# Hidden Liquidity: An Analysis of Order Exposure Strategies in Electronic Stock Markets*

Hendrik Bessembinder
University of Utah
finhb@business.utah.edu

Marios Panayides
University of Utah
finmp@business.utah.edu

Kumar Venkataraman
Southern Methodist University
kumar@mail.cox.smu.edu

This Draft
February 2008

Comments Appreciated

* We thank Alex Butler, Robert Battalio, Charles Jones, Chitru Fernando, Amar Gande, Michael Goldstein, Rick Harris, Joel Hasbrouck, Ohad Kadan, Qin Lei, Rajesh Narayanan, Michael Pagano, Venkatesh Panchapagesan, Paul Schultz, Rex Thompson, Andrew Waisburd, Kelsey Wei, and in particular, Harold Zhang and Avanidhar Subrahmanyam, and seminar participants at American Economic Association Conference, NBER Market Microstructure Conference, University of Cyprus, Notre Dame University, University of Texas at Dallas, University of Oklahoma, Ohio University, and Southern Methodist University for valuable comments and discussion, Machiko Hollifield for programming assistance, and Marianne Demarchi of Euronext-Paris for assistance in obtaining the data.

# Hidden Liquidity: An Analysis of Order Exposure Strategies in Electronic Stock Markets


### Abstract

We study limit order traders' decisions regarding order exposure in a market where they have the option to hide a portion of order size. Using order-level data from Euronext-Paris, we document that hidden orders are used extensively by market participants, representing approximately 44% of order volume. All else equal, hidden orders are associated with smaller opportunity costs and lower implementation shortfall costs. However, hidden orders are associated with lower probability of full execution and longer times to execution. We document that a logistical model relying on observable firm characteristics, market conditions, and order characteristics is useful in detecting hidden orders. However, our findings also indicate that hidden orders allow limit order traders to partly conceal their trading intentions, and that hidden orders are used primarily by uninformed traders to lower the option value of standing orders on the book.

## 1. Introduction

Electronic limit order markets, which automatically execute traders' orders on the basis of specified priority rules, account for a large and increasing percentage of global financial and commodity trading.[1] As a consequence, understanding order submission decisions in electronic markets is becoming increasingly important to investors as well as to those who regulate and design automated markets. Those who wish to transact in an electronic limit order market submit buy or sell orders that specify size, i.e., the maximum number of shares to transact, and price, i.e., the highest price to be paid or lowest price to be received. In many markets, traders may also specify that a portion of order size be hidden, rather than displayed to other market participants.

In this paper, we use data drawn from the Euronext Paris market to examine several issues related to order submission decisions. First, we measure some costs and benefits associated with traders' selection of aggressive versus passive limit prices and associated with the decision to exposure or hide the full quantity of the order. More specifically, we quantify the effects of order price aggressiveness and order exposure on the likelihood of that the order will execute in full, on the expected time-to-completion for the order, and on order execution costs as measured by the "implementation shortfall" method. Second, we estimate a pooled logistic model to assess the factors that govern the decision to hide a portion of the order size. The results indicate that the presence of undisclosed size is related to a number of observable variables, including characteristics of the firm, market conditions, and other order attributes. Third, we assess the extent to which traders can use observable information to forecast the likelihood that an incoming order contains a hidden size component, We document that the existence of undisclosed size can be forecast to a significant, but imperfect, degree. That the ability to detect hidden size is imperfect implies that hiding size can reduce the option value of leaving large orders in the limit order book.

[1] In a study on stock exchanges around the world, Jain (2005) reports that electronic trading is the leading stock market structure in 101 of the 120 countries that the study investigates. Furthermore, of these 101 exchanges, 85 are fully electronic, with no floor trading.

Trades occur in financial markets as the successful outcome of a bilateral search for trading partners. The odds of locating a trading partner typically increase if a potential trader disseminates widely and credibly their interest in trading. For this reason, stock exchanges, which have an interest in promoting trading activity, typically implement price and time priority rules that encourage potential traders to be the first to submit attractively priced limit orders. Under a typical priority system, those orders with limit prices aggressive enough to execute immediately are matched first with standing orders displaying the best limit prices (highest for purchase limits and lowest for sell limits), and among orders with the same price, against the order placed earliest.

Many limit order stock markets, including the Toronto Stock Exchange, Euronext, the Swiss Stock Exchange, the Madrid Stock Exchange, the Australian Stock Exchange, and the Electronic Communications Networks (ECNs) that trade U.S. stocks, offer traders the ability to enter buy or sell orders that are partially or wholly hidden from market participants.[2] Other electronic markets, such as the Hong Kong Stock Exchange, do not permit hidden orders. A hidden (or "iceberg") order's price is displayed to other investors, but only a portion of the order's full size is displayed, typically subject to a minimum displayed size requirement. Marketable orders will execute against hidden quantities only after exhausting all displayed size at the same price. Thus, hidden orders typically maintain price priority, but lose time priority to other orders at the same price.

Traders considering whether to expose the full size of their orders face both costs and benefits of doing so. Exposing an order increases the chance that it will attract a counterparty who is sufficiently interested in trading to monitor the market, but who has not yet revealed herself. On the other hand, exposing an order could cause other traders to withdraw liquidity if they infer that the limit order submitter may have access to private information regarding security value. Or, other traders could employ front-running strategies that take advantage of information conveyed by a standing order. These

[2] Under the new NYSE Hybrid Market, floor brokers are offered the privilege to use hidden orders when they are not present at the specialist's post (see Abrokwah and Sofianos (2006)). Some markets, such as U.S.-based INET, allow limit orders to be fully hidden while other markets, such as Euronext, require limit orders to display a minimum size (also called "iceberg" orders). For expositional ease, we refer to orders with any unexposed quantity to be hidden.

considerations are likely to be magnified if the order is larger. In electronic markets, hidden orders allow liquidity suppliers to control the order exposure risk, thus lowering front-running costs and the implicit option value provided to other traders by their limit order.[3] The inferences drawn by market participants on the information content of an order is likely to be related to the price aggressiveness of the order and the observed order size, since informed traders typically wish to complete trades before their information becomes public. Therefore, from the perspective of traders' selecting order attributes, we anticipate that the decision to expose order size will depend in part on the limit price selected and in part on the total order size. Further, to the extent that hidden orders allow traders' to conceal their trading intentions, we anticipate that the observed (or displayed) order size will be less informative for market participants in predicting hidden liquidity than total order size.

To examine the tradeoffs associated with important attributes of order submission, we study a sample of 100 stocks traded on Euronext-Paris during April 2003. The sample includes a broad cross-section of stocks ranging from the most actively traded to illiquid stocks that trade less than once per day on average. We document that hidden orders are used extensively on Euronext. For the full sample, 18% of the incoming orders include a hidden size and 44% of the order volume is hidden. The usage of hidden orders is more prevalent for the less liquid firms, increasing from 30% of order volume for firms in the most liquid quintile to around 50% for firms in the less liquid quintiles, and for larger orders, increasing from 5% of order volume for order sizes less than €5,000 to over 70% for order sizes greater than €50,000.

We present empirical evidence on the benefits and costs associated with the trader's exposure decision. Since exposed orders gain time priority versus hidden orders at the same price, and may be more effective in drawing trading interests from passive traders (Harris (1996)), we test the hypothesis that exposing an order increases the likelihood of full execution and lowers the time between order

---

3 In the context of floor-based market structures, several studies have argued that the floor broker acts as a *smart* limit order, displaying only a portion of the total order size to the entire market to minimize front running strategies, and selectively exposing the trading interests to those counterparties that are most likely to take the other side of the transaction. (See, for example, Hasbrouck and Sofianos (1993), Venkataraman (2001), Sofianos and Werner (2003) and Battalio, Ellul and Jennings (2007) for related discussions.)

submission and execution. Consistent with this prediction, we find that fully displayed orders are more likely to execute completely. Using the survival analysis approach described in Lo, Mackinlay and Zhang (2002), we document that the time-to-completion is longer for less aggressively priced orders, for larger orders and during active market conditions. Importantly, after controlling for other order attributes, the choice to expose more of an order is associated with shorter time-to-completion, indicating that order exposure is effective in decreasing investors' execution price risk. To our knowledge, this comprises the first documentation of a tangible benefit to traders of exposing order size in markets that provide the option to hide size.

Next, we investigate whether execution costs are affected by the trader's decision to hide or display orders. To measure execution costs, we rely on the implementation shortfall approach proposed by Perold (1988), which incorporates not only the *price impact* on the portion of order that is filled but also imputes a penalty, or *opportunity cost*, for any portion of the order that goes unfilled. We find that hidden orders are associated with smaller opportunity costs and lower implementation shortfall costs. Finding lower opportunity costs for hidden orders despite a decreased likelihood of full execution is consistent with the reasoning that hidden orders tend to be used by traders who do not possess information regarding future changes in security price. Thus, traders select the optimal exposure strategies on the basis of both their private trading motives and the tradeoffs involved in selecting more aggressive prices and exposing their orders. Explicitly incorporating the trader's motive for order submission in the econometric analysis is beyond the scope of this paper due to lack of empirical proxies but presents an important avenue for future research.

The extensive use of hidden orders on Euronext suggests that the option to hide order size is valuable to traders' submitting limit orders. However, impatient traders who rely on marketable orders and competing limit order traders both have an interest in detecting the existence and quantity of hidden size in the limit order book. We assess the extent to which the presence of undisclosed order size can be inferred on the basis of observable variables, including stock characteristics, market conditions, and observable order attributes. In addition to detecting hidden size, observable attributes of the order – price aggressiveness and displayed order size – may be useful to market participants in imperfectly assessing trader's private motives for order submission. We use a logistical model that conditions on observable information, and document that it is possible to infer the presence of hidden order size to a statistically significant extent. Of course, if market participants could *perfectly* assess the existence and magnitude of hidden size, the option to hide size would be useless., To gauge whether hidden orders allow traders to partially conceal their trading intentions, we also examine a logistical model that conditions on total size rather than displayed size. Superior performance of the latter model would indicate that unobservable size remains an important state variable.

We find that observable order attributes and prevailing market conditions help detect hidden orders. Specifically, the likelihood of an order with hidden size is high when order arrival rates are low, when the order book on opposite side is deep, and before the final trading hour of the day, consistent with those reported by DeWinne and D'Hondt (2007). While the former study finds that order aggressiveness has a positive effect on the likelihood that the order contains hidden size, we find that price aggressiveness affects the exposure decision only when the order is placed between the quotes. For less aggressive orders (i.e., sell orders above ask and buy orders below bid), price aggressiveness is not informative in revealing hidden size. This is consistent with the reasoning that traders posting limit orders between the quotes may be particularly concerned about front running costs and the implicit option value provided by their limit order to other traders (see Harris (1996)). We also document that orders containing hidden size are more likely when spreads are wide, suggesting that traders may hide order size during periods when information asymmetry is high. Hidden orders are also more likely when recent transactions are large and when recent executions reveal hidden liquidity on either side of the book, implying a degree of momentum in the order exposure decision. Finally, we find that, cross-sectionally, orders are less likely to be hidden for liquid stocks, less volatility stocks and for stocks with a larger relative tick size, consistent with predictions in Harris (1996).

Two results are worth emphasizing. First, an order is less likely to contain hidden size when there are standing limit orders at the same price in the book, reflecting that exposed orders gain time priority versus hidden orders at the same price. Second, while we find that, consistent with prior work, total order size is positively related to the presence of hidden size, the displayed order size has the opposite effect. That is, all else equal, an order with large displayed size is *less* likely to contain a hidden component. The different impact of total order size and displayed order size is quite striking and indicates that large traders tend to conceal their intentions by hiding orders size, consistent with theory regarding strategic order submission strategies (see Geottler, Parlour and Rajan (2005)). Further, as market participants observe only the revealed size, empirical results based on total size (as reported by De Winne and D'Hondt (2007), for example) are likely to be misleading.

We use the results of the logistical model that assesses the presence of hidden order size to create a variable that we term the "H-Score" (for Hidden Score). This closely follows Dechow, Ge, Larson and Sloan (2007), who implement a logistical model detecting accounting manipulation by firms. The H-Score is measured for each order as the predicted probability from the model divided by the unconditional sample probability that an order contains hidden size. An H-score of 1.00 indicates that the order has the same probability of containing hidden size as the overall sample. We calculate the H-score for each order and rank all orders by H-Score. More than 28% of orders containing hidden size are represented among the highest quintile of all H-Scores. In addition, we find that over 40% of all hidden orders have an H-score greater than 1.00.

The logistical model better "predicts" the existence of hidden size when displayed size is replaced by total order size. For example, over 42% of orders with hidden size are then represented among the highest quintile of all H-Scores and over 57% of the hidden orders then have an H-score greater than 1.00. However, total size is not observable to traders; the inferior results when relying on displayed size as compared to total size indicates that, although market participants can detect the presence of hidden size to a statistically significant degree, they cannot perfectly detect hidden size.

We present a simple application on how the H-Score can inform market participants in their order submission decisions. We report the frequency of *Type I (*the model predicts that the order has hidden size when it does not) and *Type II* (the model fails to detect hidden size when it exists). The probability of each error depends on the minimum magnitude of H-Score that is deemed to provide a positive forecast of hidden size, which we refer to as the "H-score cutoff". Individual traders can choose H-Score cutoffs based on their own assessment of the relative costs of Type I versus Type II errors.

