution is its momentum. In particular, we aim to capture the investors' perception of the potential risk of non-execution for a limit order when the price is quickly moving away from the current level. We compute a momentum

[8] We do not explicitly consider the alternative of routing the order to regional exchanges with shorter limit order queues when there is a long queue on the same side. If this alternative is a standard market practice, the *competition* effect would not manifest itself in more aggressive orders at the NYSE.

indicator (MOM) at time t as the ratio between the stock price P_t and an exponential moving average (EMA_t) of the price itself. The numerical evaluation of the moving average is efficient because of the exponential form of the kernel, which leads to a simple iterative formula:[9]

$$\begin{aligned} EMA_t(P_i) &= (1-\lambda)\sum_{i=0}^{t}\lambda^{t-i}P_i = \lambda EMA_{t-1}(P_i) + (1-\lambda)P_t \\ MOM_t &= \frac{P_t}{EMA_t(P_i)} = \frac{P_t}{\lambda EMA_{t-1}(P_i) + (1-\lambda)P_t}, \end{aligned}$$

where P_0 is the first price of each day. The estimation depends on a decay factor λ, bounded between zero and one, which specifies the relative weights applied to the observations and the actual amount of data used in the estimation. In our analysis, λ is set to 0.95.[10] A stock price up-trend or down-trend entails a momentum indicator diverging from one, whereas a stock price showing no specific directional movement leads to a momentum indicator close to one. We expect to find a positive (negative) relation between buy (sell) order aggressiveness and momentum.

Volatility

A second characteristic of a stock price time-series is its volatility. We use an exponential moving average of the squared returns computed on transaction prices to obtain a time-varying indicator of volatility, where the latest observations carry the highest weight in the volatility estimate. In particular, for a decay factor λ equal to 0.95, the volatility estimator is:

$$\hat{\sigma}_t = EMA_t\left(r_i^2\right) = \sqrt{\lambda EMA_{t-1}\left(r_i^2\right) + (1-\lambda)r_t^2}.$$

The literature has identified various effects that volatility may have on order submission

[9] A simple proof of the iterative formula is provided, among others, in J.P. Morgan (1996).

[10] Techniques using the root mean squared error to estimate the optimal λ are described in J.P. Morgan (1996). For daily purposes, they obtain an optimal estimate for λ equal to 0.94. We examined some different decay factors to make sure that our findings are not driven by an arbitrary choice. The results presented in the text are robust in these respects.

strategies. First, the option-like feature of limit orders (Copeland and Galai, 1983) implies that posting a bid or an offer is more costly when volatility is higher. Limit order traders are therefore less aggressive, because of the risk of being picked off by informed traders. Second, the probability of the stock price hitting a limit price barrier increases with greater volatility (Lo et al., 2002). Hence, assuming that investors prefer a quick expected execution time, higher volatility should reduce order aggressiveness. Finally, risk-averse investors reward a certain outcome (Cohen et al., 1981). Higher volatility increases the dispersion of results in a limit order strategy and thus risk-averse investors prefer market orders.

The last mentioned effect of volatility on order aggressiveness is at odds with the previous ones. Moreover, if we consider an equilibrium setting where the actions of some agents affect the behavior of others (e.g., Foucault, 1999), we could possibly observe offsetting effects. If higher volatility induces a shift to limit orders, the use of market orders in equilibrium decreases, the probabilities of execution are therefore reduced, and the initial shift may be partially offset. The lack of a dominant view on the relation between volatility and order submission strategies is confirmed by the mixed results of the empirical studies in the literature (e.g., Hasbrouck and Saar, 2002; Bae et al., 2003).

Trading Activity

We describe a stock's trading activity using two indicators: the transacted volume and the time between transactions. The former is obtained as the sum of the number of shares transacted during the 20 minutes prior to each order submission. The latter is computed as the average time in seconds between the transactions occurred in the previous 20 minutes. The two measures capture different aspects of the trading activity. The transacted volume takes into account the size of the trades, but ignores their timing, whereas the time between transactions indicator focuses on the importance of time durations, overlooking quantities.

Previous studies have linked trading activity to the actions of informed traders or liquidity traders. Informed traders can be quickly distinguished by their large volume trades (Easley and O'Hara, 1987), or by short time durations between trades (Easley and O'Hara, 1992).

Alternatively, volume shocks can reflect a lack of consensus among market participants (Harris and Raviv, 1993; Shalen, 1993), or the activity of discretionary liquidity investors trading together (Admati and Pfleiderer, 1988). Hence, the order aggressiveness response to an increase in trading activity depends on which of these two stories is perceived to hold true by the investor.

Furthermore, trading volume could convey information about the current price trend. Theoretical models (e.g., Blume et al., 1994) predict a positive correlation between absolute price changes and volume, because of the role of volume as a signal of the precision of beliefs. This role for volume is confirmed by a number of empirical studies (e.g., Gallant et al., 1992), besides being remarkably similar to that claimed by proponents of technical analysis. During a stock price up-trend, an increase in trading volume should command more aggressive buy orders and less aggressive sell orders, according to the same logic we explained for the momentum indicator.

In summary, given the manyfold possible interpretations of a change in trading activity, the effect on order aggressiveness is ultimately an empirical question.

Time of the day

We include dummy variables to control for potential time-of-the-day effects. We use eight dummies for the nine intradaily subperiods defined in Table 2. We expect traders to submit more aggressive orders when the end of the trading day approaches, as predicted by Harris (1998).

2.3 Information-Based Trading

A crucial aspect of an investor's order submission strategy is the degree of information she owns with respect to other market participants. Unfortunately, we do not observe the characteristics of an investor submitting an order in our sample. Even at a more aggregate level, the extent of private information is not directly observable.

We employ, however, a measure of the probability of information-based trading along the lines of the Easley et al. (1996) model, combining trade data and order data in a structural market microstructure model.[11] This empirical technique relies on the information conveyed by the frequency and imbalance of trades. Although conceptually simple, this approach has been shown to obtain reasonable results in a variety of applications. A detailed description of the model can be found in Easley et al. (1996). Here we just recall the basic features for completeness.

Consider a trading game between a market maker and a trader, repeated over I days. New information arrives at the beginning of the trading day with probability α and this could be good news or bad news for the value of the underlying, with probability $1-\delta$ and δ, respectively. Traders arrive according to a Poisson process with intensity ϵ for uninformed traders and intensity μ, just on information event days, for informed traders. Informed agents buy if they observe good news and sell if they observe bad news. The market maker sets prices to buy or sell, observes the trade and updates her beliefs.

The probability of information-based trading is the ratio between the estimated arrival rate of informed trades and the estimated arrival rate of all trades:

$$\widehat{PI} = \frac{\hat{\alpha}\hat{\mu}}{\hat{\alpha}\hat{\mu} + 2\hat{\epsilon}}. \tag{1}$$

We estimate the underlying structural parameters $\theta = \{\alpha, \delta, \mu, \epsilon\}$, and thus the PI indicator, by maximizing the following likelihood function, using a sequence of buy trades B_i and sell

[11] Since our paper deals with high-volume stocks, we do not use the no-trade intervals, as suggested in the discrete time trading model developed in Easley et al. (1997a). In fact, the discrete time likelihood function developed in that paper cannot be computed for data sets with many trades per day.

trades S_i for each day i over I days:

$$
\begin{aligned}
L_i(B_i, S_i|\theta) &= (1-\alpha)e^{-\epsilon}\frac{\epsilon^{B_i}}{B_i!}e^{-\epsilon}\frac{\epsilon^{S_i}}{S_i!} \\
&+ \alpha\delta e^{-\epsilon}\frac{\epsilon^{B_i}}{B_i!}e^{-(\mu+\epsilon)}\frac{-(\mu+\epsilon)^{S_i}}{S_i!} \\
&+ \alpha(1-\delta)e^{-(\mu+\epsilon)}\frac{-(\mu+\epsilon)^{B_i}}{B_i!}e^{-\epsilon}\frac{\epsilon^{S_i}}{S_i!} \qquad (2) \\
L(B_i^I, S_i^I|\theta) &= \prod_{i=1}^{I} L_i(B_i, S_i|\theta). \qquad (3)
\end{aligned}
$$

The likelihood for a single trading day L_i is a mixture of distributions, where trades are weighted by the probabilities of being in a good news day, $\alpha(1-\delta)$, a bad news day, $\alpha\delta$, or a no news day, $(1-\alpha)$. Under the assumption of independence between days, the likelihood L over I days is just the product of the daily likelihoods. This technique to estimate the rate of informed and uninformed trading has been used in a series of papers by Easley et al. (1996, 1997a, 1997b).

