In Search of Liquidity: An Analysis of Order Submission Strategies in Automated Markets*

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Abstract

We study limit order traders' joint decisions regarding order price, order size, and 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 estimate the joint determinants of order price aggressiveness, order exposure, and order size, using a simultaneous equation framework. Traders electing to post less aggressively priced orders tend to hide order size. Further, traders choose to hide a larger portion of their orders when they have also selected larger orders. Overall, the evidence indicates 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 the decision process underlying order submission 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 study the factors that affect limit order traders' selection of order price, order size, and order exposure. While prior studies (reviewed in Section 2) have considered aspects of limit price and order exposure decisions separately, our study is distinguished in part by our modeling of limit price, size, and exposure as simultaneous decisions, which allows assessment of the extent to which traders use these order attributes as complements or substitutes. We also document some of the costs and benefits associated with order decisions by assessing the marginal effects of order exposure, size, and price on expected time to completion for the order and on "implementation shortfall" costs.

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

[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.

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.[3] Marketable orders execute against both the displayed and the undisplayed size of hidden orders. If the marketable order does not fully exhaust the hidden portion of the order, the specified displayed size for the order becomes visible, but any remaining size stays hidden. 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 considerations are likely to be magnified if the order is larger. Hidden orders allow liquidity suppliers to control their risk of order exposure, thus lowering front-running costs and the value of the implicit option provided to other traders by their limit order.[4] 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, we anticipate that the decision to expose order size will depend in part on the limit price selected and in part on order size, so that limit price, order size, and order exposure will optimally be selected simultaneously.

To examine the determinants of order size, aggressiveness, and exposure, we rely on a sample of 100 stocks traded on Euronext-Paris during April 2003. The sample includes a broad

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[2] In addition, 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

[3] In some cases, e.g. on the INET ECN or the Madrid Stock Exchange, hidden orders are not displayed at all.

[4] Many studies that examine the New York Stock Exchange's floor-based market structure 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.)

cross-section of stocks ranging from the most actively traded to illiquid stocks that trade less than once per day on average. We find that hidden orders are used extensively on Euronext. For the full sample, we document that 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. Using the survival analysis approach described in Lo, Mackinlay and Zhang (2002), we document that order exposure increases the likelihood of full execution and lowers the time between order submission and execution. However, hidden orders are also associated with smaller opportunity costs and lower implementation shortfall costs, as defined by Perold (1988). 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 for trader motive, but presents an important and interesting avenue for future research.

We model the simultaneous choice of the limit price, order size, and portion of the order to be displayed in a simultaneous regression framework. Building on prior work, we document that orders are less aggressive when the spread is wide, when recent trading activity is high, and when market conditions are turbulent. We find that the hidden order usage increases when the spread is wide and when the average waiting time between orders, a proxy for market conditions, is high, suggesting that a slower order arrival rate reduces the cost of losing time priority on the hidden portion of the order. We document that traders select larger order sizes when there is greater depth at the quotes (on both the same and opposite side of the book), when more trades have recently executed, when the prior trade execution was large, and during the last hour before the close of trading. Interestingly, traders tend to respond to a trade execution that reveals hidden liquidity on the opposite side by submitting large, aggressively priced orders. This is consistent with the use of 'pinging' strategies to search for hidden liquidity, as also documented on the U.S.-based INET by Hasbrouck and Saar (2004). We also find that, cross-sectionally, orders are less likely to be hidden for stocks with a larger minimum tick size, which is consistent with the predictions of Harris (1996).

With regard to the endogenously determined variables, we document that greater order exposure (a lesser percentage hidden) is accompanied by the use of more aggressive limit prices, suggesting that aggressively priced orders are intended to execute quickly, either by taking liquidity from the book or by drawing out passive traders by exposing size. For orders placed outside the quotes (i.e., sell orders above ask and buy orders below bid), we find that traders tend to expose the least shares for orders that are the least price aggressive. This is consistent with the reasoning that patient (uninformed) traders hide order size when the order is expected to remain on the book longer as they are reluctant to provide free trading options to market participants. In contrast, for aggressively priced orders that are expected to execute immediately at least in part against the book, increased price aggressiveness is associated with an increase in hidden usage, suggesting that aggressive (informed) traders may be concerned about front running strategies that take advantage of the non-executed portion of an aggressive orders. Together, these findings indicate that the option to hide order size is used differently by traders who supply versus demand liquidity. Regarding the role of endogenously selected order size, we find that, consistent with Harris (1996) and Aitkin et al (2001), traders choose to hide a larger portion of their orders when they have also selected larger orders. Thus, the data indicates that order exposure and order size are substitutes on balance. In contrast, we find no relation between endogenously selected order size and order price aggressiveness.