Our findings have important implications for stock exchanges, market regulators and institutional trading desks. The portfolio of order types that traders can submit represents an important dimension of trading system design. That a substantial volume of the incoming order flow in Euronext includes a hidden size indicates that hidden orders are an important tool for market participants to control order exposure risk. In the absence of such tools, market participants may choose alternative means to complete their transactions e.g. relying on informal upstairs markets to selectively expose orders, thereby lowering market quality and price efficiency in the electronic exchange. Our findings may also prove useful for institutional trading desks responsible for executing block orders received from portfolio managers. By modeling the hidden dimension of liquidity for firms with varying liquidity characteristics and by relating order exposure to market conditions, we provide insights on the circumstances when liquidity is likely to be hidden and when the search for hidden liquidity is likely to be more important.

## 2. Literature Review

### 2.1 The Literature on Price Aggressiveness

Prior literature on order submission strategies have mainly focused on the determinants of limit order price aggressiveness. Using data on order flow on the Paris Bourse (one of the three markets that subsequently merged to form Euronext), Biais, Hillion and Spatt (1995) report that traders monitor the evolution of the book and submit limit orders rather quickly when the bid-ask spread widens or depth declines, which they attribute to motivational effect of time priority rules. They also find that a large fraction of the limit orders submitted are at prices at or within the quotes, which they attribute to price competition stemming from price priority rules. Nevertheless, they find that the bulk of the unexecuted orders in the limit order book tend to be at prices away from the quotes, reflecting that less competitive orders take longer to execute.

Griffiths, Smith, Turnbull and White (2000) and Ranaldo (2006) find that limit order trades are more aggressive when there is more depth on the opposite side (at the bid price for sales and at the ask price for purchases), resulting in improved execution probabilities in these more competitive market states, which is consistent with the "crowding out" hypothesis formally developed by Parlour (1998). Ranaldo (2006) finds that increased recent volatility is associated with more aggressive orders. In contrast, Handa and Schwartz (1996) and Ahn, Bae and Chan (2002) find that increased recent volatility induces more liquidity provision, which is consistent with the theoretical prediction in Foucault (1999).[4]

## 2.2 The Literature on Hidden Orders

The existing work on hidden orders is primarily descriptive. However, Harris (1996 and 1997) has articulated some important economic reasoning relevant to understanding hidden order usage. He observes that some traders follow a passive strategy, where they wait for other traders to indicate their interest in trading on favorable terms. The presence of passive or "reactive" traders increases the attractiveness of publicly displaying one's own interest in trading, in order to draw out the passive traders. Other traders, in contrast, follow what Harris terms "defensive" and "parasitic" strategies. If a display of trading interest, e.g. the posting of a large buy limit order, conveys that the limit order trader may possess positive private information regarding security values, *defensive* traders may react by ceasing to submit market sell orders and/or canceling existing limit sell orders.[5] Building on this reasoning, Moinas (2006) presents a theoretical model which predicts that displaying a large limit order would decrease the execution probability, as defensive liquidity demanders may withdraw their trading interests. *Parasitic* traders may seek to exploit the existence of the large buy order by "front running" the order, or by using "order matching" strategies, i.e. by posting a limit order at a price one tick more favorable than the

4 Other studies, such as Harris and Hasbrouck (1995), Chakravarty and Holden (1995), Bae, Jang, and Park (2003), Anand, Chakravarty and Martell (2005), Ellul, Holden, Jain, and Jennings (2007) examine the traders choice of market versus limit orders.

5 Consistent with this reasoning, Biais et al (1995) document that traders in the Paris Bourse cancel sell (buy) limit orders after observing large buyer (seller) initiated transactions.

existing order.[6] Harris (1996) finds that traders on the Paris Bourse are more likely to display their orders when the tick size is larger, which increases the cost of quote matching strategies.

Aitken, Berkman, and Mak (2001) study the Australian Stock Exchange (ASX), where hidden orders need to meet a minimum size threshold and are displayed to the public as having size "U" (for undisplayed). Hence, market participants can identify with certainty all hidden orders on this market. In contrast, orders that include a hidden quantity are not labeled as such on most other markets that allow them. This distinction is important, because it implies that traders on most markets can detect hidden orders with certainty *only* by firmly committing to trade through the use of a marketable order, while ASX traders need not do so. Further, in contrast to most other markets, the hidden portion of an order at the ASX does not lose time priority. Aitken et al. find that price impact of hidden orders does not differ from that of other limit orders, and conclude from this evidence that hidden orders are not primarily used by informed traders.[7] In a cross-sectional analysis that is similar to Harris (1996), Aitken et al report that hidden order usage is negatively related to tick size and positively related to volatility and order size.

Two other published papers provide evidence on hidden orders. Bessembinder and Venkataraman (2004) show that hidden orders were commonly used on the Paris Bourse during their 1997-98 sample. In particular, they find that the implied transaction costs for block-sized marketable orders walking up the limit order book were on average only half as large when hidden orders were considered as compared to costs that would have been incurred had the limit order book contained only the displayed liquidity. Anand and Weaver (2004) examine the abolition in 1996 and reintroduction in 2002 of hidden orders on the Toronto Stock Exchange. They find that the size of the publicly displayed orders at the inside quote did not change after either event, implying that total order size decreased when orders could not be hidden.

[6] The quote matching strategy relies on the fact that if the buy limit order is executed the quote matcher will capture any upward movement in prices, while if prices fall she can sell to the party that posted the original buy limit order and lose only one tick.
[7] However, this evidence may not be conclusive. Price impact is measured as the signed difference between the execution price and a benchmark price at order submission. Conditional on execution, price impact so measured is determined only by the aggressiveness of the limit price.

Hasbrouck and Saar (2002) study the Island ECN during the fourth quarter of 1999. They document the extensive use of fleeting orders, which are limit orders that are cancelled within a few seconds of order submission. These fleeting orders are likely used by aggressive traders searching for hidden orders, which on Island may not be displayed at all. Tuttle (2006) notes that Nasdaq market markers may hide a portion of their quotation size on Nasdaq's SuperSOES system, and that they make use of hidden quotation size in more risky stocks.

In addition, two recent papers consider aspects of hidden order usage. Pardo and Pascual (2003) examine 79 stocks traded on the Madrid Stock Exchange during the second half of 2000, documenting that spreads do not widen and depth does not shrink after hidden order executions, and that hidden orders can be forecast to a degree based on lagged hidden orders and returns. A limitation of Pardo and Pascual (2003) is the absence of actual data on hidden orders, implying that hidden orders that are never traded against are not included in the study.

De Winne and D'Hondt (2007), like us, study Euronext stocks, relying on data from the fourth quarter of 2002. These authors also report results of a logistic analysis of the decision to hide order size, but their analysis differs from ours in several was. First, they only examine the highly liquid CAC40 stocks, while we consider a broad cross section of stocks, and document that firm characteristics are important to the order exposure decision. Further, they consider only a sample of large (greater than median) hidden limit orders and an equal number of random non-hidden large limit orders. In contrast, we apply the logistic analysis to all orders to obtain insights applicable to smaller orders as well Finally, and most importantly, the most significant variables in their logistical analysis are those derived from total order size. While these results may be useful in understanding the behavior of an trader who has decided to submit a large order (and who knows the total size), they are not applicable to traders who have decided to submit an order of smaller size, or to market participants other than the order submitter who do not know the total order size. In contrast, our pooled logistical analysis applies to orders of all sizes, and is designed to only incorporate information actually available to market participants. The differential insights are non-trivial. For example, while larger total order size is associated with greater use of hidden size, traders who display larger size are *less* likely to have also hidden a portion of their order,.

## 2.3 Our Contributions and Testable Predictions

Our paper is related to the literature on the determinants of order exposure decision. It is distinguished from the existing literature in part because the order exposure decision has been relatively unstudied but also because the focus of our investigation is different. While prior work has examined the impact of detecting hidden depth on price aggressiveness of subsequent orders, we examine whether market participants can detect hidden depth based on observable order attributes, market conditions and firm characteristics. Such an analysis is informative about the extent to which hidden orders allow traders to conceal trading motives. Further, we examine the marginal effects of order exposure on several dimensions of execution quality, including the likelihood of achieving full execution, the expected time-to-completion and implementation shortfall cost.

Limit-order traders are likely to better attract trading interest from passive traders by either posting a more aggressive price or by exposing the size of their order. However, these two methods of attracting passive traders differ in their relative costs and benefits. A more aggressive order gains price priority over orders at inferior prices, while a fully exposed order gains time priority versus hidden orders at the same price. Further, the relative costs and benefits are likely to depend on the limit price selected. The model presented by Easley and O'Hara (1987) implies that, other things equal, informed traders are likely to submit larger and more aggressive orders, because they typically have an interest in assuming large positions before their information becomes public. Large, aggressively priced orders are therefore likely to be perceived as originating from informed traders, which can cause defensive traders to exit the market, or parasitic traders to indulge in front running strategies. The limit order trader may be able to counteract this effect by hiding a portion of their trading interest, suggesting that both larger and more aggressively priced orders are more likely to be hidden.

The discussions in Moinas (2006) suggest that exposing a large limit order would decrease the probability of full execution and increase the time-to-completion, as defensive liquidity demanders may withdraw their trading interests in response to observing a large order. On the other hand, the arguments in Harris (1996) suggest that order exposure would likely attract trading interests from passive trades, thus increasing probability of full execution and decreasing the time-to-completion. The liquidity demanders' response to order exposure is related at least in part to perceptions on whether limit order traders are informed or uninformed. Moinas (2006) presents a theoretical framework where an informed trader with long-lived private information on true value of a security may supply liquidity by submitting limit orders. She argues that informed traders will submit large limit orders with hidden depth in an attempt to mimic the behavior of uninformed liquidity suppliers. In contrast, Harris (1996) argues that uninformed traders can mitigate the option value of standing limit orders by hiding the order's size. Further, since aggressively priced orders provide more valuable options to other trades, such orders are more likely to be hidden. Controlling for price aggressiveness, it may be optimal for traders to hide size when suitable trading opportunities are rare, i.e., when the order is expected to stand in the book for long, such as during slow moving markets or for less actively traded stocks.

As Harris and Hasbrouck (1996) observe, publicly-available databases rarely provide detailed information on traders' identities (e.g., investor types), information sets, motives (e.g., trading horizon), or overall trading programs (e.g., order splitting). Although we separately examine orders that make versus take liquidity, the lack of data on trader identities makes it difficult to compare the advantages of hidden orders over dynamic order submission strategies or to directly observe variations in order exposure for traders' with differing motives. In light of the data limitation, our approach to empirically understand whether traders who hide size are informed or uninformed relies on price patterns observed subsequent to order submission. Specifically, if traders motivated by information submit hidden orders, we expect stock prices to move away (rise for buy orders and fall for sell orders) after order submission.

These discussions support the following testable hypothesis:

*Hypothesis IA: Order exposure will increase execution probability and decrease time-to-completion. (Harris (1996)).*

*Hypothesis IB: Order exposure will decrease execution probability and increase time-to-completion. `(Moinas (2006)).*

*Hypothesis IIA: Hidden orders are used primarily by (uninformed) traders to mitigate the option value of a standing limit order (Harris (1996)).*
*Hypothesis 1IB: Hidden orders are used primarily by (informed) traders to protect themselves against defensive and/or parasitic trading strategies (Moinas (2006)).*

*Hypothesis III: The decision to hide orders depends on the total order size, underlying market conditions and the stock's relative tick size (Harris (1996)).*

## 3. Sample selection and descriptive statistics

### 3.1. Sample selection

Our objective is to obtain a better understanding of the order submission strategies for a broad cross-section of firms. Our initial sample consists of all stocks that are listed on Euronext-Paris (N=1,109) in the Base de Donnees de Marche (BDM) database in April 2003. We retain common stocks that have listed "France" as the home country, as prior research documents that home country stocks exhibit trading patterns than differ significantly from cross-listed stocks. Less-liquid stocks on Euronext trade in a call auction market structure with auctions occurring either once or twice a day. We eliminate stocks that trade in the call auction and focus on stocks traded continuously, so that the analysis can capture the decision to make or take liquidity at the time of order submission.[8] Prior research also suggests that initial public offerings (IPOs) exhibit unusual trading patterns in the initial months after listing, partly reflecting the market making activity of the underwriting syndicate. We therefore eliminate stocks that appear for the first time in the BDM database after December 2002. We also eliminate stocks that switched from continuous trading to call auctions (or vice-versa) or were de-listed from the exchange in 2003. These screens reduce the sample size to 320 firms.

From these, we select a sample of firms with wide variation in market liquidity and adverse selection risk in a point in time prior to the April 2003 sample period. Trade, quote, and order data are obtained from the BDM database. Based on the number of transactions in January 2003, the sample firms are sorted into liquidity quintiles, with quintile 5 being most liquid and quintile 1 being least liquid. The

[8] For the same reason, we only examine orders that arrive during regular trading hours, thereby excluding orders submitted for the opening and closing batch auction. However, note that the limit order book is constructed using all orders submitted for the stock. We also implement a series of error filters.

final sample consists of 20 firms selected randomly from each liquidity quintiles, resulting in a final sample size of 100 firms.