The likelihood function in equation (3) depends on the number of buys and sells each day for each stock in our sample. We classify precisely the number of buyer- and seller-initiated trades to avoid the biases induced by inaccurate trade classification of the Lee and Ready (1991) algorithm. We match orders in the TORQ order file with trades in the TORQ audit file, following the procedure suggested in Hasbrouck (1992) and Odders-White (2000). The initiator of each transaction can be identified comparing order dates and times for the buy and sell side of the transaction.

Using the number of buys and sells, we maximize the likelihood function (3) over the structural parameters θ, for each stock separately and for different subperiods in the sample, using a minimum of 21 trading days. The maximum likelihood estimation converges for all the stocks, in almost all the subperiods, and we obtain economically reasonable estimates without imposing any constraints on the parameters.[12] We use the estimated probability

[12]The minimum of 21 days is considered to be a suitable interval for our maximum likelihood estimation,

of information-based trading in Section 5, to isolate three environments characterized by different degrees of asymmetric information.

3 Econometric model

3.1 The ordered probit model

The empirical analysis of order aggressiveness is conducted using an ordered probit model, a method introduced in the market microstructure literature by Hausman et al. (1992) to study the nature of discrete price changes.

We assume that the aggressiveness of an order, as described in Section 1.2, is the realization of an unobserved random variable, K_t^*, defined by the following expression:

$$K_t^* = X_t'\beta + \varepsilon_t \tag{4}$$

where the matrix X_t includes a set of predetermined variables that affect the conditional mean of K_t^* and ε_t is conditionally normally distributed with mean zero and variance σ_t^2.

The ordered probit model relates the observed aggressiveness K_t to the continuous variable K_t^* via:

$$K_t = s_j \text{ iff } K_t^* \in A_j, j = 1, 2, ..., J \tag{5}$$

where the A_j's form an ordered partition of the state space of K_t^* into J disjoint intervals, and s_j's are the discrete values comprising the state space of K_t. The probability that the order choice takes on the value s_j is equal to the probability that K_t^* falls into the appropriate partition, A_j.

given the attained convergence of the optimization, the economic meaning of the estimates, the precise criteria used to identify buyer- vs. seller-initiated trades, and finally the fact that the number of days affects the estimation of just two parameters, α and δ.

The corresponding intervals for the unobservable latent variable K_t^* are defined by:

$$\begin{aligned} A_1 &= (-\infty, \alpha_1] \\ A_2 &= (\alpha_1, \alpha_2] \\ &\dots \\ A_J &= (\alpha_{J-1}, \infty) \end{aligned} \tag{6}$$

The partition parameters, $\{\alpha_1, ..., \alpha_{J-1}\}$, are estimated jointly with the other parameters of the model.

The conditional probability of observing a particular category depends on the location of the conditional mean of the underlying response variable, $\beta' x$, relative to the partitions α_i. For Gaussian ε_t's, the conditional probability is given by:

$$P(K_t \in A_j) = \begin{cases} \Phi\left(\frac{\alpha_1 - X_t'\beta}{\sigma_t}\right), j = 1 \\ \Phi\left(\frac{\alpha_j - X_t'\beta}{\sigma_t}\right) - \Phi\left(\frac{\alpha_{j-1} - X_t'\beta}{\sigma_t}\right), 1 < j < J \\ 1 - \Phi\left(\frac{\alpha_{J-1} - X_t'\beta}{\sigma_t}\right), j = J \end{cases} \tag{7}$$

where Φ is the normal cumulative density function. Let Y_{ik} be an indicator variable which takes on the value one if the realization of the tth observation K_t is the jth state s_j. The likelihood function assumes the following form:

$$\begin{aligned} L(K|X) &= \sum_{t=1}^{n} \left\{ Y_{1t} \log \Phi\left(\frac{\alpha_1 - X_t'\beta}{\sigma_t}\right) \right. \\ &+ \sum_{j=2}^{J-1} Y_{it} \log \left[\Phi\left(\frac{\alpha_j - X_t'\beta}{\sigma_t}\right) - \Phi\left(\frac{\alpha_{j-1} - X_t'\beta}{\sigma_t}\right)\right] \\ &+ \left. Y_{Jt} \log \left[1 - \Phi\left(\frac{\alpha_{J-1} - X_t'\beta}{\sigma_t}\right)\right]\right\}. \end{aligned} \tag{8}$$

The marginal effects of the regressors X_t on the outcomes' probabilities are not equal to the estimated coefficients β, because of the ambiguous effect on the middle partitions (Greene, 2000). In order to understand upon what or in what direction the effects of a change in the explanatory variables are exerted, the marginal effects for each outcome j are computed as follows:

$$\begin{aligned}
\frac{\partial Pr\left(K_t = s_1\right)}{\partial X_t} &= -\phi\left(\beta' X_t\right)\beta && \text{for j = 1,} \\
\frac{\partial Pr\left(K_t = s_j\right)}{\partial X_t} &= \left[\phi\left(-\beta' X_t\right) - \phi\left(\alpha_{j-1} - \beta' X_t\right)\right]\beta && \text{for 1 < j < J,} \\
\frac{\partial Pr\left(K_t = s_J\right)}{\partial X_t} &= \phi\left(\alpha_{J-1} - \beta' X_t\right)\beta && \text{for j = J,}
\end{aligned} \tag{9}$$

where ϕ is the normal probability density function. We calculate the marginal effect on the choice probabilities using equation (9) on the unconditional mean of each continuous explanatory variable and the change from 0 to 1 for each dummy variable.

We have assumed so far that all the observations are independent. A natural extension of the model is to allow observations to be dependent within a group, even though still independent across groups. In our setting, orders for the same stock might share similarities, while orders for different stocks can still be independent observations. If this is the case, the model will be misspecified and the usual standard errors will therefore be incorrect. We address this issue by computing robust standard errors along the lines of White (1982), but changing the random sampling with a group sampling scheme.

We just sketch the derivation here. If the likelihood function in (8) is correctly specified, it can be shown that the estimated variance of the parameters β is asymptotically given by -$\mathbf{H}^{-1}$, where $\mathbf{H}$ is the Hessian (matrix of second derivatives) of the likelihood with respect to the parameters. However, if $L()$ is not the true density function of X_t, the previous result does not necessarily hold. We can start by writing a general identity for the variance of the parameters:

$$Var\left(\hat{\beta}\right) \approx \mathbf{H}\left(\hat{\beta}\right)^{-1} Var\left(g\left(\hat{\beta}\right)\right) \mathbf{H}\left(\hat{\beta}\right)^{-1}, \tag{10}$$

where $g()$ is the score vector. We can plug in an empirical estimate of $Var(g(\hat{\beta}))$, obtaining:

$$Var\left(\hat{\beta}\right) \approx \mathbf{H}\left(\hat{\beta}\right)^{-1}\left(\frac{N}{N-1}\sum_{j=1}^{N} g_j g_j'\right)\mathbf{H}\left(\hat{\beta}\right)^{-1}. \tag{11}$$

This is the robust variance estimator. We consider N super-observations made up of the sum of the score vector g_j for a single stock j. These super-observations are independent.

In the empirical Section, we employ the general version of the ordered probit model and we check the results for robustness, using this last extension that accounts for potential cross-sectional dependencies.

4 Empirical Results

In this Section, we present the results of estimating an ordered probit model separately on the sample of buy and sell orders. In Table 3, Panel A, we present the maximum likelihood estimates of equation (8), where we indicate the relation between order aggressiveness and each of the explanatory variables. In Table 3, Panel B, we illustrate the marginal effects.

Bid-Ask Spread

The relation between order aggressiveness and the bid-ask spread is significantly negative for both buy and sell orders. This evidence is robust to the consideration of a comprehensive set of explanatory variables. Since the bid-ask spread is a measure of the cost of trading by market orders, traders reasonably prefer to demand liquidity when the price of liquidity is low.

An analysis of the marginal effects in Table 3, Panel B, reveals that an increase in the bid-ask spread reduces the probability of order submissions in categories 1 and 2, whereas the likelihood of observing less aggressive orders increases, especially for limit orders placed at the quotes (category 4). We also notice that a change in the bid-ask spread affects buy order aggressiveness slightly more than sell order aggressiveness.

It seems possible that the relation between the width of the spread and order aggressiveness is nonlinear. When the spread is particularly wide, traders may be more likely to place orders inside the spread and less likely to place market orders or orders far from the quotes. We allow for these potential non-linear effects by adding the square of the spread to the explanatory variables. The results, not reported, do not change. The quadratic term, however, has a significantly positive coefficient, suggesting that the hypothesized trader behavior takes place to some extent.

Depth

We find that both buyers and sellers submit more aggressive orders when the depth on the same side of the book is thicker. However, buyers and sellers have different reactions to a change in the opposite side depth. A larger depth at the ask reduces the aggressiveness of buy orders, in accordance with theoretical predictions. Sellers, in contrast, become more aggressive when the liquidity supply on the other side of the book is greater. The latter behavior is inconsistent with sellers expecting a crowding out effect on the buy side.