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 more likely to be hidden and when the search for hidden liquidity is likely to be most important.

2. Our Analysis in Relation to the Recent Literature

Our paper is related to both the literature on the determinants of limit order price aggressiveness and to that addressing the decision to use hidden limit orders. It is distinguished from the existing literature in part because the order exposure decision and the order size decision has been relatively unstudied, but also because we explicitly accommodate the fact that order price aggressiveness, order size, and order exposure decisions are made simultaneously, because we relate order submission strategies to market conditions and firm characteristics, and in that we document the effect of hiding orders on expected time-to-execution and implementation-shortfall costs.

2.1 The Literature on Order Submission Strategies.

Biais, Hillion and Spatt, (1995) were among the first to study order submission strategies, using data on order flow on the Paris Bourse (one of the three markets that subsequently merged to form Euronext). They 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) study limit order submissions on the Toronto Stock Exchange during June of 1997, focusing on relations between order price aggressiveness and orders' price impacts (or execution costs), measured as the difference between an order's weighted average execution price and the quote midpoint at order submission time. They report a monotone positive relation between price aggressiveness and price impacts. The authors also report that narrower spreads and more depth on the same side (at the bid price for sales and at the ask price for purchases) lead to more aggressive orders, resulting in improved execution probabilities in these more competitive market states.

Ronaldo (2006) generalizes Griffiths et. al. by also investigating the effect of market volatility on price aggressiveness, and by investigating asymmetries in buy versus sell orders. His study focuses on fifteen Swiss Stock Exchange issues during the months of March and April 1997. Like Griffiths et. al. he finds that limit order traders are more aggressive when the own side of the book is thicker, which he attributes to the "crowding out" hypothesis formally developed by Parlour (1998). He also 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).

Ellul, Holden, Jain, and Jennings (2007) provide a recent analysis of limit orders submissions on the NYSE, focusing in particular on the autocorrelation properties of various order types and interaction between orders that take and those that replenish liquidity. In addition, a number of authors, including Chakravarty and Holden (1995), Anand, Chakravarty and Martell (2005), and Bae, Jang, and Park (2003) have studied traders choice of market versus limit orders. However, in many markets, including Euronext Paris, the distinction between market and limit orders is simply a matter of the degree of price aggressiveness: all orders are limit orders; some are marketable (i.e. prices are aggressive enough that the order can be immediately executed in whole or part against orders already in the book) while orders with less aggressive prices are non-marketable, and enter the book.

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, waiting 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, 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, which decrease the chance that the buy limit order will execute.[5] 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 existing order.[6] This reasoning implies that traders will be more likely to display orders when passive traders are predominant, and will be more likely to hide orders in situations where traders will become defensive or in the presence of parasitic traders. Consistent with this reasoning, 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

[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.
[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.

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. Their key finding is 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.

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 are not 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.[8]

2.3 Our Contributions and Testable Predictions

The studies described in the preceding sections examine order price aggressiveness and order exposure, while effectively treating the two decisions as independent. The order size decision appears to have been little studied. However, it is likely that limit order traders will select the three attributes of their order decision, including order size, order price, and order exposure, *simultaneously* in order to optimize their trading objectives.[9] A formal model of traders' decisions is beyond the scope of this empirical paper. We simply note that the three first-order conditions that would emerge from a formal optimization model would, except under restrictive assumptions, typically include each of the other choice variables. That is, the first order condition for order size would typically also include as arguments price aggressiveness and

[8] In addition, several recent working papers consider aspects of hidden order usage. De Winne and D'Hondt (2005) study 82 blue-chip Euronext stocks during the fourth quarter of 2002, and report that price aggressiveness depends in part on the presence of hidden orders at the best quote, indicating that traders can infer to some extent that hidden orders exist. D'Hondt, De Winne and Francois-Heude (2003) provide descriptive data regarding six Euronext Paris stocks during December 2000, finding that hidden orders are concentrated at the five price increments closest to the best quotes. Pardo and Pascual (2004) 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 (2004) is the absence of actual data on hidden orders, implying that hidden orders that are never traded against are not included in the study.