### 3.2 Descriptive statistics

Table 1, Panel A, presents summary statistics for the full sample, and Panel B presents the statistics by liquidity groups. For the full sample, the mean (median) stock price and market capitalization in April 2003 are €54 (€43) and €2,990 million (€386 million), respectively. The mean stock price does not differ markedly across liquidity groups, increasing from €42 for the least liquid to €60 for the most liquid group. However, within groups, the distribution of stock price displays considerable variation. As expected, the average market size increases monotonically across liquidity groups, from €101 million for the least liquid to €12,155 million for the most liquid group.

The market activity in a stock, measured as number of monthly trades, quote updates, incoming orders or cumulative trading volume, exhibit wide variation across sample firms, as evidenced by the significant difference between the mean and median statistic. In April 2003, the average firm in the sample reported 4,920 trades, 6,475 quote updates, 20,840 order submissions, and a cumulative monthly trading volume of 3.5 million shares. However, the average firm in the least liquid quintile reported only 62 trades, 79 quote updates, 296 order submissions, and a cumulative monthly trading volume of 13,563 shares. In sharp contrast, the average firm in the most liquid quintile reported 22,227 trades, 29,180 quote updates, 92,229 order submissions, and a cumulative monthly trading volume of 16.9 million shares. The average trade size and order size increases monotonically from the least liquid to the most liquid group.

## 4. Univariate Analysis of Order Submissions

### 4.1. Institutional features

On Euronext, the order precedence rules are price, exposure, and time. Specifically, an aggressively-priced incoming buy (sell) order will first exhaust the depth on the best offer (bid) and walk up (down) the book. At any price, the hidden portion is filled only after an incoming order has exhausted the displayed portion. When the displayed size of a hidden order is filled, the system immediately replenishes in full the initial disclosed quantity specified during order submission and positions the order behind displayed quantities at the same price. Thus, the cost of hidden order submission is the loss in time priority, as the hidden portion of an order is executed only after exhausting all displayed size at the same price, including orders that have arrived after the hidden order was submitted. While some markets, such as U.S.-based INET, allow limit orders to be fully hidden ('no display' option), Euronext requires that each order must display at least 10 times the minimum trading lot (i.e., display at least 10 shares).[9] Hidden orders on Euronext are therefore what have been described as "iceberg" orders; a portion of the order size is exposed, and a portion unobservable to other traders remains hidden.

### 4.2. Univariate analysis of Firm Liquidity and Exposure Strategies

Table 2, Panel A, presents statistics on the percentage of orders that were submitted with some hidden size. We calculate the relevant statistic for each firm during April 2003 and report the average across sample firms. For the full sample, 18% of the orders include a hidden size. The usage of hidden orders is more prevalent for less liquid firms, increasing from 9% of orders for firms in the most liquid quintile to over 20% of orders for firms in the less liquid quintiles. This pattern in hidden order usage may reflect the longer expected waiting time until execution for limit orders in less liquid firms, due to lower order arrival rate.

Consistent with the notion that hidden orders are particularly useful for large transactions (*Hypothesis II*), there is a positive monotonic relation between hidden order usage and total order size. For the full sample, only 1% of orders with size less than €1,000 have a hidden size. In contrast, over 75% of orders with size greater than €50,000 have a hidden size. Controlling for order size, hidden orders are used more frequently in less liquid firms.

Table 2, Panel B, presents statistics on the percentage of order volume that is hidden. Remarkably, for the full sample, 44% of the incoming order flow in shares is hidden. The percentage of

[9] Until April 23, 2001, brokerage firms on Euronext Paris could observe the identification codes for broker-dealers submitting limit orders. Since then, the limit order book is anonymous. Foucault, Moinas and Theissen (2007) find that concealing liquidity suppliers' identities can help improve market liquidity and price efficiency.

order volume that is hidden increases from 30% for firms in the most liquid group to over 50% for firms in the less liquid groups. Consistent with Panel A, hidden order volume increases with order size and, after controlling for order size, hidden order usage is more prevalent in less liquid firms.

Panel C, Table 2, presents statistics on hidden volume for those orders that include a hidden size. For the full sample, the percentage of order volume that is hidden, conditional on some hidden size, is 75%. Consistent with earlier results, the percentage of hidden volume is higher for larger orders. However, the percentage of hidden order volume, conditional on a hidden size, does not differ significantly across liquidity groups, suggesting that the motivation for hidden order usage might be similar across firms.

### 4.3 Univariate Analysis of Price Aggressiveness and Exposure Strategies

We follow Biais, Hillion and Spatt (1995) in defining categories of price aggressiveness on each side of the market. The first four categories represent orders that demand liquidity from the book and the last three categories represent orders that supply liquidity to the book. The *Most Aggressive* orders (*category 1*) represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book until the order is fully executed. *Category 2* represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book, but the order specifies a limit price such that the order is not expected to execute fully based on displayed book. Such an order may execute fully due to the hidden liquidity but there exists the possibility that the order clears the book until the limit price and converts into a standing limit order. *Category 3* represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order sizes greater than those displayed in the inside ask (bid). Such an order may execute fully due to hidden liquidity in the inside quote but there exists the possibility that it converts into a standing limit order. *Category 4* represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order size less than those displayed in the inside ask (bid). These orders are expected to immediately execute the full size. *Category 5* represents orders with limit prices that lie within the inside bid and ask prices. *Category 6* represents buy (sell) orders with limit price equal to the inside bid (ask).

Finally, *Category 7* represents buy (sell) orders with limit price less (greater) than to the inside bid (ask).[10]

We reconstruct from the BDM data estimates of the limit order book, including liquidity that is publicly displayed and liquidity that is hidden, at the time of each order submission. Our reconstruction of the limit order book (LOB) closely follows the approach described in Appendix B of Bessembinder and Venkataraman (2004).[11] We categorize orders in aggressiveness groups based on the order's limit price and order size relative to reconstructed book's characteristics at the time of order submission.

Table 3, Panel A, presents statistics on the percentage of orders with hidden size, by price aggressiveness groups, for the full sample. Traders who submit orders that are expected to execute fully based on displayed depth, category 1 and 4, are least likely to use hidden orders. Only 1% of the orders in category 4 and 7% of orders in category 1 are submitted with a hidden size. In contrast, traders are more likely to hide orders that would be left standing in the book. Almost 20% of orders that are not expected to execute immediately, categories 5, 6 and 7, have hidden depth. Similarly, orders that are expected to be left standing in the book after partial execution, category 2 and 3, also exhibit a higher proportion of hidden orders.

Table 3, Panel B, presents statistics on the percentage of order volume that is hidden. Consistent with Panel A, hidden order usage is more prevalent for less aggressive orders, where almost 50% of the order volume is not publicly displayed. We observe a similar relation between price aggressiveness and exposure after controlling for order size. Interestingly, for order size greater than €50,000, traders who submit less aggressive orders choose to hide over 75% of the order size. From Panel C, we observe that, conditional on a hidden size, the percentage of order volume that is hidden is higher for orders that are expected to be left standing relative to orders that are expected to execute fully.

[10] Biais, Hillion and Spatt (1995) define six categories of orders, as they combine categories 1 and 2 defined above into a single category. Our definitions are consistent with Biais et al for the other categories.

[11] Changes in the composition of the dataset required some minor modification of the approach. Details are available on request.

## 5. Order Submission Strategies and Execution Time

While exposing an order could cause other traders to withdraw liquidity or employ front-running strategies, exposed orders gain time priority versus hidden orders at the same price, and may be more effective in drawing trading interest from passive traders. This reasoning suggests that exposing an order should increase the likelihood of order execution. Figure 1 displays the empirical probability of complete execution for fully displayed orders and for orders with a hidden size, by price aggressiveness category. Consistent with *hypothesis IA*, the Figure shows that fully displayed orders are more likely to execute completely.

Similarly, *Hypothesis IA* suggest that exposing an order would reduce the elapsed time from order submission to execution, after controlling for the effects of order size and price aggressiveness (Harris (1996)). To test this reasoning we estimate an econometric model of limit order time to execution using survival analysis, following closely the approach described in Lo, MacKinlay and Zhang (2002). Briefly, survival analysis allows estimation of the conditional distribution of limit order execution times as a function of order characteristics and market conditions, while explicitly accounting for limit orders that expire or are cancelled before they are executed. Following Lo et al (2002), we estimate the survival function assuming that the distribution of failure times follows a generalized gamma distribution, which nests a number of other distributions as special cases. Explanatory variables are incorporated using the accelerated failure time approach, as detailed by Lo et al (2002).

We construct a set of explanatory variables measured at the time of order submission similar to those used by Lo et al (2002), and supplement these variables with an indicator for the presence of hidden size. The variables include the proportional distance of the order's limit price from quote mid-point as a measure of price aggressiveness; a buy indicator variable that equals one if the prior trade is buyer-initiated and equals zero otherwise; same side depth is the displayed depth at the best bid (ask) for a buy (sell) order (normalized); the square of the previous measure to account for non-linearity in the relation; opposite side depth is the displayed depth at the best ask (bid) for a buy (sell) order; order size is the total (exposed plus hidden) size of the order; trade frequency is the number of trades in the last hour; relative trade frequency is the number of trades in the last half hour divided by the number of trades in the last hour; and hidden order is an indicator valuable that equals one if the order has hidden size and equals zero otherwise.

Table IV reports the resulting parameters, first estimated for each firm and then aggregated across sample firms based on the Bayesian framework of DuMouchel (1994) (also, see Panayides (2007)). The method assumes that for each estimated firm i coefficient, $\hat{\beta}_i$ :

$$\hat{\beta}_i \mid \beta_i \sim i.i.d.N(\beta_i, s_i^2)$$

$$\beta_i \sim i.i.d.N(\beta, \sigma^2)$$

where *N* is the Gaussian distribution. $\beta$ and $\sigma^2$ are estimated by maximum likelihood. The aggregated $\beta$ estimate is obtained from the N individual firm estimates as:

$$\hat{\beta} = \frac{\sum_{i=1}^{N} \frac{\hat{\beta}_i}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{1}$$

The variance of the aggregate estimate is:

$$Var(\hat{\beta}) = \frac{1}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{2}$$

where $\hat{\sigma}_{m.l.e}^2$ is the maximum likelihood estimator of $\sigma^2$. The aggregate t-statistic is based on the aggregated coefficient estimate relative to the standard error of the aggregate estimate. This method allows for variation across stocks in the true $\beta_i$, and also for cross-sectional difference in the precision with which $\hat{\beta}_i$ is estimated, placing more weight on more precise estimates.[12]

---

[12] Our conclusions are unchanged if we aggregate the regression coefficients following the approach in Dodd and Warner (1983), Warner et al. (1988), Chung et al. (1999), among others, and examine the T-value of the t-statistics, which is the average t-statistic relative to the cross-sectional standard error of the t-statistics. Results are available from the authors on request.

Columns (1) and (2) of Table IV report results of the time-to-completion model for buy and sell limit orders, respectively. The parameter estimates are generally consistent with those reported in Lo et al (2002). Specifically, the positive (negative) sign on *price aggressiveness*, when explaining time to execution for buy (sell) orders, indicates that the time-to-completion is longer for less aggressively priced orders. The positive estimated coefficient on *same side depth*, which captures book depth on the same side that have higher priority for execution, indicates that the time-to-completion for buy orders increases when more shares have priority over the current order. The negative estimated coefficient on *opposite side depth* suggests that the expected time-to-completion is lower when the opposite side is deeper. The positive coefficient on *order size* indicates that the time-to-completion is higher for larger orders, on both buy and sell sides. This result can be contrasted with the puzzling lack of a relation between order size and time to completion that was reported by Lo et al. The negative coefficient on *trade frequency* indicates that both buy and sell orders execute more quickly during active market conditions. The estimated *shape parameters* are statistically significantly different from one, the value consistent with simple distributions, suggesting that the generalized gamma distribution is an appropriate assumption for the survival analysis.

Most importantly, we obtain a significantly positive coefficient estimate for *Hidden Order* in both buy limit order model (t-statistic = 9.8) and sell limit order model (t-statistic = 3.3). These results imply that, after controlling for price aggressiveness, order size, and market conditions, the choice to expose less of an order is associated with a longer time-to-completion and an increase in investors' price risk of a delayed trade. Conversely, exposing size shortens the time-to-completion by providing time priority over hidden orders at the same price and by attracting passive traders (Harris (1996)), thereby lowering the option value of standing orders. To our best knowledge, this comprises the first documentation of a tangible benefit to traders of exposing order size in markets that provide the option to hide size.

## 6. Order Submission Strategies and Execution Costs

The evidence reported in the prior section indicates that order exposure increases the probability of full execution and reduces the anticipated time from order submission to execution. However, almost 18% of the incoming orders include a hidden size, implying that at least some market participants also perceive tangible benefits to limiting order exposure. In this section, we investigate whether execution costs are affected by the trader's decision to hide or display orders.

To measure execution costs, we rely on the implementation shortfall approach proposed by Perold (1988), which incorporates not only the *price impact* on the portion of order that is filled but also imputes a penalty, or *opportunity cost*, for any portion of the order that goes unfilled. Following Harris and Hasbrouck (1996) and Griffiths et al (2000), we calculate the two components of implementation shortfall as follows. The *price impact* is the appropriately signed difference between the fill price and the quote mid-point at the time of order submission. It is expected to be positive for orders that demand liquidity (aggressiveness groups = 1, 2, 3, and 4) and is expected to be negative for orders that post liquidity (aggressiveness groups = 5, 6 and 7). For a passive order that goes unfilled (fill rate = 0%), the price impact is be zero. For orders that are not completely filled due to cancellation or expiration, the *opportunity cost* is the appropriately signed difference between the closing price on the order expiration or cancellation date and the quote mid-point at the time of order submission.[13] If prices move away (rise for buy orders or fall for sell orders) after order submission, the opportunity cost will be positive, reflecting the cost of delayed execution. The opportunity cost for a fully executed order (fill rate = 100%) is zero. The *implementation shortfall cost* for an order is the weighted sum of the *price impact* and the *opportunity cost*, where the weights are the proportion of the order size that is filled and unfilled, respectively.