The asymmetry in buyers and sellers trading attitude is supported by previous empirical evidence (e.g., Keim and Madhavan, 1995). Sellers are more impatient to trade than buyers. Given the decision to sell, a slow execution when the market moves down can result in a realized loss, while a slowly executed buy order when prices are going up represents an opportunity cost. Moreover, as sellers are considered to be more liquidity-driven than buyers, a higher liquidity supply on the buy side reduces the cost of acquiring liquidity, spurring the use of more aggressive orders.

The marginal effects in Table 3, Panel B, show that a change in the same side depth is the most important variable affecting order aggressiveness. In particular, increasing the depth at the bid will substantially heighten the probability of more aggressive buy orders and generate slightly more aggressive sell orders. An increase in the depth at the ask will slightly reduce buy order aggressiveness and substantially increase sell order aggressiveness.

The greater effect on aggressiveness of the same side over the opposite side depth confirms the theoretical prediction of a stronger *competition* versus *strategic* effect.

Momentum

We find that, when the stock price moves up from its moving average (i.e., when the stock price momentum increases), buy orders become more aggressive and sell orders less aggressive. Traders perceive that a positive price trend reduces the probability of execution of passive buy orders, but increases the probability of execution of sell limit orders. We obtain the opposite result for negative price trends.

The analysis of the marginal effects in Table 3, Panel B, shows that momentum is one of the most important variables in affecting order aggressiveness. Momentum has relatively stronger effects on the likelihood of observing market and marketable orders (category 2) and orders just off the best quote (category 5).

Volatility

An increase in volatility drives more passive orders, for both the buy and the sell side. This result is consistent with our volatility measure being a proxy for information-driven trading: when volatility rises, a limit order trader enlarges her reservation spread, because of the risk of being picked off by an informed trader on the other side of the market. As a result, the expected cost of market order trading increases and the submission of less aggressive orders turns out to be the optimal strategy.

The marginal effect of a change in volatility on order aggressiveness is one of the least important. Our interpretation is that the pick-off risk effect of volatility can be partially offset, on one hand by the behavior of risk-averse investors, who prefer the definite outcome of market orders, and on the other hand by equilibrium effects. In particular, if limit orders represent short position in options, an increase in volatility causes an increase in the cost of limit orders that can only be compensated by changing the strike price, i.e. submitting less aggressive orders, or simply avoided by switching to market orders. Our results show that the first effect is likely to be prevailing.

Transacted Volume and Time between Transactions

We obtain contrasting evidence from the two variables describing trading activity. Higher transacted volume drives more aggressive buy and less aggressive sell orders, whereas a shorter time between transactions, i.e. a higher trading frequency, is associated with less aggressive buy and more aggressive sell orders. These results confirm that the two indicators measure different aspects of the trading activity. More specifically, the analysis of the multipliers in Table 3, Panel B, reveals that the effect of transacted volume on order aggressiveness is more relevant than the effect of time between transactions, especially on the sell side.

The results on transacted volume are consistent with information being revealed by large volume trades generally on the buy side: sell orders become less aggressive because of the higher pick-off risk. An alternative sensible interpretation is the role of transacted volume as a validation of the current price trend. Since we observe persistent rising prices for most of the stocks in our sample period, higher transacted volumes generally confirm an up-trend, triggering therefore more aggressive buy orders and less aggressive sell orders. This interpretation holds even if we control for a high-frequency measure of momentum. In fact, large volume trades may either validate a lower frequency positive price trend, or large volumes could independently contain information about future stock returns as shown, for example, in Gervais et al. (2001).

The results on time between transactions are consistent with liquidity-based trading clustering on the sell side *à la* Admati and Pfleiderer (1988). The submission of sell market orders decreases the time between transactions, thus generating even more aggressive sell orders, with a further decrease in time between transactions.

Time of the Day

The coefficients for the time-of-the-day dummy variables confirm the preliminary unconditional analysis in Section 1: orders become increasingly aggressive during the day, as explained by a monotonic increment of the coefficients (results not reported).

The marginal effects, computed as a change in order aggressiveness probabilities due to a change from 0 to 1 in the dummy, reveal that the time of the day is more important in affecting buy order aggressiveness than sell order aggressiveness.

Robustness Checks

We provide two sets of robustness checks, both related to the model specification.

First, the empirical results could depend on our particular aggressiveness definition. For this reason, we repeat the same analysis using five other different classifications, that merge or split the six categories used so far, according to reasonable criteria. Three of these aggressiveness specifications are noteworthy. First, we separate *marketable* limit orders from market orders in categories 1 and 2, in light of the documented differences in execution costs (Peterson and Sirri, 2002). All of the previous results do not change. Second, we define five aggressiveness categories using just a price criteria, instead of the standard price-quantity criteria. We employ, however, the ordered quantity as one of the regressors. The relation between aggressiveness and the other variables is unchanged. Moreover, larger ordered quantities imply less aggressive orders, both on the buy- and on the sell-side. Finally, we study the limiting case where orders are divided in two broad categories of market and limit orders. We observe different results just on the buy side, where the opposite side depth coefficient is now significantly positive, while volatility and time between transactions are not significant. Order submission strategies seem thus to be more sophisticated for buy orders than for sell orders. For example, an increase in volatility encourages the submission of less aggressive buy orders without affecting the mix market/limit orders, whereas on the sell side we just observe less market orders.

The second set of robustness checks verifies whether our empirical results are different when the order submission strategies potential dependence within each stock is taken into account. A straightforward approach is to use the robust ordered probit model, developed in the last part of Section 3, where standard errors are corrected for potential dependence between orders on the same stock. The results are generally confirmed. We just notice that the time between transactions is not significant anymore on the sell side. We can accomplish the same task by estimating the standard ordered probit model separately for each stock and for each side of the market. There is not an obvious way to summarize the results and, for less traded stocks, we could also have small sample problems. However, if we employ the average coefficients and standard errors to evaluate significance levels, we generally confirm the previous results. This evidence is important to alleviate concerns that the results are driven by the stocks with the most orders.[13]

5 Asymmetric Information and Aggressiveness

In this Section we investigate empirically how the probability of information-based trading affects order submission strategies. At the outset, we consider two different situations, where we can unravel different degrees of asymmetric information. For each case, we analyze how an investor modifies her order submission strategies. We proceed in two steps. First, we use the model estimated in the previous Section to compute predicted levels of aggressiveness that we then compare with actual levels of aggressiveness for each case. Second, we examine how a higher probability of information-based trading affects the relation between order submission strategies and the investor information set. We conclude with an analysis of the price impact for orders in different categories of aggressiveness.

[13]We do not report the robustness checks results. They are available on request from the authors.

5.1 Information-based Trading and Firm's Transacted Volume

The literature has generally determined a negative relation between private information and a firm's transacted volume. For example, the theoretical model of Diamond and Verrecchia (1991) predicts lower information asymmetry for large firms attracting larger volume of market transactions, as they benefit in disclosing more information. The empirical results in Brennan and Subrahmanyam (1995) support the notion that an increase in analyst coverage leads to less asymmetric information, because of the enhanced competition between informed agents. They document a strong positive relation between the number of analysts and the trading volume. Easley et al. (1996) show the existence of higher information-based trading in low volume stocks; although information events occur more rarely for these stocks, their impact on trading is greater.

As noted before, we observe substantial cross-sectional variation in our sample, although we consider the ten most transacted stocks of the TORQ data: the first stock, IBM, transacts about 15 times the volume of the last stock, CL (see Table 1). In order to support the intuition of the literature for our sample, we exploit the indicator of probability of information-based trading described in Section 2.3. We create three groups with homogeneous average transacted volume. The first group (IBM, MO, GE) is characterized by about twice the average volume of the second group (XON, FNM, T, BA), and about six times the average volume of the third group (SLB, GLX, CL). We compute a rolling PI for each stock, that is we estimate PI on the first month of data, we then drop the first trading day, insert the first day of the following month and recompute the PI indicator. We proceed by adding a new day, dropping the oldest one and re-estimating PI.

Figure 1 illustrates the evolution of the average PI over time for the three groups of stocks. We notice a stable difference in the PI of the three groups for almost two thirds of the sample period, with the low volume group being characterized by the highest level of asymmetric information. We also observe remarkable stability in the time series parameter estimates for the two larger-volume groups, adding new evidence on the short-term behavior of PI to the evidence obtained on longer time spans (Easley et al., 2002).