[9] Indeed, a number of studies, including Lee, Mucklow and Ready (1993), Kavajecz (1999), Ready (1999), and Goldstein and Kavajecz (2004) have documented substitutability between the price and depth dimensions of quoted spreads on the NYSE.

order exposure, etc. If one decision variable, e.g. order size, enters the first order condition of another decision variable, e.g. the percentage of the order exposed, with a positive (negative) coefficient, then order size is a complement (substitute) to order exposure.

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 informed 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. We therefore anticipate that informed traders are likely to view price aggressiveness and order exposure as substitutes, and are also likely to view order size and order exposure as substitutes.

The option value granted to other traders by a limit order depends both on price aggressiveness and on the exposure decision. A trader who primarily wishes to transact quickly will price their limit order aggressively so as to transact against orders in the book and/or attract passive traders. An order that is immediately executed in part (full) provides less valuable (no) options to other traders, implying a reduced benefit to hiding order size. In contrast, a more patient trader can post a less aggressively priced order in hopes that the market price will move towards the limit price. A less aggressive order will likely remain in the book longer, thereby providing a more valuable option to other traders, and more of need to mitigate the option value by hiding the order's size. This line of reasoning suggests that limit order price aggressiveness and limit order exposure may be used by more patient traders as complements, i.e. patient traders who price their orders more aggressively will also choose to expose more of their orders' size, while traders choosing less aggressive prices will more likely choose to hide order size. Further, 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. These considerations are only enhanced for larger orders.

These discussions support the following testable hypothesis:

Hypothesis IA: Hidden orders are used primarily by traders to protect themselves against defensive and/or parasitic trading strategies. Thus, aggressively priced orders will tend to be hidden and less aggressively priced orders will tend to be exposed.

Hypothesis 1B: Hidden orders are used primarily by patient traders whose orders are likely to remain on the books. Thus, aggressively priced orders will tend to be exposed and less aggressively priced orders will tend to be hidden.

Hypothesis II: Traders who submit larger orders will expose less size.

Hypothesis III: Hidden order usage is expected to be smaller for stocks with larger relative tick size (Harris (1996)).

Some limitations of this analysis should be noted. 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 allow for endogeneity in order size and separately examine the relation for orders that make versus take liquidity, we can not control directly for variation in traders' motives for trading. It is possible that the degree to which order size, price aggressiveness, and order exposure are viewed as substitutes or complements vary depending on trader type; e.g., information-motivated and liquidity-motivated traders. Therefore, our empirical results should be interpreted as providing evidence for the body of traders in aggregate, and not necessarily reflecting the objective function of any individual trader.

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.[10] 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.[11] 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.[12] 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.

We select 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 final sample consists of 20 firms that are selected randomly from each of the 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,

[10] See Bacidore and Sofianos (2002) and Eleswarapu and Venkataraman (2006) for recent evidence on trading patterns of U.S. and cross-listed securities (ADR's) on the NYSE.

[11] 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.

[12] See Corwin, Harris and Lipson (2004) for evidence from NYSE and Ellis, Michaely and O'Hara (2002) for evidence from NASDAQ.

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 the Order Submission Strategies

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 refreshes the 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).

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 a 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% for firms in the most liquid quintile to over 20% 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 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 that, 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).[13]

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).[14] 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

[13] 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.
[14] Changes in the composition of the dataset required some minor modification of the approach. Details are available on request.

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.

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 this reasoning, the Figure shows that fully displayed orders are more likely to execute completely.