Table V presents coefficients obtained in regressions of implementation shortfall, price impact, and opportunity costs, respectively, on order characteristics and market conditions. The coefficients are estimated for each firm and aggregated across firms using the Bayesian approach described in Section 5. For the price impact measure, column (2) present coefficients based on all orders and column (3) presents

[13] For NYSE SuperDot orders, Harris and Hasbrouck (1996) assume that an expired buy (sell) order is filled at the closing ask (bid) price on expiration date. Since Euronext implements a closing call auction for our sample stocks, we have assumed that both expired buys and sells are executed at the closing (call auction clearing) price.

coefficients obtained when the sample includes only orders with either partial or full execution (that is, fill rates>0%, price impact≠0). Similarly, for the opportunity cost measure, column (4) present coefficients based on all orders and column (5) presents coefficients estimated for orders with either partial or full non-execution (that is, fill rates<100%, opportunity cost≠0). The interpretation of coefficients differs across specifications. Columns (2) and (4) represent unconditional effects, while columns (3) and (5) represent effects conditional on execution or lack of execution, respectively. Note that measures of price impact conditional on execution are effectively measures of the aggressiveness of the order's limit price.

As might be expected, price impact is larger for more aggressive orders, whether or not conditioned on order execution. Focusing on column (2), price impact is greater for large orders, for buy orders, and for orders submitted when markets are more active. However, each of these results can be attributed to variation in execution rates; coefficient estimates in column (3) indicate that, conditional on execution, order size and order direction do not affect the price impact. Interestingly, price impact increases with recent volatility and declines with market activity, conditional on execution.

Focusing on columns (4) and (5), opportunity costs are higher for more aggressive orders and for buy orders, and are lower for orders submitted when market are more active. To the extent that the information that motivates informed traders becomes public before the close of trading, these results suggest that aggressively priced orders and buy orders tend to be placed by informed traders.

We are most interested in coefficients estimated on the hidden-size indicator. Coefficient estimates in columns (2) and (4) indicate lower price impact and lower opportunity costs for orders containing a hidden component. However, the estimate reported in column (3) indicates that there is no significant effect of hiding size on price impact, conditional on execution. Equivalently, the negative coefficient on the hidden indicator in column (2) simply reflects the lower execution rate for hidden orders (see figure 1), not more favorable execution prices.

In contrast, comparing results across columns (4) and (5) we observe a stronger negative effect of the hidden indicator on opportunity costs when we condition on non-execution of the order. Other things equal, non-execution should imply larger opportunity costs. Finding smaller opportunity costs associated with hidden orders even conditional on non-execution therefore implies less adverse movement in market prices from order submission to the close of trading for those orders with a hidden component. This evidence is consistent with the reasoning that fully exposed orders tend to be used by informed traders and that the information that motivated these orders tends to become public before the close of trading. It could also reflect that exposed orders are subject to increased front-running by other traders. On balance, these findings are consistent with the reasoning that informed traders choose to place aggressive orders that are fully displayed so as to execute quickly, either by taking liquidity from the book or by drawing out passive traders. Further, hidden orders are used primarily by uninformed traders to mitigate the option value of a standing limit order (Harris (1996)), consistent with *Hypothesis IA*.

Finally, column (1) presents coefficients when the implementation shortfall, which is the sum of price impact and opportunity cost, is the dependent variable. As might be expected, the implementation shortfall is smaller when markets are more active. Consistent with prior literature, implementation shortfall costs are higher for aggressively priced orders, for larger order sizes and for buyer initiated orders.[14] Most important for this analysis, implementation shortfall costs are lower for orders that hide a portion of the order size.

These empirical results indicate both cost-benefit tradeoffs and self selection in order exposure decisions. On average, exposing an order increases the likelihood of full execution and lowers the time between order submission and execution. However, despite more rapid executions and higher execution rates, exposed orders have higher opportunity costs and a larger implementation shortfall. These results likely reflect self-selection by which informed traders tend to expose orders. Explicitly incorporating trader self-selection in the econometric analysis is beyond the scope of this paper due to lack of empirical proxies for trader motivation, but presents an important and interesting avenue for future research.

---

[14] We also find that the implementation shortfall cost is lowest for a buy (sell) order submitted at the prevailing bid (ask) (i.e., for price aggressiveness group = 6). These findings are consistent with those documented by Harris and Hasbrouck (1996) and Griffiths et al (2000). Results are not reported in the paper for the sake of brevity but are available from the authors on request.

## 7. The Determinants of Order Exposure

In this section, we examine the order exposure decision, from two perspectives. First, we examine the determinants of order exposure from the perspective of the initiating trader, who chooses the order price and total order size, and decides what portion of the size to expose. Second, we assess the extent to which other market participants have any ability to detect the presence of the hidden size. The choice of the explanatory variables in each analysis is guided by prior theoretical and empirical literature, described in section 2. The explanatory variables include firm characteristics and market conditions at the time of order submission that likely affect the limit order trader's choice of order exposure. The crucial distinction between examining order exposure from the perspective of initiating trader versus market participants lies in the information set – market participants observe only the displayed order size, while the order initiator knows also the total size of the order. We examine the extent to which a logistical model that conditions on the information set of market participants is successful in detecting the presence of hidden orders (model 1), and compare the predictive ability of model 1 with those of a second model (model 2) that conditions on the richer information set of the initiating trader.

The empirical specification includes variables that capture (1) the state of the limit order book, including the bid-ask spread and the displayed depth, cumulative book order imbalance, standing limit orders at the same price as the incoming order, and revelation of hidden orders at the inside quotes by the most recent transaction, (2) trading conditions for the stock, such as recent volatility, the trading frequency and the waiting time between recent order arrivals, (3) the order attributes, such as price aggressiveness and order size,[15] (4) variables to control for recent industry volatility, overall market volatility, and time-of-the-day effects, and (5) characteristics of the stock traded, including market capitalization, overall trading volume, stock-specific return volatility, and relative tick size. Industry and market volatility variables control for any commonality in economic fundamentals on order submission

[15] We recognize that traders may select many order attributes simultaneously, including the limit price, the order size, and the decision to hide a portion of the order size. In this analysis, we treat these endogenously determined order attributes as exogenous variables and model the determinants of order exposure. In an earlier draft of the paper, we model the limit order traders' choice of price aggressiveness, order size and order exposure in a simultaneous equation framework. Results are available from the authors on request.

(see Chordia, Roll and Subrahmanyam (2000)). A detailed description of all variables is provided in the Appendix. To render results more comparable across stocks, we normalize some variables. The depth and spread variables are each normalized by dividing the actual observation by the median for that stock during the month, while order size and trade size are normalized by dividing the actual observations by the stock's average daily trading volume.

### 7.1. Results Regarding the Order Exposure Decision

Table VI reports the estimated regression coefficients from a pooled logistical analysis across sample stocks, along with corresponding t-statistics. The analysis uses data from the first fifteen trading days of the sample, while the remaining five days are reserved for examining out-of-sample predictive ability. The dependent variable equals one for orders that contain hidden size, and zero for orders that do not. We separately examine aggressively priced orders that consume liquidity (marketable orders) and less aggressively priced orders that provide liquidity (non-marketable orders) as the trading motives for the two order types can be different. We observe, from column (1) that the observable order attributes and prevailing market conditions are useful in detecting orders containing hidden size. Specifically, for non-marketable orders, the positive coefficient on waiting time between order arrival and the negative coefficient on trading frequency indicates that likelihood of a hidden order increases when markets are more active. A slower order arrival rate implies a decreased likelihood that a subsequent limit order will arrive at the same price, meaning that the loss of time priority due to hiding a portion of the order is less costly. Also, we find that the likelihood of that an order contains hidden size is lower when same side of the order book is deep, reflecting that the loss in time priority is costly when competition from traders on the same side is high. The finding helps reconcile the puzzling finding in DeWinne and D'Hondt (2007) that larger same side book depth increases the use of hidden orders.

While the former study finds that aggressively priced orders tend to be hidden, we find that price aggressiveness affects exposure *only for orders* placed at prices between the best quotes. For less aggressive orders (i.e., sell orders above ask and buy orders below bid), price aggressiveness is not informative in detecting hidden liquidity. Since aggressively priced orders are likely to be perceived to be information motivated, these findings suggest that aggressive traders may be less inclined to expose order size, as doing so may cause opposite side traders to withdraw liquidity, thus leading to non-execution of an aggressive order. In contrast, for marketable orders, which execute immediately at least in part, (column (3)), the negative coefficient on price aggressiveness indicates that orders that are placed at prices only slightly beyond the opposite quote (e.g. buy orders at prices slightly above ask) tend to contain hidden size more often than more aggressive orders. Since, these less aggressive orders are more likely to remain standing in the book after partial execution, this result suggests that traders hide a portion of the order size to mitigate the option value provided to other traders. Together, these findings indicate that the option to hide order size is used differently by traders who supply versus demand liquidity.

In contrast to findings reported in DeWinne and D'Hondt (2007), we find that traders also choose to hide more of their orders when the bid ask spread is large, suggesting that traders may hide order size during periods when information asymmetry is high. Traders choose to hide more of their orders when the prior trade reveals the presence of hidden orders on either same or opposite side of the book, implying a degree of momentum in the order exposure decision. Also, an order is less likely to be hidden when their exists standing limit orders at the same price in the book, reflecting that exposed orders gain time priority versus hidden orders at the same price. Somewhat surprisingly, greater own firm return volatility is associated with a lower likelihood of hidden order while greater industry volatility and market volatility is associated with a higher likelihood of hidden order. Finally, we find that, cross-sectionally, hidden order usage is higher for less liquid stocks, more volatile stocks, and for stocks with a smaller relative tick size. The last finding provides empirical support for Harris' (1996) prediction that traders will display more size when the relative tick size is larger (*Hypothesis III*).

An important determinant of order exposure identified by prior literature is total order size (see Harris (1996), Aitken et al (2001), DeWinne and D'Hondt (2007)). Consistent with the prior work, we find (column (2) of Table VII) a positive and significant coefficient on total order size, implying that traders who have selected a large order size are more likely to hide a portion of the size. However, other market participants only have information on displayed order size. We therefore examine whether displayed order size is informative in detecting hidden liquidity. The estimated coefficient on displayed order size is significantly *negative*, for both marketable and non-marketable orders, implying that orders with larger displayed sizes are *less* likely contain a hidden component. In light of the findings on opportunity costs described earlier, the collective evidence indicates that large uninformed traders with some urgency to complete transactions tend to use aggressively priced orders with substantial hidden size to mitigate the option value of the limit order. In addition, the McFadden's $R^2$ suggests that the predictive ability of the model based on displayed sizes (columns 1) is not as strong as the one based on total sizes (columns 2) suggesting that hiding size meaningfully reduces the information available to other market participants.

**7.2. Development of Hidden Score (H-Score)**

To evaluate the predictive ability of the logistical model, we sort and rank each order into quintiles based on the predicted probability that the order contains a hidden component. Predicted probabilities are based on estimated model coefficients and the order attributes, market conditions and firm characteristics that correspond to each order. We then calculate a *Hidden-Score (H-Score)* for each order by dividing the predicted probability from model by the unconditional probability of hidden order usage, which is the number of orders in the sample with some hidden size divided by the total number of orders. Our approach follows Dechow et al (2007), who implement a similar design for detecting accounting manipulations by firms. An H-Score of 1.00 indicates that the order has same likelihood of containing hidden size as the overall sample, while H-Scores less (greater) than one indicate lower (higher) probabilities of containing hidden size. For example, an H-Score of 2.00 indicates that the order is twice as likely to contain a hidden component as a random order selected from the full sample.

In Panel B of Table VI, we report the percentage of all sample hidden orders and all sample fully displayed (non-hidden) orders that fall within each H-Score quintile. Results are reported separately for the in-sample period during which the pooled logit model was estimated (the first 15 trading days of April 2003) and during a later out-of-sample period (the remaining 5 trading days of April 2003). If the model has no predictive ability hidden and non-hidden orders will be randomly dispersed across quintiles;

implying that 20 percent of both hidden and non-hidden orders should be allocated to each H-score quintile. In contrast, if the model does a good job of detecting hidden orders, the highest percentage of hidden orders should be concentrated in quintile 5 and the lowest percentage should be found within quintile 1.

Focusing first on Column (1), which pertains to in-sample results for non-marketable orders, we find that 28 percent of hidden orders are in quintile 5, compared to only 12 percent in quintile 1. Further, the hidden order percentages increase monotonically as we move from quintile 1 to quintile 5. Results for marketable orders (Column 5) within sample are even stronger, with 39 percent of orders actually containing hidden size being allocated to the largest H-score quintile, compared to only 12 percent allocated to quintiles 1 and 2. Out of sample, the model assigns 24 percent of non-marketable orders actually containing hidden size to the highest H-score quintile (Column 2), compared to 14 percent allocated to the lowest H-score quintile. Somewhat surprisingly, the model actually performs better out-of-sample than in sample for marketable orders. Thirty nine percent of out-of-sample marketable orders actually containing hidden size (Column 6) are assigned to the largest H-score quintile, compared to only 8 percent assigned to the lowest H-score quintile.