We expect to observe differences in order submission strategies for the stocks where the probability of information-based trading is higher, i.e. the stocks of group 3. Table 4 breaks down buy and sell orders in different categories of aggressiveness for each group. We compare the empirical frequency distribution with the theoretical distribution. The theoretical frequencies are computed as the mean of the probabilities predicted by the ordered probit model, estimated in the previous Section, for the information set of each order in the sub-sample. The use of a conditional methodology implies that any observed divergence with the general case does not depend on the different information set, but indeed on different order submission strategies. We observe that actual order submission strategies are less aggressive than predicted for lower volume stocks and the differences between actual and predicted strategies are all statistically significant. More specifically, traders submit sell orders between the quotes and at the ask price (category 3 and 4) more frequently than in the general case, while they use fewer market orders (category 2) and less limit orders far from the quotes (category 6). This pattern is less pronounced on the buy side.

In Table 5, Panel A, we examine if asymmetric information changes the relation between the investor's information set and order submission strategies with respect to the general case. We focus our analysis on the subsample where we notice greater differences in terms of aggressiveness, i.e. sell orders for stocks of group 3. The opposite side depth and the time between transactions have contrary effects on the submission strategies with respect to the general case. Specifically, a thick book at the bid and a shorter time between transactions stimulate the submission of less aggressive sell orders. The marginal effects in Panel B show that now the relation of the opposite side depth with aggressiveness is more important.

We interpret these findings as the effect of the presence of more informed traders on the sell side, in comparison with the standard setting. The results are consistent with informed traders being less impatient to sell the asset with respect to liquidity traders. They may be willing to wait for the potential *crowding out* effect at the bid or they may want to exploit the higher probability of execution induced by more frequent trades. Alternatively, informed traders could be constrained in short-selling and therefore they could try to reduce transaction costs through less aggressive orders.

5.2 Information-based Trading and Earnings Announcements

There is ample evidence in the literature of an increase in information asymmetry risk before anticipated news events, such as earnings announcements. Any leakage of information prior to an earnings announcement increases information asymmetry and, even in the absence of leakage, the different learning time of private information by the investors can create information advantages. For example, Lee et al. (1993) and Kavajecz (1999) show how the depth provided by the specialists and by the limit order book is reduced before earnings announcements, in order to minimize the cost of trading with more informed traders.

In our sample period, seven stocks release earnings figures, for which we obtain precise dates and times from Dow Jones Business Wire.[14] We compute an average PI indicator for these stocks using trades for an interval gradually approaching the release date. The PI indicator estimated during the month before the earnings announcement is significantly higher than the PI estimated during the preceding month for six of the seven stocks releasing figures.[15] Furthermore, Figure 2 illustrates a pattern of increasing asymmetric information when the computation interval starts including days that are close enough to the announcement date. We thus confirm for our sample the evidence of higher asymmetric information before announcements provided in the previous literature.

We select a sample of orders submitted for each of the seven stocks during the ten trading days preceding an earnings announcement. We have an ideal setting here to infer that the

[14]The seven stocks announcing earnings in our sample period are the seven largest in terms of average transacted volume: BA, FNM, GE, IBM, MO, T, XON.

[15]We calculate the standard error for the PI estimate using the delta method, as in Easley et al. (1996). The results are available on request from the authors.

buy side is the informed side of the market: prices of stocks releasing earnings increased substantially prior to the announcement, five of the seven releases turned out to be positive news, and the ten days time period is short enough to sensibly assume informed trading just on one side of the market.[16,17] We show in Table 6 the actual and theoretical distribution of orders with respect to aggressiveness. Actual and predicted order submission strategies are all statistically different at conventional confidence levels. Buyers are less aggressive than expected: in particular, they submit more frequently the least aggressive type of order (category 6). Sellers, in contrast, submit more market orders and less limit orders at the ask price.[18]

Table 7, Panel A, shows the results of estimating the ordered probit model on the pre-announcement period. We focus our analysis on the buy side, where informed trading is supposed to take place and we notice greater differences in terms of aggressiveness. Investors interpret the opposite side depth and the time between transactions variables in a different manner with respect to the general case. The opposite side depth and the trading frequency have now a positive relation with aggressiveness: when the liquidity supply at the ask increases or the time between transactions decreases, buyers submit relatively more aggressive orders. Interestingly, the variables of the information set that change in sign before the earnings announcements are the same ones that change sign for the sell orders submitted on stocks of group 3.

[16]The approach of using a performance measure to infer the informed side of the market has been used, for example, in Chakravarty (2001), where stocks that displayed at least a 5% price increase were selected, in order to maximize the probability of detecting private information-based trading.

[17]BA and MO reported bad news, i.e. the released earnings figure was lower than the analysts consensus. We verified that our results are qualitatively the same whether we use all the seven stocks in our analysis or just the five stocks reporting good news.

To control for potential speculative trading on the day before the earnings release, we repeat the analysis excluding orders submitted on that day. We obtain theoretical frequencies that are not statistically different with respect to the full pre-announcement sample and we also confirm all the other results.

[18]When the level of asymmetric information in the market increases, discretionary uninformed traders delay trades to avoid the informed trader's large informational edge, like in Admati and Pfleiderer (1988) and Foster and Viswanathan (1990) models, or they prefer to use aggressive strategies to avoid the risk of being picked off by informed traders (Handa and Schwartz, 1996). Under the assumption that noise traders are equally distributed on both sides of the market and informed traders are concentrated on the buy side, we claim that the aggressive selling strategy before a positive earning surprise is mainly driven by the behavior of liquidity traders.

These results lead to the following scenario. There are more informed traders on the buy side, ready to profit from their information by aggressively taking limit orders on the sell side. In this case, however, information will be impounded into prices within a few trading periods. Informed traders submit therefore higher proportions of less aggressive orders, that allow them to protect their advantage and to trade at better prices. Three considerations can discourage this strategy. First, less aggressive orders are exposed to execution risk. This argument could explain the increase in aggressiveness following the increase in trading frequency as a signal of competition among informed traders. Second, higher ask depths allow the informed traders to accumulate shares through aggressive buy orders without a substantial impact on the price. Finally, we can expect that informed traders will not succeed completely in hiding their information, because ultimately their profits depend also on the quantities they manage to accumulate, and this incentive creates inevitably price pressures and consequent information revelation and imitation. This last reasoning is supported by the multiplier effect of transacted volume in Table 7, Panel B, that turns out to be the most important variable in affecting order submission strategies in this sub-sample.

5.3 How does Order Aggressiveness Impact Prices?

The revelation of private information through the trading process is a major mechanism for changes in asset prices besides the public information flow. Trades have a price impact including both a temporary component, as a compensation for liquidity provision, and a permanent component, reflecting any new information revealed by the trade. In this paper, we conjecture that informed traders act strategically and use also limit orders. If this is the case, the order book becomes informative and orders, not only trades, will have a permanent price impact as a result of private information revelation.

An analysis of the price impact for different categories of orders can thus provide useful insights about their information content. However, the direction of any potential bias of ignoring the temporary price change component is difficult to specify without additional assumptions about its magnitude and durations. In order to capture the permanent effect of information, we analyze the price impact of orders with different aggressiveness in the general setting and when the probability of information-based trading is higher.

We hypothesize that more aggressive orders have a greater price impact, since they exert an immediate mechanical effect, regardless of their information content. For example, the submission of a buy market order for a quantity equal to the quoted depth increases the ask price. If the order is not informed, the price should revert back to its *efficient* value, but this may take an unspecified amount of time. In contrast, a buy limit order has only an indirect effect, providing more liquidity on the bid-side and thus reducing the price impact of subsequent sell market orders. Consistent with our conjecture, Hopman (2002) shows a monotonic decrease of the price impact for less and less aggressive orders in an empirical study of the Paris stock exchange. Under the joint hypothesis that informed traders use less aggressive orders and stock price changes are mainly due to private information revealed through the trading process, we expect to observe a weaker ordering of price impacts with respect to aggressiveness, when the probability of information-based trading is higher. Our tests concentrate on this empirical prediction.

The methodology relies on the same logic that inspired models on the bid-ask spread decomposition (e.g., Madhavan et al., 1997), but we do not impose any specific structure on the trading process and estimate price impacts for buys and sells separately. For each order, we compute a measure of total price impact as the difference between the logarithms of the mid-quotes after the order submission and the mid-quotes prevailing at the time of the order submission. There are no theoretical guidelines for the choice of an appropriate horizon for the price impact measurement. In our tests we use one hour as the benchmark horizon, but we check for the robustness of our results at the horizons of 30, 20 and ten minutes.

As an illustration of price impacts in our sample, Figure 3 shows the 60-minute impact of buy orders on the price of GE as a non-parametric function of the ordered quantity. In order to ease the exposition, we aggregate the former six categories of aggressiveness in three classes: high aggressiveness - market orders and *marketable* limit orders (former categories 1 and 2); medium aggressiveness - orders with a limit price between the bid and the ask or on the same side best quote (former categories 3 and 4); low aggressiveness - orders placed outside the best quotes (former categories 5 and 6). As expected, the most aggressive orders have the greatest price impact for a given size. We obtain similar relations for the other stocks in our sample.