Similarly, exposing an order might be expected to reduce the elapsed time from order submission to execution, after controlling for the effects of order size and price aggressiveness. 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 from the order's limit price from the 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) (see Panayides (2007) for details). 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. β and σ^2 are estimated by maximum likelihood. The aggregated β estimate is obtained from the N individual firm estimates as:

$$\hat{\beta} = \frac{\sum_{i=1}^{N} \frac{\hat{\beta}_i}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{4}$$

The variance of the aggregate estimate is:

$$Var(\hat{\beta}) = \frac{1}{\sum_{i=1}^{N} \frac{1}{(s_i^2 + \hat{\sigma}_{m.l.e}^2)}} \tag{5}$$

where $\hat{\sigma}_{m.l.e}^2$ is the maximum likelihood estimator of σ^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 β_i, and also for cross-sectional difference in the precision with which $\hat{\beta}_i$ is estimated, placing more weight on more precise estimates.

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, thereby lowering the option value of standing orders on the book. 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 and the quote mid-point at the time of order submission.[15] 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 VII 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 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

[15] 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.

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.

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.[16] 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.

6. The Joint Determinants of Price Aggressiveness, Size, and Exposure

6.1 Simultaneous Equations Model of Order Attributes

In this section, we report the results of multivariate analyses of limit order traders' price aggressiveness, size, and exposure decision. We explicitly allow for traders simultaneous selection of their limit price, the order size, and the portion of their order size that will be hidden by modeling the order attributes as a system of three simultaneous equations. The choice of the exogenous explanatory variables in each equation is guided by prior theoretical and empirical literature, described in section 2, and reflect market conditions at the time of order submission that likely affect the limit order trader's choice of order attributes. The empirical specification includes variables that capture (1) the state of the limit order book, including the bid-ask spread, the displayed depth on inside bid and ask prices, cumulative book order imbalance, and revelation of hidden orders at the inside quotes by the most recent transaction, (2) trading conditions for the stock, such as stock volatility, the trading frequency and the traded share imbalance during the previous hour, and the average waiting time between recent order arrivals, (3) the most recent transaction size and attributes of the most recent order, and (4) variables to control for recent industry and overall market volatility, and time-of-the-day effects. Industry and market volatility variables control for any commonality in economic fundamentals or order

[16] 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.

submission strategies. A detailed description of all variables is provided in Appendix A.

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. We employ the two-stage least squares (2SLS) to estimate the simultaneous equations model. We considered also the use of three-stage least squares (3SLS). However, the Hausman (1978) test rejects 2SLS in favor of 3SLS for only 3 of the 100 sample firms, and for these three firms the estimates based on 2SLS and 3SLS are similar.[17]

The simultaneous equation model is identified by specifying exclusion restrictions, based to the extent possible on economic theory. However, in the absence of fully developed economic models of optimal order submission strategies, we rely in part on economic intuition. In order to convey the extent to which our results are or are not sensitive to choices of econometric specification, we report on Table VI the results of estimating three distinct specifications. Column (1) reports results of OLS estimation. Although OLS estimators are biased in the presence of endogenous dependent variables, they provide a useful point of comparison (see Kennedy (2002)). Column (2) reports results estimated by 2SLS, relying only on the standard assumption that lagged values of endogenous variables can be viewed as exogenous.[18] For results reported in column (3) of Table IV, we exclude one additional variable from each equation. From the order exposure equation, we exclude *HiddenOppSide*, which is an indicator variable that equals one if the prior transaction revealed the presence of hidden depth on the opposite side quote (i.e., the ask quote for a buy order, and vice-versa). The intuition is that *HiddenOppSide* is likely to have a first order effect on price aggressiveness and order size but will be relatively less important for the exposure decision, after accounting for the information contained in other exogenous variables. Based on similar reasoning, we exclude *HiddenSameSide* from the price aggressiveness and size equations.[19] Our discussions focus on column (3) for the sake of brevity, while results in columns (1) and (2) are informative regarding

[17] Further, Kennedy (2002) observed that "Monte Carlo studies have shown that its (2SLS) desirable properties are insensitive to the presence of other estimating problems such as multicollinearity and specification errors." Kavajecz and Odders-White (2001) also discuss advantages of 2SLS over 3SLS.