For comparison, Panel B of Table 6 also obtains results obtained when H scores are computed from an information set that includes total rather than exposed order size. Not surprisingly, the "predictive" power of the model is improved. For example, the percentage of out-of-sample non-marketable orders actually containing hidden size that are allocated to the largest H-score quintile is 38 percent when total order size is used as an explanatory variable (Column 4), compared to 24 percent when exposed order size is used as the explanatory variable. For out-of-sample marketable orders the improvement due to using total size instead of exposed size is smaller; corresponding figures are 40 percent when using total size (Column 8) versus 39 percent when using exposed size (Column 6).

However, traders other than the order submitter cannot observe total size. The superior predictive performance obtained when using total order size therefore implies that hiding size meaningfully reduces the information available to other market participants. We conclude from this analysis that market participants can infer to a significant, but imperfect, extent the presence of hidden order size based on observable variables.

In Panel C of Table 6, we report additional statistics on model fit; the percentage of orders that are correctly classified as hidden or non-hidden (correct classification); the percentage of hidden orders that are incorrectly classified by the model as non-hidden (*Type II error*) and conversely, the percentage of non-hidden orders that incorrectly classified by the model as hidden (*Type I error*). Following Dechow et al (2007), we also report a "Sensitivity" statistic, which is one minus the probability of a Type II error, i.e. the percentage of hidden orders that are correctly detected.

Evaluation of these statistics is intrinsically linked to the costs and benefits of correctly and falsely identifying hidden liquidity. Descriptive statistics reported on Table II indicate that 82 percent of sample orders containing no hidden size. Consequently, in this sample a naïve forecasting model predicting that no orders contain hidden liquidity would achieve 82 percent correct classifications, which exceeds the percentage of correct classifications that we report. However, this method would yield a sensitivity statistic of zero, as no hidden orders would be detected. The methods used here achieve higher sensitivity (i.e. they succeed in identifying some hidden orders), but at a cost in terms of the overall success rate.

The relative costs of Type I and Type II errors may well differ across traders depending on their trading motives. For example, a trader interested in splitting a marketable order across fragmented market venues might wish to minimize *Type II* errors (i.e., hidden depth exists on a market, but is not detected) so as to allocate orders to markets with the greatest actual depth. On the other hand, a patient trader executing a non-marketable order may prioritize gaining time priority over standing limit orders. He might prefer to reduce *Type I* errors, since the cost of incorrect identification of a hidden order will not punitive.

Traders can alter the probability of Type I versus Type II errors by selection of a "H-score cutoff", whereby orders with H-scores above the cutoff are forecast to contain hidden order size and orders with H-scores below the cutoff are forecast to not include hidden size. Figure 2 displays rates of Type I and Type II errors for the out-of-sample period, for various possible H-score cutoffs. H-score cutoffs below about 0.8 lead to a very low rate of Type I errors (false identification of hidden size), but a very high rate of Type II errors (failure to detect hidden liquidity). Conversely, H-score cutoffs above about 1.5 lead to very low rates of Type II errors, but frequent Type I errors. H-score cutoffs between these extremes lead to meaningful tradeoffs between Type I errors (false positives) and Sensitivity (ability to detect hidden orders). The optimal H-score can only be assessed in light of information on traders' motives and the relative cost to the individual trader of each type of error.

For illustrative purposes we report on Panel C of Table VI results obtained with an H-Score cutoff of 1.00, so that all orders with conditional probabilities of containing hidden size greater than the unconditional probability are assumed to be hidden. Focusing first on in-sample performance for non-marketable orders (Column 1), the frequency of correct classifications is 66.7% and the sensitivity ratio (percentage of hidden orders detected) is 40.0%. The corresponding out-of-sample performance (column 2) is slightly weaker, as the frequency of correct classifications falls to 63.2% and sensitivity falls to 37.1%. For marketable orders in sample, (Column 5) the in sample success rate is 56.9% and the sensitivity is a remarkable 65.3 percent. Interestingly, performance improves slightly out of sample for marketable orders (Column 6), to a correct classification rate of 57.0 percent and a sensitivity rate of 65.6 percent.

Success rates and sensitivity scores for non-marketable orders are considerably higher when the pooled logit model includes total order size rather than displayed order size. For example, the out-of-sample sensitivity rate when using total order size (Column 4) is 55.7%, compared to 37.1% (Column 2) when relying on displayed order size. However, as previously noted, market participants cannot observe total size, and can not condition their forecasts on total size. That H-scores have non-trivial ability to detect hidden liquidity out-of-sample indicates that hidden liquidity can be forecast to a significant extent based on observable variables. That the ability would hypothetically be improved if total order size were observable indicates that hiding size succeeds in withholding some information from other market participants. That is, market participants have some ability to detect hidden based on observable order attributes and market conditions. However, the findings also indicate that hiding order size allows large traders to partially conceal their trading intentions and lower the option value of the limit order. These findings provide direct empirical support for the important debate on whether hidden orders are an important tool for market participants in controlling the risk of order exposure.

## 8. Conclusions and Extensions

Hidden orders are allowed on most limit order based markets to enable liquidity providers control their order exposure risk. Traders considering whether to expose the size of their orders face both costs and benefits of doing so. Exposing an order increases the chance that it will attract counterparties. On the other hand, exposing an order could cause other traders to withdraw liquidity, or employ front-running strategies. We study 100 stocks traded on Euronext-Paris during the month of April 2003. We find that hidden orders are used extensively on Euronext, and more so for larger orders and for less actively traded stocks.

We assess the relative costs and benefits of hiding order size by examining the impact of order exposure on several dimensions of execution quality, namely the likelihood of full execution, the time-to-completion and implementation shortfall costs. Hidden orders are associated with smaller opportunity costs and lower implementation shortfall costs. On the downside, even after controlling for price aggressiveness, order size, and market conditions, hidden orders take longer to execute and have larger non-execution rates. Thus, traders select the optimal exposure strategies on the basis of both their private trading motives and the tradeoffs involved in selecting more aggressive prices and exposing their orders. Collectively, the finding that hidden orders have smaller opportunity costs; i.e., smaller price drifts subsequent to order submission time, suggests that hidden orders are used by uninformed traders to mitigate the option value of standing orders to other traders.

We examine whether a logistical model that conditions on the information set of market participants is useful in detecting hidden orders. We find that prevailing market conditions, such as order arrival rates; bid-ask spread; the displayed depth on the same and opposite side of the limit order book;

book imbalance; recent transaction size; and the time of the day, help detect the presence of hidden orders. Interestingly, hidden order usage is related to the revelation of hidden liquidity on either side of the book by a recent transaction, implying a degree of momentum in order exposure, and to the existence of standing limit orders at the same price in the book, reflecting the effect of the competition for liquidity provision. While we find that, consistent with prior work, the total order size is positively related to the likelihood of detecting hidden liquidity, the displayed order size has the opposite effect. Further, displayed order size is less informative in detecting hidden liquidity than the total order size, suggesting that the option to hide order size helps large traders in concealing their trading motives

These findings have important implications for market centers that are moving toward implementing fully automated trading systems, such as the New York Stock Exchange, and for market centers that currently operate automated trading systems but require traders to fully display orders, such as the Hong Kong Stock Exchange. The set of order types that traders can submit represents an important dimension of trading system design. Our findings suggest that hidden orders represent an important risk control tool for traders submitting larger orders. Thus, market centers may be more successful in attracting large orders if they allow traders to hide order size.

Our findings may also be of interest to market regulators, academics and institutional trading desks. A better understanding of trader behavior in electronic limit order markets would enable regulators to more accurately assess the impact of new regulation on market liquidity. The empirical evidence on order submission strategies, and in particular, order exposure, may help theorists in developing more comprehensive models on trader behavior. Finally, institutional trading desks, responsible for executing block orders received from portfolio managers, are facing new challenges in the search for liquidity pools in an increasingly fragmented and automated U.S. market place (see, for example, Abrokwah and Sofianos (2006)). By modeling the hidden dimension of liquidity for firms with differing liquidity characteristics and by relating order exposure to market conditions, we provide insights on the circumstances when the search for hidden liquidity is likely to be most successful.

**Appendix – Variable Definitions**

We model the following set of parsimonious logistic regression models predicting the decision to hide order size:

$$Supply.Id.HiddenOrder_{it} = \alpha_0 + \alpha_{11}PriceAggressive_{it}*D_1 + \alpha_{21}PriceAggressive_{it}*D_2 + \alpha_2 DisplayedOrderSize_{it} + \alpha_3 Spread_{it} + \alpha_4 DepthSame_{it} + \alpha_5 Volatil_{it} + \alpha_6 WaitTime_{it} + \alpha_7 TradesHour_{it} + \alpha_8 HiddenSameSide_{it-1} + \alpha_9 HiddenOppSide_{it-1} + \alpha_{10} SamePriceDisplayedDepth_{it} + \alpha_{11} BookOrderImbalance_{it} + \alpha_{12} PriceAggressive_{it-1} + \alpha_{13} TradesSize_{it-1} + \alpha_{14} MktVolatility_{it-1} + \alpha_{15} Ind.Volatility_{it-1} + \alpha_{16} LastHour_{it} + \alpha_{17} MarketCap_i + \alpha_{18} RelativeTickSize_i + \alpha_{19} Volume_i + \alpha_{20} Volatility_i + \alpha_{21} LiquidityGroup_i \quad (A1)$$

$$Demand.Id.HiddenOrder_{it} = \gamma_0 + \gamma_{11}PriceAggressive_{it}*D_3 + \gamma_2 DisplayedOrderSize_{it} + \gamma_3 Spread_{it} + \gamma_4 DepthSame_{it} + \gamma_5 DepthOpp_{it} + \gamma_6 Volatil_{it} + \gamma_7 TradesHour_{it} + \gamma_8 HiddenOppSide_{it-1} + \gamma_9 Cum.OppositeDisplayedDepth_{it} + \gamma_{10} DisplayedOrderSize_{it-1} + \gamma_{11} TradesSize_{it-1} + \gamma_{12} MktVolatility_{it-1} + \gamma_{13} Ind.Volatility_{it-1} + \gamma_{14} LastHour_{it} + \gamma_{15} MarketCap_i + \gamma_{16} RelativeTickSize_i + \gamma_{17} Volume_i \quad (A2)$$

The subscript "i,t" refers to the time t order in stock i. The two dependent variables are Indicator variables for hidden orders when these orders supply liquidity (standing hidden orders) *Supply.Id.HiddenOrder* and demand liquidity (marketable limit orders) *Demand.Id.HiddenOrder*. The exogenous variables are defined as follows: *PriceAggressive* is defined as the distance of the order's limit price from the opposite quote price, suitably signed (positive aggressiveness indicates the order will execute in whole or part, and thus, is taking liquidity from the book, while negative aggressiveness implies the order will not immediately execute, and thus provides liquidity) divided by the quote midpoint; *DisplayedOrderSize* is exposed size of the order divided by the average daily trading volume; *Spread* is the percentage bid-ask spread; *DepthSame* is the displayed depth at the best bid (ask) for a buy (sell) order divided by the monthly median; *DepthOpp* is the displayed depth at the best ask (bid) for a buy (sell) order divided by the monthly median; *Volatil* is the standard deviation of quote midpoint returns over the preceding hour; *WaitTime* is the average elapsed time between the prior three order arrivals on the same side, refreshing the time clock each day; *TradesHour* is the number of transactions in the last hour; *HiddenSameSide* is the hidden size revealed for orders on the same side by the most recent transaction (i.e., at the bid side for a buy order) divided by the monthly median; *HiddenOppSide* is the hidden size revealed on the opposite side by the most recent transaction (i.e., at the ask size for a buy order) divided by the monthly median; *TradesSize* is the size of the most recent transaction divided by the average daily trading volume; $SamePriceDisplayedDepth_{it}$ is the current depth at the price level of the limit order that is submitted divided by the average daily trading volume; *Cum.OppositeDisplayedDepth* is the cumulative displayed depth of the opposite side of the book divided by the average daily trading volume; *BookOrderImbalance* is the percentage difference between the displayed liquidity in the best five prices on the buy and sell side of the book, suitable signed (i.e., the variable is positive when same size liquidity exceeds opposite side liquidity); *Ind.Volatility* is the return volatility of a portfolio of stocks in the same industry during the prior hour; *Mkt.Volatility* is the return volatility of the CAC40 Index during the prior hour; *Last Hour* is an indicator variable that equals one for orders submitted in the last hour of the trading day and is zero otherwise; *MarketCap* is the stock market capitalization in billion shares; *RelativeTickSize* is the tick size for each stock divided by the average price for that stock; *Volume* is the stock volume in million shares; *Volatility* is the standard deviation of the stock returns for the month under investigation; *LiquidityGroup* denotes the liquidity quintile group for each stock. $D_1$ is an indicator variable that equals one for limit orders priced outside the best same-side quote (less price aggressive orders) and zero otherwise; $D_2$ is an indicator variable that equals one for limit orders priced in the range from best ask to best bid and zero otherwise; $D_3$ is an indicator variable that equals one for limit orders priced beyond the opposite side quote (more price aggressive orders ) and zero otherwise. In the paper we also investigate models replacing *DisplayedOrderSize* with the order's total size divided by the average daily trading volume.