We use a non-parametric Wilcoxon statistic to test whether the price impact of orders in an aggressive category is significantly larger than the price impact of orders in a less aggressive category.[19] We sort out orders in three size classes - small, medium and large - using the same quantity thresholds used in Barclay and Warner (1993). We do not attempt to disentangle the temporary and the permanent components of the price impact, but we compare the results for the general case with the results for sub-samples with higher probability of information-based trading. We argue that any difference is due to the order submission strategies of informed traders.

Table 8 illustrates the results for medium sized orders sorted out in three categories of aggressiveness.[20] We report the ratio between the mean price impact for the row category and the mean price impact for the column category and we test for significant differences. In Panel A, we compare the price impact of buy orders submitted during the month of November with the price impact of buy orders submitted during the 20 trading days preceding the earnings announcement for five stocks releasing higher figures than expected.[21] The

[19]Since the price impact of an order is a non-linear function of the ordered quantity and the observations are overlapped and not independent, it would be problematic to estimate classical parametric models. However, we complemented our analysis with a non-linear regression of the price impact on the ordered quantities and on dummies for the aggressiveness categories. The results are qualitatively the same and are available on request from the authors.

[20]Barclay and Warner (1993) support the stealth-trading hypothesis showing that the medium size orders have the greatest information content. Since our purpose is to describe the behavior of informed traders, we show the results for this size-category.

[21]In the current analysis we employ 20 days of orders before earnings announcements, whereas in the analysis of Section 5.2 we used 10 days. The longer length chosen here is necessary to have enough observations in each aggressiveness and size category for the non-parametric tests and to have a fair comparison with the month of November. Furthermore, any bias would make our results more conservative, since we are likely to include days with a lower probability of information-based trading.

pattern of decreasing price impacts for less aggressive orders is well documented in November, with highly significant differences for all the five stocks. However, when the probability of information-based trading is higher, this pattern does not hold anymore. For example, buy orders placed at the bid or between the quotes for FNM, GE and IBM now have a larger impact on prices than market orders or *marketable* limit orders. The least aggressive buy limit orders placed below the bid have a larger impact than orders between the quotes for GE and XON. We argue that the order submission strategies of informed traders determine the greater relative price impact of less aggressive orders, in the same spirit of the stealth trading hypothesis of Barclay and Warner (1993).

Panel B of Table 8 presents similar results by comparing sell orders for large and comparatively smaller stocks. The most aggressive sell orders have always a significantly larger negative impact than the less aggressive ones on the prices of GE, IBM and MO. In contrast, this relation is not significant for CL and GLX, and it is even reversed for SLB, for which sell orders between the quotes have larger negative price impacts than market orders. We argue again that the different pattern of price impacts and aggressiveness is determined by less aggressive order submission strategies of informed traders.

6 Conclusions

In this paper we investigate the order submission strategies of investors on the NYSE. We find that a number of microstructure-related variables and stock market-related variables representing the investor's information set are significantly affecting the decision to submit an aggressive versus a passive order. In particular, the depth at the same side of the book and a momentum indicator are the most important determinants of the order choice.

When we examine situations of higher probability of information-based trading, we discover a strategic behavior of informed traders in timing their order arrivals. Rather than exploiting their private information right away by aggressively taking limit orders on the opposite side, we find evidence of informed traders trying to hide their information through the submission of passive limit orders. The process of price adjustment can change the value of their private information, and is therefore closely monitored by informed traders. This conjecture is supported by a different relation between aggressiveness and some of the variables defining the investor's information set when the probability of information-based trading is higher. Specifically, the opposite side depth and the time between transactions have contrary effects with respect to the general case. The main consequence of these findings is that the order flow conveys information regarding subsequent price movements. An analysis of the price impact of orders with different levels of aggressiveness supports our conjecture.

Our study suggests interesting directions for future research. Given the role of the order flow in the mechanism of price formation, it could be interesting to measure in what respects order submission strategies and asymmetric information are related in different institutional settings or market designs. In particular, researchers are looking at how recent changes in the minimum price variation might impact order submissions (e.g., Bacidore et al., 2003). These changes offer an opportunity to gain further insights into informed trader strategies, by comparing the results from different regimes. Moreover, the recent introduction of *NYSE OpenBook*, where traders can also have information about prices and depths in the remainder of the limit order book, could stimulate similar research topics.

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Table 1: Sample Stocks Features

This table presents summary statistics for the ten stocks in our sample. *Price* is the closing price on November 1, 1990. *Capital* is the market capitalization on November 1, 1990 (in millions). *Volume* is the average value of transaction volume during the period under consideration (November 1, 1990–January 31, 1991) (in millions). Limit and market orders do not add up to the total number of orders, because the latter includes cancellations, tick-sensitive and stop orders.

Company	Symbol	Price	Capital	Volume	N. of orders		Market orders		Limit orders	
Boeing	BA	44.250	15,333	1,065,880	52,543	12.06%	22,107	42.07%	22,536	42.89%
Colgate Palmolive Co	CL	66.750	4,419	282,367	11,063	2.54%	3,763	34.01%	4,221	38.15%
Federal National Mortgage Assn	FNM	28.375	6,779	1,074,770	30,009	6.89%	8,219	27.39%	16,754	55.83%
General Eletric Co	GE	52.375	46,541	1,941,730	62,483	14.35%	25,329	40.54%	25,005	40.02%
Glaxo Holdings Plc	GLX	29.000	2,859	507,835	23,593	5.42%	9,568	40.55%	11,708	49.62%
International Business Machs Corp	IBM	107.250	61,438	4,223,160	67,521	15.50%	28,302	41.92%	25,475	37.73%
Philip Morris Cos Inc	MO	47.875	44,256	2,048,720	65,788	15.11%	31,422	47.76%	23,042	35.02%
Schlumberger Ltd	SLB	57.375	13,636	650,493	18,217	4.18%	7,748	42.53%	6,816	37.42%
American Telephone & Teleg	T	34.750	37,845	1,106,150	68,957	15.83%	33,882	49.13%	25,696	37.26%
Exxon Corp	XON	49.750	62,042	1,109,160	35,339	8.11%	17,607	49.82%	10,251	29.01%
					435,513	100.00%	187,947	43.16%	171,504	39.38%

Table 2: Intradaily Pattern of Aggressiveness

This table presents the number and relative frequency of orders registered in our sample period for each of the six categories of aggressiveness (*aggr*). Cat. 1 includes buy (sell) market orders and buy (sell) limit orders for a price greater (less) or equal to the best ask (bid), and size larger than the quoted depth. Cat. 2 includes buy (sell) market orders and buy (sell) limit orders for a price greater (less) or equal to the ask (bid). Cat. 3, 4, 5 and 6 include buy (sell) limit orders priced between the bid and the ask, at the bid (ask), up to four ticks from the best quote, and more than four ticks from the best quote, respectively.

Buy side

	TOTAL		9:30-10:00		10:00-11:00		11:00-12:00		12:00-13:00		13:00-14:00		14:00-15:00		15:00-15:30		15:30-15:45		15:45-16:00	
aggr	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%
1	1,996	1.08	280	1.45	283	0.83	307	0.99	271	1.13	195	0.93	246	0.99	175	1.21	111	1.44	128	1.57
2	111,616	60.48	11,012	56.85	19,655	57.65	18,929	61.24	14,515	60.71	12,835	61.29	15,440	61.83	9,158	63.07	4,861	63.13	5,211	64.12
3	11,145	6.04	1,207	6.23	1,977	5.80	1,805	5.84	1,438	6.01	1,303	6.22	1,527	6.11	897	6.18	500	6.49	491	6.04
4	32,153	17.42	3,328	17.18	6,410	18.80	5,235	16.94	4,170	17.44	3,676	17.55	4,349	17.41	2,482	17.09	1,245	16.17	1,258	15.48
5	14,596	7.91	2,007	10.36	3,210	9.42	2,321	7.51	1,790	7.49	1,484	7.09	1,749	7.00	944	6.50	525	6.82	566	6.96
6	13,034	7.06	1,535	7.93	2,559	7.51	2,311	7.48	1,725	7.21	1,447	6.91	1,662	6.66	864	5.95	458	5.95	473	5.82
	184540	100	19369	100	34094	100	30908	100	23909	100	20940	100	24973	100	14520	100	7700	100	8127	100