[18] We do, however, allow for autocorrelation as documented for example by Griffiths et al (2000), by including the lagged value of that equation's dependent variable.

[19] All three regression specifications are tested for over-identification using Basmann's (1960) test. The tests produce an overall rejection rate that suggests that the model is correctly specified and that the instruments are valid.

the sensitivity of findings to specification.

6.1.1 Results Regarding the Choice of Price Aggressiveness

Table VI reports estimated regression coefficients aggregated across sample stocks, using the Bayesian framework described in Section 5, along with corresponding t-statistics. We focus first on results obtained when the dependent variable is a continuous measure of price aggressiveness, defined proportional distance from the order's limit price to the opposite quote price, appropriately signed. The most significant variable in column (3) in Table VI when explaining price aggressiveness is the bid-ask spread. Consistent with the results reported by Griffiths et al (2000), the negative coefficient implies that orders are less aggressive when the spread is wide, as limit order traders prefer to provide liquidity rather than take liquidity from the book. We obtain a positive and significant coefficient on lagged price aggressiveness, which is also consistent with results reported by Griffiths (et al), and implies a degree of momentum in price aggressiveness. We estimate a significant negative coefficient on firm volatility, implying that orders are less aggressive when market conditions are turbulent. This likely reflects limit order traders concerns that their orders may be "picked off" by better-informed traders during times of greater uncertainty. The positive coefficient on relative trading frequency and the negative coefficient on waiting time suggest that orders are more aggressive when recent trading activity has been high. The positive coefficient on the traded share imbalance suggests that buy orders are more aggressive when buying activity exceeds selling activity in the prior hour, and vice-versa. Our results do not support the "crowding out" hypothesis of Parlour (1998), as we do not detect a significant effect on price aggressiveness of depth on either the same or the opposite side. The positive and significant coefficient on HiddenOppSid is consistent with the reasoning that the revelation of hidden depth attracts reactive traders seeking additional hidden size.

Most central to this analysis, we estimate a significant negative coefficient (t-statistic = -2.4) on the proportion of the order that is hidden, after allowing for endogeneity and time series variation in other explanatory variables. This implies that traders who choose to expose more of an order (a lesser proportion hidden) tend to use aggressive limit prices and traders who choose to hide orders tend to submit limit orders that are placed away from the best quotes. This likely reflects that aggressively priced orders are intended to execute quickly, either by taking liquidity from the book or by drawing out passive traders. Exposing these orders helps to attract passive traders, and a quick execution implies that costs associated with defensive traders withdrawing from the market or predatory traders attempting quote matching strategies are mitigated.

The economic magnitude of the estimated relation between price aggressiveness is substantial. The coefficient estimate of -0.003 implies that orders that are (nearly) fully hidden are submitted with a limit price that is 30 basis points less aggressive, on average, as compared to otherwise similar orders that are fully exposed. This differential is substantial as compared, for example, to the median bid-ask spread in the sample, which is 240 basis points.

6.1.2 Results Regarding the Decision to Expose the Order

A significant determinant of the decision to hide orders is the simultaneous selection of order size (t-statistic = 6.5). The positive coefficient implies that traders choose to hide a greater percentage of their orders when they have also elected to use a large order size. The result, consistent with that of Harris (1996) and Aitkin et al (2001) without allowances for simultaneity, likely reflects that large limit order traders seek to mitigate reactions by either defensive or predatory traders that would result from the public exposure of a large order. Traders also choose to hide more of their orders when the bid ask spread is large (t-statistic = 3.3) but hide less of their orders when the displayed depth on the same side is large (t-statistic = -3.1), reflecting the impact of competition from traders on the same side. Further, the percentage of the order that is hidden is positively related (t-statistic = 2.6) to average waiting time between orders. 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. Traders choose to hide more of their orders when the prior order has a hidden component and when the execution of the prior trade reveals the presence of hidden orders on the same (t-statistic = 4.7) side, implying a degree of momentum in the order exposure decision. Somewhat surprisingly, own firm return volatility does not significantly affect the exposure decision. In contrast, greater industry volatility and market volatility is associated with a significant decrease in the percentage of orders that is hidden.