## References


Abrokwah, K., and G. Sofianos, 2006, Accessing displayed and non-displayed liquidity, Journal of Trading, 47-57.

Ahn, H., Bae, K., and K. Chan, 2001, Limit orders, depth, and volatility, *Journal of Finance,* 56, 767-788.

Aitken, M., Berkman, H., and D. Mak, 2001, The use of undisclosed limit orders on the Australian Stock Exchange, *Journal of Banking and Finance*, 25, 1589-1603.

Anand, A., S. Chakravarty, and T. Martell, 2005, "Empirical Evidence on the Evolution of Liquidity: Choice of Market versus Limit Orders", *Journal of Financial Markets*, 8, 265-287.

Anand, A., and D.G. Weaver, 2004, Can order exposure be mandated? *Journal of Financial Markets*, forthcoming.

Bae, K., H. Jang, and K. Park, 2003, Traders' choice between limit and market orders: Evidence from NYSE stocks, *Journal of Financial Markets*, 6, 517-538.

Battalio, R., A. Ellul and R. Jennings, 2007, Reputation effects in trading on the New York Stock Exchange, *Journal of Finance*, 62 (3), 1243-1271.

Bessembinder, H., and K. Venkataraman, 2004, Does an Electronic Stock Exchange need an Upstairs Market? *Journal of Financial Economics*, 73, pg. 3-36..

Biais, B., Hillion, P. and C. Spatt, 1995, An empirical analysis of the limit order book and the order flow in the Paris bourse, *Journal of Finance* 50(5), 1655-1689.

Chakravarty, S., and C. Holden, 1995, An integrated model of market and limit orders, *Journal of Finance,* 4, 213-241.

Chordia, T., Roll, R., and A. Subrahmanyam, 2000, Commonality in Liquidity, *Journal of Financial Economics*, 56, 3-28.

Chung, K., L., Van Ness, B., F., and Van Ness, R., A., 1999, Limit Orders and the Bid-Ask Spread, Journal of Financial Economics, 53, 255-287

Dechow, P., W. Ge, C.R. Larson, and R.G. Sloan, 2007, Predicting Material Accounting Manipulations, Working paper – University of California, Berkeley.

D'Hondt, C., and R. De Winne, 2007, Hide-and-Seek in the Market: Placing and Detecting Hidden Orders, *Review of Finance*, 1-30.

Dodd, O., and Warner, J., 1983. On Corporate Governance: A study of Proxy Contests, *Journal of Financial Economics,* 11, 401-438.

DuMouchel, W., 1994, "Hierarchical Bayes Linear Models for Meta-Analysis," National Institute of Statistical Sciences, Technical Report 27.

Easley, D. and M. O'Hara, 1987, "Price, Trade Size and Information in Securities Markets," Journal of Financial Economics, 18, 69-90.

Ellul, A., Holden, C., Jain, P., and R. Jennings, 2007, "Order Dynamics, Recent Evidence from the NYSE", Journal of Empirical Finance, forthcoming.

Foucault, T., S. Moinas, and E. Theissen, 2007, Does anonymity matter in electronic limit order markets? *Review of Financial Studies*, 20(5), 1707-1747.

Foucault, T., 1999, Order flow composition and trading costs in a dynamic limit order market, *Journal of Financial Markets*, 2, 193-226.

Parlour, C., R.L. Goettler and U. Rajan, 2005, Equilibrium in a Dynamic Limit Order Market, *Journal of Finance*, 60 (5), 2149–2192.

Griffiths, M., Smith, B., Turnbull, D. and R. White, 2000, The costs and determinants of order aggressiveness, *Journal of Financial Economics* 56, 65{88}.

Handa, P., and R., Schwartz, 1996, Limit order trading, *Journal of Finance*, 51, 1835-1861.

Harris, L., 1996, Does a minimum price variation encourages order exposure?, *Working Paper*, Marshall School of Business.

Harris, L., 1997, Order Exposure and Parasitic Traders, *Working Paper*, Marshall School of Business.

Harris, L., and J. Hasbrouck, 1996, Market vs. limit orders: the SuperDOT evidence on order submission strategy, *Journal of Financial and Quantitative Analysis* 31, 213-31.

Hasbrouck, J., and G. Sofianos, 1993, The trades of market makers: An analysis of NYSE specialist, *Journal of Finance*, 48, 1565-1594.

Hasbrouck, J., and G. Saar, 2004, Limit Orders and Volatility in a Hybrid Market: The Island ECN, Working Paper, NYU Stern School of Business.

Jain, P., 2005, Financial Market Design and the Equity Premium: Electronic versus Floor Trading, *Journal of Finance,* 60(6), 2955-2985.

Lo, A.W., MacKinlay, C., and J. Zhang, 2002, Econometric models of limit-order executions, *Journal of Financial Economics*, 65, 31-71.

Moinas, S., 2006, Hidden limit orders and liquidity in limit order markets, Working paper – Toulouse Business School.

Pardo, A. & Pascual, R., 2004, On the hidden side of liquidity, Working Paper - University of Valencia.

Ranaldo, A., 2004, Order aggressiveness in limit order book markets, *Journal of Financial Markets* 7, 53-74.

Panayides, M., 2007, Affirmative Obligations and Market Making with Inventory, *Journal of Financial Economics*, forthcoming.

Parlour, C., 1998, "Price dynamics in limit order markets", *Review of Financial Studies*, 11, 789-816.

Perold, A., 1988, The implementation shortfall: Paper versus Reality, *Journal of Portfolio Management*, 14, 4-9.

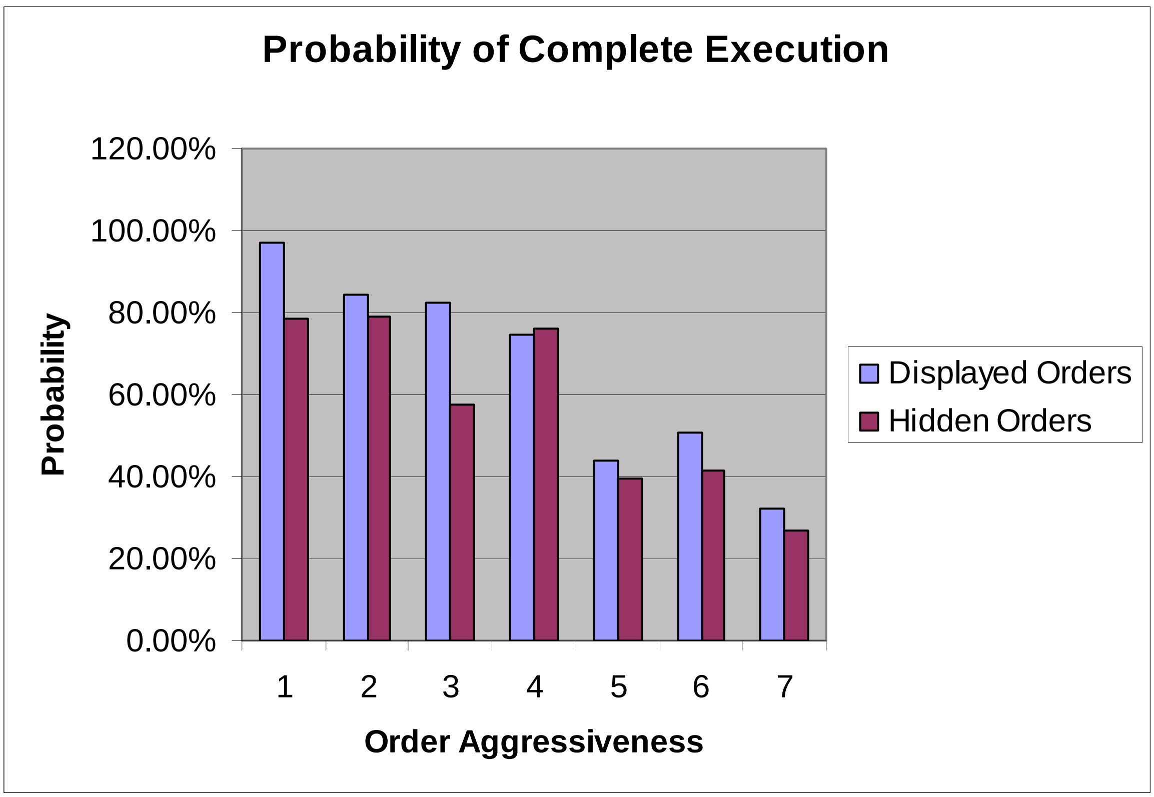
Sofianos, G., and I., Werner, 2003, The trades of NYSE floor brokers, *Journal of Financial Markets*, 139-176.

Tuttle, L. 2006, Hidden orders, trading costs, and information, working paper, University of Kansas.

Venkataraman, K., 2001, Automated versus Floor Trading: An analysis of execution costs on the Paris and New York exchanges, *Journal of Finance*, 56 (4), 1445-1885.

**Figure 1**

Figure 1 shows the empirical probabilities of full execution for orders characterized by whether a portion of the order size is hidden. Orders are further classified by price aggressiveness. For each order, price aggressiveness is defined as a discrete value between 1 and 7 by comparing the order's limit price to the price of the opposite quote at the time of submission, similarly to Biais et al (1995). The first four categories represent orders that demand liquidity (values of 1-4) from the book (values 1 to 4) and the last three categories represent orders that supply liquidity to the book (values 5 to 7). The empirical probabilities of complete execution are defined as the ratio of the number of orders that are completely executed over the total number of orders submitted. The ratio is calculated separately for each type of order (Displayed, Hidden) and each price aggressiveness category (1-7).



## Figure 2

Figure 2 shows the Type I and Type II error rates with respect to different cut-off values of the H-Score, based on the model predicting non-marketable hidden orders from the perspective of market participants. Type I error represent the percentage of non-hidden orders that are misclassified as hidden and Type II error represent the percentage of hidden orders that are misclassified as non-hidden. The H-score for each order is the order's predicted probability of containing hidden size divided by the unconditional probability of hidden order usage in the sample period, i.e., first 15 days of April 2003. The H-score cutoff is the critical H score above which orders are forecast to contain a hidden component. Error rates are calculated for the out-of sample period, i.e., the last 5 days of April 2003.

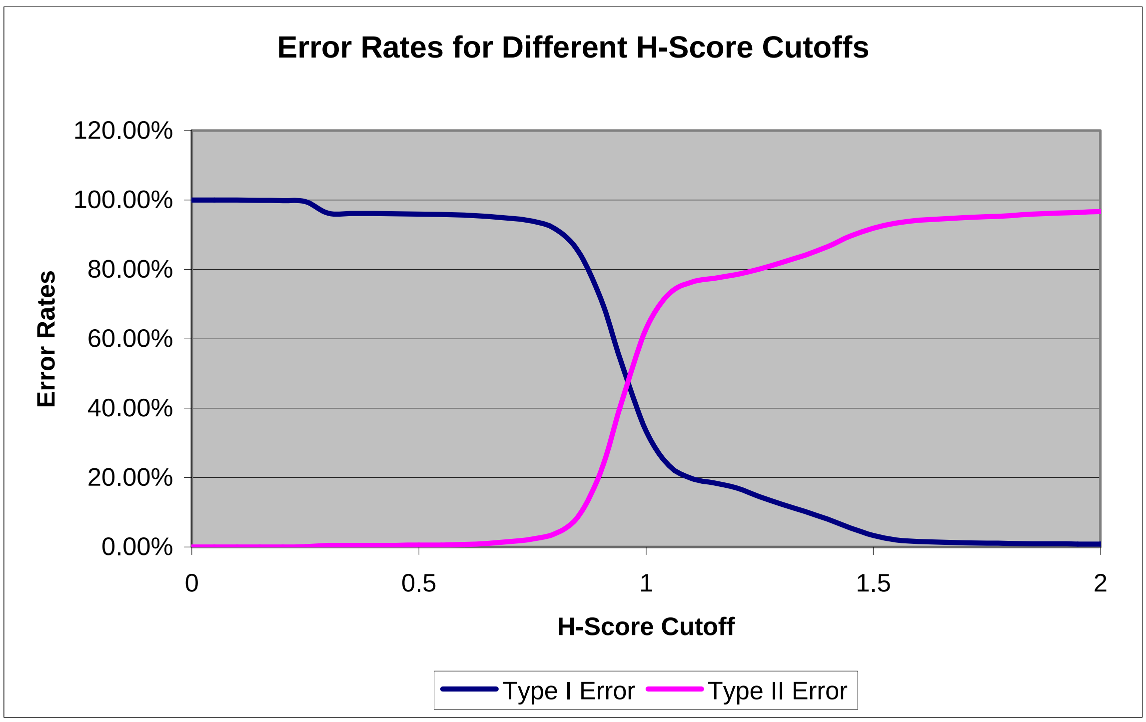


**Table I**
**Descriptive Statistics on Sample**

Reported are the descriptive statistics - market capitalization, stock price, daily return volatility, monthly trading activity, trade size, and order size - in April 2003 for the overall sample (in Panel A) and for each liquidity group (in Panel B). The data are obtained from the Base de Donnees de Marche (BDM) database made available by Euronext-Paris. Stocks listed on Euronext that trade in the continuous market are sorted into liquidity quintiles based on the number of trades in January 2003. We randomly select 20 firms from each liquidity quintile, resulting in the final sample of 100 firms.