Sell side

	TOTAL		9:30-10:00		10:00-11:00		11:00-12:00		12:00-13:00		13:00-14:00		14:00-15:00		15:00-15:30		15:30-15:45		15:45-16:00	
aggr	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%	N.	%
1	1,669	1.00	193	1.15	249	0.79	198	0.72	167	0.80	222	1.18	319	1.37	141	1.13	103	1.41	77	1.00
2	101,904	61.34	9,714	57.83	18,945	60.23	16,964	61.78	12,608	60.62	11,512	61.28	14,673	63.08	7,999	63.82	4,518	61.81	4,971	64.30
3	9,280	5.59	1,031	6.14	1,637	5.20	1,465	5.34	1,149	5.52	1099	5.85	1,354	5.82	712	5.68	438	5.99	395	5.11
4	30,375	18.28	2,992	17.81	5,752	18.29	4,948	18.02	4,051	19.48	3,576	19.04	4,147	17.83	2,265	18.07	1,324	18.11	1,320	17.07
5	15,110	9.10	1,846	10.99	3,155	10.03	2,481	9.04	1,842	8.86	1,572	8.37	1,871	8.04	982	7.84	645	8.82	716	9.26
6	7,790	4.69	1,021	6.08	1,719	5.46	1,401	5.10	980	4.71	805	4.29	897	3.86	434	3.46	281	3.84	252	3.26
	166128	100	16797	100	31457	100	27457	100	20797	100	18786	100	23261	100	12533	100	7309	100	7731	100

Table 3: Order Submission Strategies

Panel A presents estimated coefficients and standard errors for an ordered probit model. The sign of the coefficient denotes the relation between the independent variable and aggressiveness. Panel B shows the marginal effects of the explanatory variables on each of the six categories of aggressiveness (*aggr*). The multipliers are standardized by their standard errors. The meaning of the abbreviations is as follows: *bas* is the bid-ask spread, *ssd* is the same side depth and *osd* is the opposite side depth (both multiplied by 0.01), *mom* is the momentum, *vola* is the volatility (multiplied by 1000), *volu* is the volume of transactions (multiplied by 1e-7), *time* is the time between transactions (multiplied by 0.01). For brevity, we do not report the results for the time-of-the-day dummies. *** and ** denote statistical significance at the 1 and 5 percent levels, respectively.

Panel A

	Buy side	**Sell side**
Bas	-26.4397***	-25.9485***
	(1.5590)	(1.7008)
Ssd	0.0288***	0.0417***
	(0.0014)	(0.0014)
Osd	-0.0079***	0.0114***
	(0.0012)	(0.0015)
Mom	8.9711***	-16.0767***
	(0.5025)	(0.5656)
Vola	-5.8883***	-5.5927***
	(0.9896)	(1.1390)
Volu	2.1759***	-4.6433***
	(0.3224)	(0.3710)
Time	0.0161***	-0.0093**
	(0.0034)	(0.0037)
χ^2 test	1646.71***	2546.89***

Panel B

			Buy side				
aggr	bas	ssd	osd	mom	vola	volu	time
1	-16.26	19.51	-6.46	17.05	-5.91	6.7	4.79
2	-16.95	20.83	-6.49	17.84	-5.95	6.75	4.81
3	16.55	-20.19	6.47	-17.45	5.94	-6.73	-4.80
4	16.91	-20.67	6.49	-17.77	5.94	-6.74	-4.81
5	16.86	-20.63	6.49	-17.80	5.94	-6.74	-4.80
6	16.86	-20.73	6.49	-17.75	5.95	-6.74	-4.81
			Sell side				
aggr	bas	ssd	osd	mom	vola	volu	time
1	-14.59	25.09	7.29	-24.55	-4.76	-12.19	-2.54
2	-15.2	28.96	7.39	-28.20	-4.79	-12.57	-2.54
3	14.87	-27.13	-7.35	26.43	4.78	12.41	2.54
4	15.17	-28.54	-7.38	27.83	4.79	12.53	2.54
5	15.17	-28.52	-7.38	28.01	4.79	12.53	2.54
6	15.06	-28.37	-7.38	27.53	4.79	12.52	2.54

Table 4: Order Aggressiveness and Groups of Stocks

This table presents a comparison between theoretical (*pre*) and actual (*act*) frequencies of orders in each category of aggressiveness (*aggr*) for the buy and the sell side. We compute theoretical frequencies as the mean of the probabilities predicted by the ordered probit model, estimated in Table 3, for the information set of each order in the subsample. Theoretical and actual frequencies are all statistically different at the 5% level. We also report an index of actual (predicted) aggressiveness (*Aggress. Index*), obtained as the ratio between the number of actual (predicted) orders of category 1-2 over the number of actual (predicted) orders of category 3-6.

Buy side

	Group 1			Group 2			Group 3		
Aggr	N.	Act (%)	Pre (%)	N.	Act(%)	Pre (%)	N.	Act (%)	Pre (%)
1	1,066	1.43	1.14	571	0.67	1.04	359	1.46	1.01
2	45,956	61.86	61.51	51,147	59.69	59.99	14,513	59.10	59.69
3	3,562	4.79	5.99	5,382	6.28	6.07	2,201	8.96	6.09
4	11,572	15.58	17.04	15,930	18.59	17.55	4,651	18.94	17.67
5	5,455	7.34	7.62	7,306	8.53	8.03	1,835	7.47	8.12
6	6,681	8.99	6.70	5,355	6.25	7.32	998	4.06	7.42
Total	74292	100	100	85691	100	100	24557	100	100
Aggress. Index		1.72	1.68		1.52	1.57		1.53	1.54

Sell side

	Group 1			Group 2			Group 3		
Aggr	N.	Act (%)	Pre (%)	N.	Act (%)	Pre (%)	N.	Act (%)	Pre (%)
1	922	1.15	1.02	484	0.72	1.04	263	1.43	0.93
2	50,282	62.74	61.61	42,396	62.77	61.46	9,226	50.03	60.21
3	3,869	4.83	5.60	3,741	5.54	5.58	1,670	9.06	5.67
4	13,202	16.47	18.19	12,560	18.59	18.19	4,613	25.01	18.70
5	7,420	9.26	8.96	5,677	8.40	9.02	2,013	10.92	9.45
6	4,445	5.55	4.62	2,688	3.98	4.71	657	3.56	5.04
Total	80,140	100	100	67,546	100	100	18,442	100	100
Aggress. Index		1.77	1.68		1.74	1.67		1.06	1.57

Table 5: Orders Submission Strategies and Groups of Stocks

Panel A presents estimated coefficients and standard errors for an ordered probit model, on samples of orders for different groups of stocks for the buy and the sell side. Panel B shows the marginal effects of the explanatory variables for the ordered probit model estimated on group 3, sell side, where we expect a higher degree of information asymmetry. The multipliers are standardized by their standard errors.

The meaning of the abbreviations is as follows: *bas* is the bid-ask spread, *ssd* is the same side depth and *osd* is the opposite side depth (both multiplied by 0.01), *mom* is the momentum, *vola* is the volatility (multiplied by 1000), *volu* is the volume of transactions (multiplied by 1e-7), *time* is the time between transactions (multiplied by 0.01). For brevity, we do not report the results for the time-of-the-day dummies.

Group 1, 2 and 3 comprise IBM, MO, GE; XON, FNM, T, BA; and SLB, GLX, CL; respectively.

Panel A

	Buy side			**Sell side**		
	Group 1	Group 2	Group 3	Group 1	Group 2	Group 3
Bas	-45.5695***	-30.5239***	-27.8985***	-7.9327*	-27.8264***	-12.5187***
	(3.8164)	(2.2647)	(4.2469)	(3.8125)	(2.6550)	(4.8006)
Ssd	0.0464***	0.0262***	0.0206***	0.0373***	0.0515***	0.0196***
	(0.0030)	(0.0017)	(0.0048)	(0.0023)	(0.0021)	(0.0039)
Osd	-0.0046**	-0.0075***	-0.0170***	-0.0098***	0.0250***	-0.0272***
	(0.0023)	(0.0016)	(0.0032)	(0.0028)	(0.0021)	(0.0049)
Mom	11.4367***	6.1691***	14.8668***	-17.8435***	-13.2593***	-19.4885***
	(0.9877)	(0.6666)	(1.3436)	(0.9880)	(0.7946)	(1.4672)
Vola	-8.5873***	-8.8330***	-3.1939	11.2503***	-15.8298***	1.0243
	(1.8678)	(1.3270)	(3.1457)	(2.0585)	(1.5422)	(3.4606)
Volu	5.9404***	1.8341***	-6.7091***	-2.7124***	-6.7302***	-17.8980***
	(0.6898)	(0.3973)	(1.7506)	(0.5946)	(0.5384)	(1.8922)
Time	-0.0499**	-0.0082	-0.0072	0.0906***	-0.0264***	0.0095*
	(0.0196)	(0.0069)	(0.0047)	(0.0181)	(0.0077)	(0.0054)
χ^2 test	783.53***	981.20***	271.62***	831.62***	1874.85***	481.70***

***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel B

	Sell side Group 3						
Aggr	bas	ssd	osd	mom	vola	volu	time
1	-2.59	4.81	-5.35	-11.54	0.30	-8.43	1.76
2	-2.61	4.96	-5.52	-13.20	0.30	-9.44	1.77
3	2.56	-4.75	5.22	10.21	-0.30	8.15	-1.76
4	2.61	-4.95	5.50	12.92	-0.30	9.31	-1.77
5	2.61	-4.95	5.50	13.02	-0.30	9.34	-1.77
6	2.60	-4.92	5.45	12.25	-0.30	9.15	-1.77

Table 6: Order Aggressiveness before Earnings Announcements

This table presents a comparison between theoretical (*pre*) and actual (*act*) frequencies of orders in each category of aggressiveness (*aggr*) for the buy and the sell side. We compute theoretical frequencies as the mean of the probabilities predicted by the ordered probit model, estimated in Table 3, for the information set of each order in the subsample. Theoretical and actual frequencies are all statistically different at the 5% level. We also report an index of actual (predicted) aggressiveness (*Aggress. Index*), obtained as the ratio between the number of actual (predicted) orders of category 1-2 over the number of actual (predicted) orders of category 3-6.