In light of the univariate evidence reported in Table III, we allow for the possibility that the relation between price aggressiveness and order exposure is non-linear. Increasing price aggressiveness beyond the opposite quote (i.e. increasing buy limit prices above the ask quote or decreasing sell limit prices below the bid quote) takes liquidity from the book and the order immediately executes, at least in part. In contrast, increasing price aggressiveness while still outside the quotes (increasing buy limit prices toward the ask, or decreasing sell limit prices toward the bid) makes the orders more attractive to passive traders, but generally still results in the order standing in the book for a period of time. To assess whether the association between trader's aggressiveness and exposure decision depends on the limit price relative to quotes, we estimate separate slope coefficients using three indicators variable. D_1 is an indicator variable that equals one for limit orders priced outside the best same-side quote (aggressiveness categories 6 and 7) 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 (aggressiveness category 5) and zero otherwise, and D_3 is an indicator variable that equals one for limit orders priced beyond the opposite side quote (aggressiveness categories 1 to 4) and zero otherwise.

The results verify that the relation is indeed highly non-linear. For orders placed outside the quotes, the negative coefficient (t-statistic = -2.5) on (*Order Agg * D1*) indicates that traders tend to expose the least shares for orders that are the least price aggressive. This is consistent with the reasoning that patient (uninformed) traders hide order size when the order is expected to remain on the book longer as they are reluctant to provide free trading options to market participants. This economic magnitude of this effect is also substantial. The point estimate of -0.963 implies that a 10% increase in price aggressiveness is associated on average with a 9.6% increase (.1*.963 = .096) in the orders shares that are exposed.

In contrast, for aggressively priced orders that are placed within the quotes or orders that are expected to execute immediately at least in part against the book, the positive coefficient on (*Order Agg*D2*) and (*Order Agg*D3*) indicates that increased price aggressiveness is associated with an increase in the proportion of the order that is hidden. Since aggressively priced orders are more 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 for a portions of an aggressive order. Together, these findings indicate that the option to hide order size is used differently by traders who supply versus demand liquidity.

6.1.3 Results Regarding the Order Size Decision

Table VI also reports results of estimating equation (3) for order size. The results are strongly consistent with the reasoning that traders increase order size when markets are active and can reasonably be expected to absorb more shares. Estimated coefficients on same side quote depth (t-statistic = 2.3), opposite side quote depth (t-statistic = 4.0), and the size of the most recent trade execution (t-statistic = 10.2) are all positive and significant. Interestingly, order size increases (t-statistic = 5.9) if the prior transaction reveals hidden depth on the opposite side, which can likely be attributed to "pinging" strategies by traders to probe for hidden depth, and during the last trading hour of the day (t-statistic = 2.4), which can likely be attributed to the traders desire to complete a trading program by the end of the trading day. [20]

Regarding interactions between the simultaneously selected variables, we document a positive (t-statistic = 3.5) effect of the percentage hidden on order size, indicating that the trader's choice of a larger order size is associated with less order exposure, which is consistent with *hypothesis II*. The estimated coefficient on price aggressiveness does not differ significantly from zero, indicating that price aggressiveness and order size are selected independently.

To summarize, these results indicate that traders do not select order size, order exposure, and price aggressiveness independently. After controlling for market conditions, large orders tend to also contain a hidden component. As orders that are expected to stand on the books become more price aggressive, traders choose to expose less size, while for orders that are expected to execute at least in part traders tend to expose more size as they choose more aggressive prices. Further, traders choose less aggressive prices for their more exposed orders, ceteris paribus.