| | N | Mean | Median | Std Dev | Maximum | Minimum |
|---|---|---|---|---|---|---|
| **Panel A: Descriptive statistics based on firm averages, full sample** | | | | | | |
| Average Stock Price (in €) | 100 | 54 | 43 | 48 | 235 | 1 |
| Market Capitalization (in € millions) | 100 | 2,990 | 386 | 7,821 | 65,121 | 3 |
| Number of monthly trades | 100 | 4,920 | 325 | 10,137 | 44,267 | 12 |
| Number of monthly quote updates | 100 | 6,475 | 379 | 13,253 | 58,309 | 15 |
| Number of monthly orders | 100 | 20,840 | 1,273 | 42,312 | 210,444 | 28 |
| Cumulative Monthly Trading Volume (in shares) | 100 | 3,512,852 | 54,619 | 11,394,139 | 98,362,569 | 723 |
| Daily Return Volatility (%) | 100 | 3 | 2 | 2 | 21 | 1 |
| Average Trade Size (in shares) | 100 | 397 | 204 | 652 | 4,323 | 20 |
| Average Order Size (in shares) | 100 | 676 | 400 | 883 | 5,821 | 26 |
| **Panel B: Descriptive statistics based on firm averages, by liquidity quintiles** | | | | | | |
| **Least Liquid Quintile** | | | | | | |
| Average Stock Price (in €) | 20 | 42 | 40 | 33 | 124 | 4 |
| Market Capitalization (in € millions) | 20 | 101 | 69 | 89 | 275 | 4 |
| Number of monthly trades | 20 | 62 | 57 | 39 | 145 | 12 |
| Number of monthly quote updates | 20 | 79 | 71 | 48 | 179 | 15 |
| Number of monthly orders | 20 | 296 | 264 | 189 | 680 | 28 |
| Cumulative Monthly Trading Volume (in shares) | 20 | 13,563 | 5,638 | 17,800 | 59,686 | 723 |
| Daily Return Volatility (%) | 20 | 4 | 3 | 4 | 21 | 1 |
| Average Trade Size (in shares) | 20 | 193 | 138 | 184 | 728 | 23 |
| Average Order Size (in shares) | 20 | 404 | 313 | 310 | 1,208 | 50 |
| **Liquidity Quintile 2** | | | | | | |
| Average Stock Price (in €) | 20 | 50 | 47 | 47 | 165 | 1 |
| Market Capitalization (in € millions) | 20 | 591 | 192 | 1,325 | 5,897 | 3 |
| Number of monthly trades | 20 | 132 | 127 | 76 | 301 | 34 |
| Number of monthly quote updates | 20 | 162 | 163 | 89 | 359 | 42 |
| Number of monthly orders | 20 | 611 | 635 | 308 | 1,183 | 171 |
| Cumulative Monthly Trading Volume (in shares) | 20 | 30,575 | 13,986 | 38,944 | 164,989 | 2,553 |
| Daily Return Volatility (%) | 20 | 2 | 2 | 1 | 5 | 1 |
| Average Trade Size (in shares) | 20 | 349 | 133 | 814 | 3,750 | 20 |
| Average Order Size (in shares) | 20 | 589 | 351 | 870 | 3,357 | 26 |

……continued

| | N | Mean | Median | Std Dev | Maximum | Minimum |
|---|---|---|---|---|---|---|
| **Liquidity Quintile 3** | | | | | | |
| Average Stock Price (in €) | 20 | 61 | 47 | 58 | 235 | 1 |
| Market Capitalization (in € millions) | 20 | 634 | 395 | 803 | 3,547 | 7 |
| Number of monthly trades | 20 | 353 | 338 | 222 | 833 | 88 |
| Number of monthly quote updates | 20 | 440 | 407 | 268 | 900 | 114 |
| Number of monthly orders | 20 | 1,835 | 1,468 | 1,621 | 7,543 | 387 |
| Cumulative Monthly Trading Volume (in shares) | 20 | 157,426 | 37,876 | 303,500 | 1,121,519 | 3,870 |
| Daily Return Volatility (%) | 20 | 2 | 2 | 2 | 9 | 1 |
| Average Trade Size (in shares) | 20 | 430 | 134 | 723 | 2,556 | 25 |
| Average Order Size (in shares) | 20 | 766 | 250 | 1,174 | 4,641 | 69 |
| **Liquidity Quintile 4** | | | | | | |
| Average Stock Price (in €) | 20 | 57 | 43 | 50 | 180 | 2 |
| Market Capitalization (in € millions) | 20 | 1,471 | 1,118 | 1,528 | 6,933 | 176 |
| Number of monthly trades | 20 | 1,828 | 1,548 | 1,135 | 4,646 | 331 |
| Number of monthly quote updates | 20 | 2,514 | 1,870 | 1,803 | 6,579 | 387 |
| Number of monthly orders | 20 | 9,230 | 6,134 | 8,206 | 30,052 | 1,003 |
| Cumulative Monthly Trading Volume (in shares) | 20 | 416,949 | 336,412 | 333,731 | 1,382,817 | 44,502 |
| Daily Return Volatility (%) | 20 | 2 | 2 | 1 | 5 | 1 |
| Average Trade Size (in shares) | 20 | 252 | 185 | 194 | 882 | 63 |
| Average Order Size (in shares) | 20 | 441 | 310 | 319 | 1,226 | 172 |
| **Most Liquid Quintile** | | | | | | |
| Average Stock Price (in €) | 20 | 60 | 48 | 52 | 199 | 2 |
| Market Capitalization (in € millions) | 20 | 12,155 | 7,904 | 14,229 | 65,122 | 219 |
| Number of monthly trades | 20 | 22,227 | 22,417 | 11,740 | 44,267 | 2,585 |
| Number of monthly quote updates | 20 | 29,180 | 27,981 | 15,143 | 58,309 | 2,733 |
| Number of monthly orders | 20 | 92,229 | 90,778 | 49,967 | 210,444 | 7,207 |
| Cumulative Monthly Trading Volume (in shares) | 20 | 16,945,746 | 12,186,656 | 20,945,750 | 98,362,569 | 1,370,177 |
| Daily Return Volatility (%) | 20 | 3 | 3 | 1 | 4 | 2 |
| Average Trade Size (in shares) | 20 | 759 | 601 | 867 | 4,323 | 202 |
| Average Order Size (in shares) | 20 | 1,177 | 987 | 1,146 | 5,821 | 352 |

## Table II
## Descriptive Statistics on Hidden Orders, by Firm Liquidity and Order Size

The table presents descriptive statistics on hidden order usage in April 2003 by liquidity quintiles and by order size. The data are obtained from the Base de Donnees de Marche (BDM) database made available by Euronext-Paris. Stocks listed on Euronext that trade in the continuous market are sorted into liquidity quintiles based on the number of trades in January 2003. We randomly select 20 firms from each liquidity quintile, resulting in the final sample of 100 firms. Panel A presents statistics on the percentage of orders that were submitted with a hidden size. Panel B presents statistics on the percentage of order volume that is hidden. Panel C presents statistics on hidden volume for those orders that include a hidden size.

| | | By Order Size (in €) | | | | |
|---|---|---|---|---|---|---|
| | All Orders | Less than 1,000 | 1,000-5,000 | 5,000-50,000 | 50,000-250,000 | Greater than 250,000 |
| **Panel A: Percentage of orders with a hidden size (based on firm average)** | | | | | | |
| Full Sample | 18% | 1% | 5% | 34% | 75% | 76% |
| Least Liquid Quintile | 21% | 1% | 6% | 46% | 87% | 80% |
| Quintile 2 | 23% | 2% | 10% | 44% | 87% | 92% |
| Quintile 3 | 21% | 1% | 6% | 46% | 88% | 75% |
| Quintile 4 | 15% | 0% | 2% | 27% | 81% | 80% |
| Most Liquid Quintile | 9% | 0% | 1% | 7% | 43% | 69% |
| **Panel B: Percentage of order volume that is hidden (based on firm average)** | | | | | | |
| Full Sample | 44% | 1% | 4% | 35% | 69% | 72% |
| Least Liquid Quintile | 45% | 0% | 5% | 48% | 82% | 73% |
| Quintile 2 | 48% | 1% | 7% | 43% | 79% | 90% |
| Quintile 3 | 53% | 1% | 5% | 46% | 80% | 74% |
| Quintile 4 | 43% | 0% | 2% | 29% | 74% | 78% |
| Most Liquid Quintile | 30% | 0% | 0% | 7% | 39% | 62% |
| **Panel C: Conditional on a hidden size, the percentage of order volume that is hidden** | | | | | | |
| Full Sample | 75% | 15% | 46% | 71% | 87% | 90% |
| Least Liquid Quintile | 79% | 9% | 37% | 79% | 92% | 92% |
| Quintile 2 | 74% | 23% | 49% | 70% | 92% | 98% |
| Quintile 3 | 75% | 9% | 49% | 74% | 90% | 88% |
| Quintile 4 | 75% | 15% | 46% | 71% | 88% | 89% |
| Most Liquid Quintile | 72% | 20% | 49% | 62% | 78% | 90% |

## Table III
## Descriptive Statistics on Hidden Orders, by Price Aggressiveness and Order Size

The table presents descriptive statistics on hidden order usage in April 2003 by Price Aggressiveness and Order Size groups. The data are obtained from the Base de Donnees de Marche (BDM) database made available by Euronext-Paris. The relevant statistic is calculated for each firm during April 2003 and the table reports the (cross-sectional) average across sample firms. The *Most Aggressive* category (*category 1*) represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book until the order is fully executed. *Category 2* represents buy (sell) orders with order size greater than those displayed in the inside ask (bid) and with instructions to walk up (down) the book, but the order specifies a limit price such that the order is not expected to execute fully based on displayed book. *Category 3* represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order sizes greater than those displayed in the inside ask (bid). *Category 4* represents buy (sell) orders with the limit price equal to the inside ask (bid) and with order size less than those displayed in the inside ask (bid). *Category 5* represents orders with limit prices that lie within the inside bid and ask prices. *Category 6* represents buy (sell) orders with limit price equal to the inside bid (ask). *Category 7* represents buy (sell) orders with limit price less (greater) than the inside bid (ask).

| | | By Order Size (in €) | | | | |
|---|---|---|---|---|---|---|
| **Variable** | **All Orders** | **Less than 1,000** | **1,000-5,000** | **5,000-50,000** | **50,000-250,000** | **Greater than 250,000** |
| **Panel A: Percentage of orders with a hidden size (based on firm average)** | | | | | | |
| Most Aggressive | 7% | 2% | 2% | 8% | 17% | 43% |
| Category 2 | 18% | 0% | 2% | 15% | 30% | 47% |
| Category 3 | 13% | 1% | 4% | 15% | 37% | 63% |
| Category 4 | 1% | 0% | 1% | 3% | 13% | 10% |
| Category 5 | 19% | 1% | 6% | 41% | 80% | 80% |
| Category 6 | 26% | 0% | 8% | 47% | 83% | 88% |
| Least Aggressive | 21% | 1% | 4% | 35% | 84% | 84% |
| **Panel B: Percentage of order volume that is hidden (based on firm average)** | | | | | | |
| Most Aggressive | 15% | 0% | 1% | 7% | 15% | 41% |
| Category 2 | 25% | 0% | 1% | 14% | 30% | 44% |
| Category 3 | 25% | 0% | 3% | 15% | 35% | 61% |
| Category 4 | 2% | 0% | 1% | 3% | 10% | 11% |
| Category 5 | 48% | 1% | 5% | 41% | 74% | 76% |
| Category 6 | 50% | 0% | 5% | 43% | 74% | 84% |
| Least Aggressive | 45% | 1% | 3% | 35% | 76% | 78% |
| **Panel C: Conditional on a hidden size, the percentage of order volume that is hidden** | | | | | | |
| Most Aggressive | 43% | 0% | 12% | 40% | 58% | 77% |
| Category 2 | 61% | 0% | 3% | 51% | 67% | 73% |
| Category 3 | 67% | 2% | 26% | 60% | 74% | 83% |
| Category 4 | 33% | 6% | 20% | 32% | 54% | 48% |
| Category 5 | 75% | 11% | 48% | 72% | 89% | 91% |
| Category 6 | 68% | 6% | 32% | 67% | 86% | 94% |
| Least Aggressive | 72% | 5% | 34% | 68% | 86% | 90% |

## Table IV
## Order Submission Strategies and Execution Time: Survival Analysis

The table reports parameter estimates of an econometric model of limit order time-to-execution using survival analysis, following closely the approach described in Lo et al (2002). The model describes an accelerated failure time specification of limit-order execution times under the generalized gamma distribution for a sample of 100 Euronext stocks in April 2003. The explanatory variables are: the distance in basis points of the order's limit price from the quote mid point (Limit Price- MidQuote); an indicator variable that equals one if the prior trade is buyer-initiated and equals zero otherwise (Last trade buy indicator); the displayed depth at the best bid (ask) for a buy (sell) order (Same side depth); the square of the previous measure to account for non-linearity (Same side depth squared); the displayed depth at the best ask (bid) for a buy (sell) order (Opposite side depth); the total (exposed plus hidden) size of the order (Order Size); the number of trades in the last half hour divided by the number of trades in the last hour (Rel. Trad frequency); the number of trades in the last hour (Trade frequency); an indicator valuable that equals one if the order has hidden size and equals zero otherwise (Hidden Order). Reported are cross-sectional mean regression coefficients estimated on a firm-by-firm basis and the t-statistics of the mean, using the Bayesian framework of DuMouchel (1994).