Buy side			
Aggr	N.	Act (%)	Pre (%)
1	303	1.15	1.11
2	15,789	59.98	60.82
3	1,223	4.65	6.02
4	3,902	14.82	17.26
5	2,006	7.62	7.80
6	3,100	11.78	6.99
Total	26,323	100.00	100.00
Aggress. Index		1.57	1.63

Sell side			
Aggr	N.	Act (%)	Pre (%)
1	233	0.89	1.04
2	17,597	67.40	61.65
3	1,243	4.76	5.58
4	3,796	14.54	18.15
5	2,123	8.13	8.95
6	1,115	4.27	4.63
Total	26,107	100.00	100.00
Aggress. Index		2.15	1.68

Table 7: Order Submission Strategies and Earnings Announcements

Panel A presents estimated coefficients and standard errors for an ordered probit model, on samples of orders submitted before earnings announcements for the buy and the sell side. Panel B shows the marginal effects of the explanatory variables for the ordered probit model estimated on the buy side, where we expect a higher degree of information asymmetry. The multipliers are standardized by their standard errors.
The meaning of the abbreviations is as follows: *bas* is the bid-ask spread, *ssd* is the same side depth and *osd* is the opposite side depth (both multiplied by 0.01), *mom* is the momentum, *vola* is the volatility (multiplied by 1000), *volu* is the volume of transactions (multiplied by 1e-7), *time* is the time between transactions (multiplied by 0.01). For brevity, we do not report the results for the time-of-the-day dummies.

Panel A

	Buy side	**Sell side**
Bas	-27.0912***	-20.7988***
	(4.1729)	(4.3557)
Ssd	0.0204***	0.0328***
	(0.0033)	(0.0036)
Osd	0.0107***	0.0113***
	(0.0037)	(0.0032)
Mom	10.0982***	-7.1625***
	(1.4725)	(1.4609)
Vola	-5.0948***	2.6685
	(1.5690)	(1.8065)
Volu	9.8421***	-7.3883***
	(1.0408)	(1.0740)
Time	-0.0422***	-0.0378**
	(0.0151)	(0.0164)
χ^2 test	395.86***	310.42***

***, ** and * denote statistical significance at the 1, 5 and 10 percent levels, respectively.

Panel B

	Buy side Pre-Announcement						
Aggr	bas	ssd	osd	mom	vola	volu	time
1	-6.23	6.02	2.87	6.57	-3.20	8.67	-2.77
2	-6.48	6.26	2.91	6.85	-3.25	9.44	-2.79
3	6.29	-6.10	-2.89	-6.67	3.22	-8.94	2.78
4	6.45	-6.22	-2.90	-6.79	3.24	-9.30	2.79
5	6.44	-6.21	-2.90	-6.79	3.24	-9.26	2.79
6	6.48	-6.25	-2.91	-6.83	3.25	-9.43	2.79

Table 8: Orders Price Impact

This table shows the ratio between the mean price impact for the row category and the mean price impact for the column category, indicating if the difference is significant in a Wilcoxon test. *** and ** denote statistical significance at the 1 and 5 percent levels, respectively. Category 1 includes market orders and *marketable* limit orders, category 2 includes orders with a limit price between the bid and the ask or on the same side best quote, and category 3 include orders placed outside the best quotes. Panel A presents the price impacts of buy orders submitted during the month of November and during the 20 trading days preceding the earnings announcements. Panel B shows the price impacts of sell orders for larger stocks (group 1) and smaller stocks (group 3).

Panel A

Buy side November			
		cat. 2	cat. 3
FNM	cat. 1	1.0622**	1.2454***
	cat. 2		1.1724***
GE	cat. 1	1.1513***	2.5653***
	cat. 2		2.2283***
IBM	cat. 1	1.2862***	1.3294***
	cat. 2		1.0336***
T	cat. 1	1.2303***	3.4551***
	cat. 2		2.8084***
XON	cat. 1	1.3908***	5.0895***
	cat. 2		3.6593***
Buy side pre-announcement			
		cat. 2	cat. 3
FNM	cat. 1	0.9766**	1.2209***
	cat. 2		1.2501***
GE	cat. 1	0.9028***	0.5218***
	cat. 2		0.5780***
IBM	cat. 1	0.8928***	2.7849***
	cat. 2		3.1192***
T $^{-}$	cat. 1	-0.2256***	0.0792***
	cat. 2		-0.3512***
XON	cat. 1	2.8663***	2.7249***
	cat. 2		0.9506***

$^{-}$: The price impact of orders in category 2 is negative.

Panel B

Sell side Group 1			
		cat. 2	cat. 3
GE^{++}	cat. 1	-4.6069***	-0.8934***
	cat. 2		0.1939***
IBM^{++}	cat. 1	-0.3853***	-0.7795***
	cat. 2		2.0228***
MO^{+}	cat. 1	1.7483***	-0.3284***
	cat. 2		-0.1878***
Sell side Group 3			
		cat. 2	cat. 3
CL	cat. 1	1.9373	2.4858***
	cat. 2		1.2831***
GLX^{++}	cat. 1	-0.8049	-0.3374***
	cat. 2		0.4192***
SLB	cat. 1	0.4572***	1.1099***
	cat. 2		2.4276***

$^{++}$: The price impact of orders in category 2 and 3 is positive;
$^{+}$: The price impact of orders in category 3 is positive;

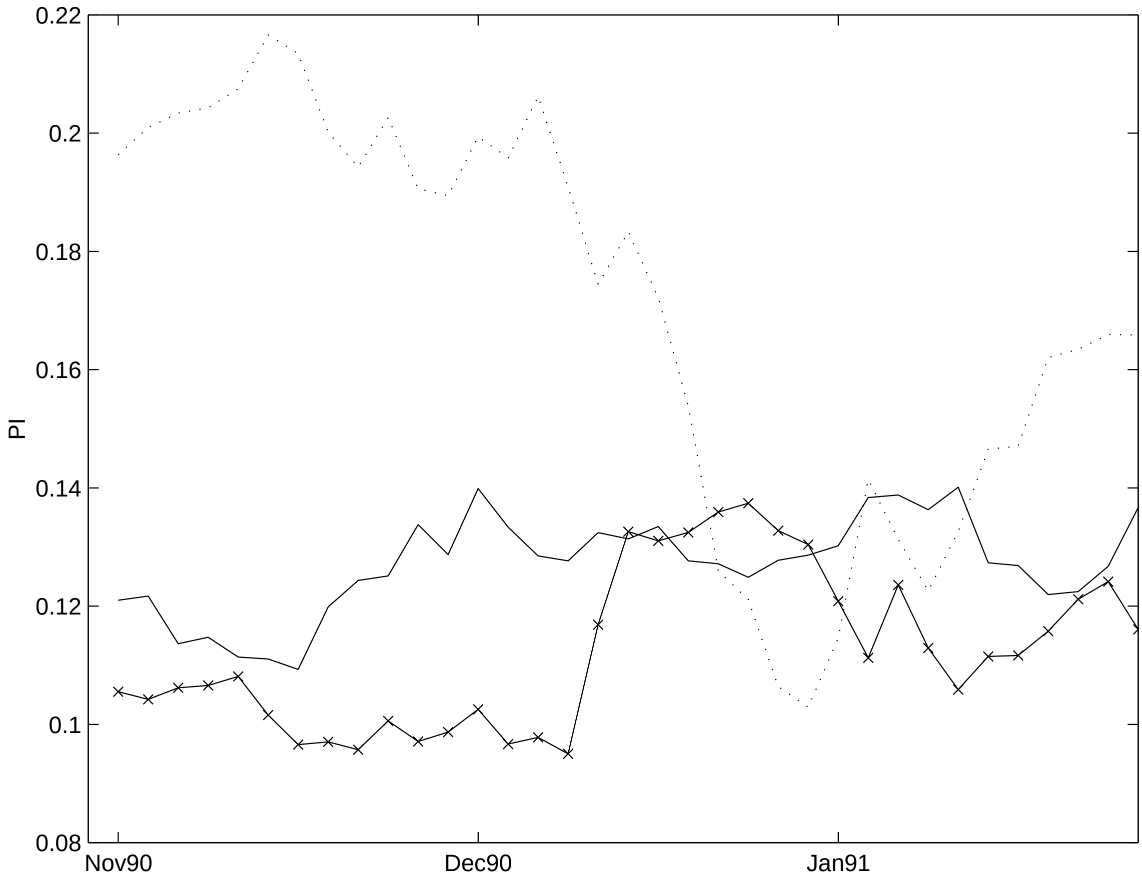

Figure 1: Probability of Information-based Trading in the Sample Period. This figure plots the rolling PI indicator for the three volume-groups of stocks. The dotted line represents the average PI for the smallest volume group (CL, GLX, SLB); the continuous line represents the average PI for the intermediate volume group (BA, FNM, T, XON); the crossed line represents the average PI for the largest volume group (GE, IBM, MO).