| | **Firm-by-Firm Regressions** | | | |
|---|---|---|---|---|
| **Variable** | **Buy limit order model** | | **Sell limit order model** | |
| | **Coefficient (1)** | **tValue** | **Coefficient (2)** | **tValue** |
| **Dependent Variable is Time-to-Completion** | | | | |
| Intercept | 9.9150 | 18.22 | 12.6886 | 18.20 |
| Limit Price - MidQuote | 3.5507 | 5.84 | -0.7210 | -2.49 |
| Last trade buy indicator | 0.0556 | 1.02 | -0.1483 | -2.32 |
| Same side depth (norm) | 0.0739 | 4.48 | 0.0167 | 0.89 |
| Same side depth squared | -0.0349 | -1.27 | 0.0056 | 2.84 |
| Opposite side depth (norm) | -0.2526 | -5.85 | -0.3016 | -7.16 |
| Order Size | 0.1125 | 4.56 | 0.1711 | 4.62 |
| Rel. Trad frequency | 0.0814 | 0.16 | 1.2435 | 1.45 |
| Trade frequency | -0.2935 | -4.99 | -0.2294 | -2.25 |
| Hidden Order Indicator | **1.4177** | **9.76** | **0.7752** | **3.27** |
| SCALE (fitted distribution) | 4.0399 | 11.99 | 1.8268 | 5.65 |
| SHAPE (fitted distribution) | -0.9183 | -2.38 | 3.2231 | 4.94 |

## Table V
## Regressions of Implementation Shortfall, Price Impact, and Opportunity Cost on Order Characteristics and Market Conditions

The table reports on regression coefficients of execution costs on order characteristics and market conditions for a sample of Euronext Paris stocks during April 2003. Execution costs are based on the implementation shortfall approach proposed by Perold (1988), defined as follows. For a buy order, *Price Impact* is defined as the difference between the filled price of each submitted order and the mid-quote price at the time of order submission. *Opportunity cost* is defined as the difference between the closing price on the day of order cancellation or expiration and the quote mid-point at the time of order submission. Each cost is regressed with respect to four variables that represent order attributes, i.e., price aggressiveness, order size, buyer-initiated order indicator, and hidden order indicator, and two variables that represent market conditions during the trading hour prior to order submission, i.e. trading frequency and return volatility. For Price Impact, we report regression results conditional on either partial or full order execution (Price Impact ≠ 0, column 3). For Opportunity Cost, we report regression results conditional on either partial or full non-execution (Opportunity Cost ≠ 0, column 5). The time series coefficients are estimated on a firm by firm basis. We report the average results across firms, including the aggregate mean coefficient and the t-statistics of the mean, using the Bayesian framework of DuMouchel (1994).

| | Aggerate Mean Coefficients, based on Firm-by-firm Regressions | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Implementation Shortfall | | Price Impact | | | | Opportunity Cost | | | |
| | All Orders | | All Orders | | If Fill rate > 0% | | All Orders | | if Fill rate < 100% | |
| | Coefficient (1) | tValue | Coefficient (2) | tValue | Coefficient (3) | tValue | Coefficient (4) | tValue | Coefficient (5) | tValue |
| **Intercept** | -0.0178 | -0.80 | -0.0626 | -8.80 | 0.0986 | 8.22 | 0.0474 | 2.20 | 0.0834 | 2.68 |
| **Price aggressiveness** | 1.2857 | 5.34 | 0.5471 | 5.80 | 29.1128 | 10.01 | 0.6699 | 3.34 | 0.9370 | 4.55 |
| **Order size** | 2.3E-06 | 3.35 | 2.6E-06 | 3.53 | 1.6E-07 | 0.27 | 7.1E-07 | 1.03 | -1.1E-07 | -0.15 |
| **Buyer-initiated order indicator** | 0.1335 | 2.83 | 0.0183 | 3.56 | 0.0006 | 1.47 | 0.1077 | 2.29 | 0.1658 | 2.44 |
| **Hidden order indicator** | -0.0213 | -3.19 | -0.0246 | -5.66 | 0.0012 | 1.64 | -0.0127 | -2.00 | -0.0329 | -2.98 |
| **Trading Frequency** | -0.0133 | -3.11 | 0.0055 | 4.75 | -0.0058 | -4.45 | -0.0199 | -4.53 | -0.0269 | -4.42 |
| **Return volatility** | 0.0115 | 0.81 | -0.0124 | -2.68 | 0.1670 | 7.73 | 0.0202 | 1.52 | 0.0146 | 0.81 |

## Table VI

The table reports logistic regression coefficients (and p-values) of different models predicting hidden orders on order attributes, market conditions and firm characteristics (Panel A), and detections rates of each model (Panels B and C). Detailed definitions of the explanatory variables used in each model in Panel A are provided in the Appendix. We investigate standing orders (supply side of liquidity) and marketable orders (demand side of liquidity) separately. For each type of order we also investigate models from the perspective of market participants (displayed size) and models from the perspective of the market initiator (total size). Detection rates in Panels B and C include in-sample (first 15 days of April 2003) and out-of-sample (last 5 days of April 2003) predictions. Panel B reports quintiles-of-risk statistics by creating ordered quintile groups of H-score and reporting the true number of hidden orders actually in each group. H-score represents the Hidden-score for each order by dividing the predicted probability from the model by the unconditional probability of hidden order usage in the in-sample period. Panel C reports prediction statistics when the H-score cut-off is set to 1. Correct Classification represent the total number of correct predictions of hidden and non-hidden orders over the total number of orders and Sensitivity represents the total number of correct predictions of hidden orders over the total number of hidden orders. Type I error represents the percentage of non-hidden orders that are misclassified as hidden and Type II error represents the percentage of hidden orders that are misclassified as non-hidden.

## Table VI, Panel A

## Logistical Regressions of the decision to hide order size on order attributes, market conditions and firm characteristics.

| 'Panel A: Pooled Logistic Regressions | Supply Side of Liquidity (non-marketable orders) | | | | Demand Side of Liquidity (marketable orders) | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | Estimate (1) | pValue | Estimate (2) | pValue | Estimate (3) | pValue | Estimate (4) | pValue |
| **Dependent Variable is Hidden Indicator (1 for Hidden and 0 for Non-Hidden Orders)** | | | | | | | | |
| **Intercept** | -0.3477 | <.0001 | -2.1429 | <.0001 | -2.4064 | <.0001 | -2.5361 | <.0001 |
| **Order Attributes** | | | | | | | | |
| Price Aggressiveness * D1 | 0.0462 | 0.3655 | 0.0864 | 0.279 | | | | |
| Price Aggressiveness * D2 | 4.53 | <.0001 | 9.0814 | <.0001 | | | | |
| Price Aggressiveness * D3 | | | | | -9.5401 | <.0001 | -9.558 | <.0001 |
| Displayed Order Size (norm) | -1.0465 | <.0001 | | | -8.6001 | <.0001 | | |
| Total Order Size (norm) | | | 10.6821 | <.0001 | | | 2.2376 | <.0001 |
| **Market Conditions** | | | | | | | | |
| Bid-ask spread (norm) | 8.4493 | <.0001 | 15.8162 | <.0001 | -25.8357 | <.0001 | -16.8573 | <.0001 |
| Depth - same side (norm) | -0.017 | <.0001 | -0.0201 | <.0001 | -0.0517 | <.0001 | -0.054 | <.0001 |
| Depth - opposite side (norm) | | | | | 0.0142 | <.0001 | 0.0155 | <.0001 |
| Conditional volatility (previous hour) | -0.102 | <.0001 | -0.7658 | <.0001 | 0.0909 | 0.0013 | 0.0878 | 0.0005 |
| WaitingTime | 0.7128 | <.0001 | 0.1647 | 0.0029 | | | | |
| Trade freq (last hour) | -0.0114 | 0.003 | -0.0229 | <.0001 | -0.0815 | <.0001 | -0.0589 | <.0001 |
| HiddenSameSide (norm) | 2.5155 | <.0001 | 9.9253 | <.0001 | | | | |
| HiddenOppSide (norm) | 1.4385 | <.0001 | 7.4253 | <.0001 | 8.5658 | <.0001 | 1.7171 | 0.0031 |
| Same Price Book Displayed Depth (norm) | -0.5064 | 0.0005 | -5.8092 | <.0001 | | | | |
| Cummulative Opposite Displayed Depth (norm) | | | | | -0.9905 | 0.0022 | -1.2809 | <.0001 |
| Book Order Imbalance (norm) | -0.1041 | <.0001 | -0.0941 | <.0001 | | | | |
| Lag (Price Aggressiveness) | 0.3773 | 0.0016 | 0.7302 | <.0001 | | | | |
| Lag (Displayed Order Size) | | | | | 0.6641 | <.0001 | -1.8485 | <.0001 |
| Last Trade Size (Norm) | 0.1904 | 0.0011 | -6.8607 | <.0001 | 2.0147 | <.0001 | -1.1844 | 0.004 |
| Market Volatility (previous hour) | -0.0116 | <.0001 | -0.012 | <.0001 | -0.00702 | 0.006 | -0.00576 | 0.0158 |
| Industry Volatility (previous hour) | -0.0216 | <.0001 | -0.0189 | <.0001 | -0.0311 | <.0001 | -0.0308 | <.0001 |
| Last Trading Hour Indicator | -0.0281 | 0.0005 | -0.0406 | <.0001 | -0.1485 | <.0001 | -0.1659 | <.0001 |
| **Stock characteristics** | | | | | | | | |
| Market Capitalizations (Billions shares) | 0.0122 | <.0001 | 0.0116 | <.0001 | -0.0119 | <.0001 | -0.0116 | <.0001 |
| Relative Tick Size | -195 | <.0001 | -163.1 | <.0001 | -497.2 | <.0001 | -485.4 | <.0001 |
| Stock Specific Traded Volume (million Shares) | -0.00514 | <.0001 | -0.00731 | <.0001 | 0.0116 | <.0001 | 0.0114 | <.0001 |
| Volatility | 0.1269 | <.0001 | 0.1388 | <.0001 | | | | |
| Liquidity Group | -0.4424 | <.0001 | -0.0573 | <.0001 | | | | |
| **McFadden $R^2$ Coefficient & Likelihood Ratio test pValue** | 0.021 | <.0001 | 0.040 | <.0001 | 0.030 | <.0001 | 0.032 | <.0001 |

## Table VI, Panel B
## Logistical Model Goodness of Fit and Predictive Ability in-sample and out-of-sample

'Panel B: H-Score Quintiles and Goodness of Fit Percentages

| | Supply Side of Liquidity (non-marketable orders) | | | | Demand Side of Liquidity (marketable orders) | | | |
|---|---|---|---|---|---|---|---|---|
| | Displayed Size | | Total Size | | Displayed Size | | Total Size | |
| | In-Sample (1) | Out-of-Sample (2) | In-Sample (3) | Out-of-Sample (4) | In-Sample (5) | Out-of-Sample (6) | In-Sample (7) | Out-of-Sample (8) |
| **H-Score Lowest Quintile** | | | | | | | | |
| Hidden Orders | 12% | 14% | 8% | 9% | 12% | 8% | 9% | 8% |
| Non-Hidden Orders | 21% | 21% | 21% | 21% | 21% | 21% | 20% | 21% |
| **H-Score Quintile 2** | | | | | | | | |
| Hidden Orders | 19% | 20% | 13% | 14% | 12% | 13% | 12% | 12% |
| Non-Hidden Orders | 20% | 20% | 21% | 21% | 20% | 20% | 20% | 20% |
| **H-Score Quintile 3** | | | | | | | | |
| Hidden Orders | 20% | 22% | 16% | 17% | 17% | 18% | 17% | 18% |
| Non-Hidden Orders | 20% | 20% | 20% | 20% | 20% | 20% | 20% | 20% |
| **H-Score Quintile 4** | | | | | | | | |
| Hidden Orders | 20% | 20% | 21% | 22% | 22% | 23% | 21% | 22% |
| Non-Hidden Orders | 20% | 20% | 20% | 20% | 20% | 20% | 20% | 20% |
| **H-Score Highest Quintile** | | | | | | | | |
| Hidden Orders | 28% | 24% | 42% | 38% | 39% | 39% | 40% | 40% |
| Non-Hidden Orders | 19% | 20% | 18% | 18% | 19% | 19% | 19% | 19% |

**Panel C: In-Sample and Out-of Sample Predictions for H-Score cutoff equal 1**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| **Correct Classification** | 66.73% | 63.23% | 67.56% | 64.98% | 56.91% | 56.98% | 57.06% | 57.48% |
| **Sensitivity** | 39.97% | 37.06% | 57.56% | 55.71% | 65.33% | 65.64% | 65.56% | 65.48% |
| **Type I Error** | 30.39% | 33.33% | 31.37% | 33.80% | 43.48% | 43.47% | 43.33% | 42.93% |
| **Type II Error** | 60.03% | 62.94% | 42.44% | 44.29% | 34.67% | 34.36% | 34.44% | 34.52% |