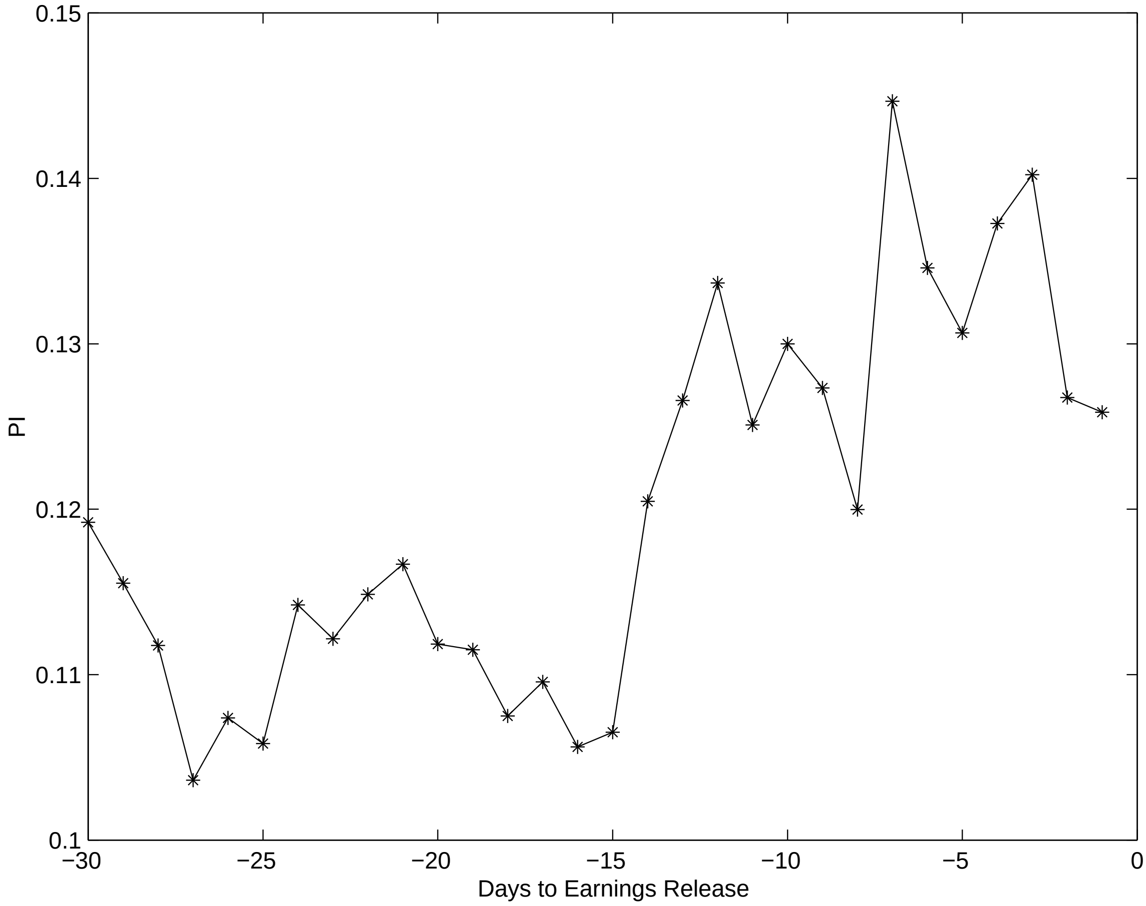

Figure 2: Probability of Information-based Trading before Earnings Announcements. This figure plots an average PI indicator for the seven stocks that are announcing earnings during our sample period. Each value is computed on an interval of 21 trading days, where the last day is gradually approaching the release date.

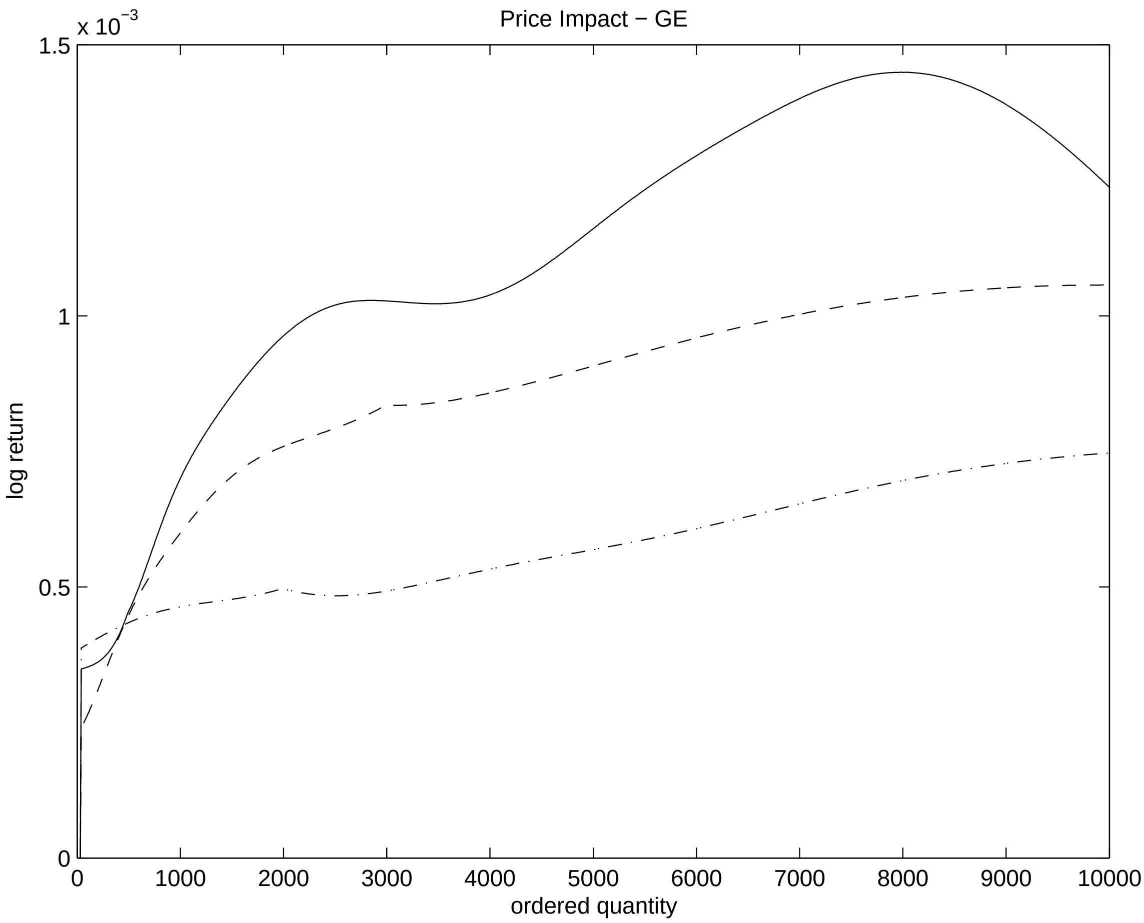

Figure 3: Impact of Buy Orders on Price of GE. This figure plots the 60-minute impact of buy orders on the price of GE as a non-parametric function of the ordered quantity. We use a kernel regression with a Gaussian kernel and a variable bandwidth to reflect the larger number of observations for smaller ordered quantities. The continuous line represents the most aggressive orders (market orders and *marketable* limit orders), the dashed line represents orders of medium aggressiveness (limit orders placed between the bid and the ask or at the bid) and the dashed-dotted line represents the least aggressive orders (limit orders placed below the bid).

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