6.2. Cross-Sectional Analysis of Order Attributes

Data restrictions forced the exclusion of some important variables from the firm-by-firm analysis reported in Table VI. For example, Harris (1996) has argued and presented evidence that the relative tick size affects order exposure decisions. In the present sample, tick size varies across stocks, but for most stocks does not vary through time. Cross-sectional estimation allows us to assess whether average price aggressiveness, the average percentage of orders that are hidden, and average order size are related to the tick size, as well as other attributes that vary across firms, but not through time.[21] In addition to the relative tick size, we include in the cross-sectional regressions the market capitalization and return volatility for the stock during the sample month. Also, to investigate whether order submission strategies depend on the presence of an exchange-designated market maker, we include an indicator variable that equals one for stocks with an assigned market maker, and zero otherwise.[22]

However, simple averages of the dependent variables computed over all observations in the sample month will be affected by outcomes on the various explanatory variables that proxy for market conditions and were included in equations (1) to (3). To assess whether tick size, market capitalization, and return volatility affect average outcomes on the dependent variables after controlling for variation in market conditions, the dependent variable for the cross-sectional regressions is comprised of intercepts obtained when estimating each firm's time series regression on these firm characteristics.[23]

Results are reported in Table VII. In the regression explaining intercepts for percentage hidden (Panel B), we observe a negative and significant coefficient on the relative tick size, which provides empirical support for Harris (1996) prediction that traders will display more size when the relative tick size is larger (*Hypothesis III*). However, market capitalization is not related to the exposure decision, indicating that the positive univariate relation between trading activity and order exposure observed in Table II can be attributed to endogeneity and variation in market conditions. Interestingly, the coefficient on return volatility is insignificant, indicating that average firm volatility has no significant effect on order exposure after controlling for market conditions, including recent volatility.

Panels A and C of Table VII report results obtained when regressing intercepts from price

[21] The relative tick size is the minimum price increment relative to the share price. The explanatory power of the relative tick size could be attributable to variation in the tick size itself, or variation in share prices. However, when we include the absolute tick size and the inverse price as separate variables in the cross-sectional regression we obtained insignificant coefficient estimates on each, indicating insufficient statistical power to distinguish the relative contributions.

[22] See Venkataraman and Waisburd (2006) for a discussion of designated market makers on Euronext Paris. We are grateful to Rick Harris for using data provided to him by Euronext to identify the firms in our sample with an assigned market maker.

[23] Regression intercepts in general measure the mean of the dependent variable, conditional on explanatory variables being set to zero. We seek to evaluate conditional means at a common level of the explanatory variables. However, outcomes of zero on the explanatory variables lie outside the economically relevant range. We therefore normalize every individual explanatory variable on the right side of each equation by deducting the full sample mean of the explanatory variable. Note that only intercepts are affected by the normalization. The new intercepts are interpreted as the conditional mean outcome on the dependent variable, evaluated for each firm at the full-sample average of the explanatory variables.

aggressiveness and order size equations, respectively, on firm characteristics. Orders are on average more aggressive when the relative tick size is smaller, suggesting that increased coarseness of the pricing grid constrains the minimum possible spread to be larger. Order size on average is smaller for more volatile stocks. Consistent with studies of the decimalization of U.S. markets, which reported that order and trade sizes decreased, as did bid-ask spreads, with the reduction in tick to one cent, we document that the coefficient on tick size is positive and highly significant (t-statistic = 2.4) when explaining order size. Finally, while the presence of a designated market maker on the percentage hidden or order size, price aggressiveness increases (t-statistic = 2.0) for stocks with a designated market maker. Overall, these results indicate that a larger tick size encourages the submission of larger orders with higher exposure, but at less aggressive prices.

7. Conclusions and Extensions

Hidden orders are allowed on most limit order based markets to help 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, and find that hidden orders are used extensively on Euronext, and more so for larger orders and for less actively traded stocks. We estimate the simultaneous choice of the limit price, order size, and the portion of the order size to be displayed in a simultaneous regression framework. The results support the notion that traders on balance view order exposure and price aggressiveness as complements, in that more price aggressive orders tend to be exposed and less price aggressive orders are more often hidden. However, the relation between price aggressiveness and order exposure is non-linear, and the most aggressive traders, i.e. those who demand liquidity, also make extensive use of hidden orders. This may reflect that aggressive traders are concerned about front running strategies that take advantage of any non-executed portion of aggressive orders. These findings indicate that the option to hide order size is used differently by traders who supply versus demand liquidity. On balance, these findings indicate that the main advantage of hiding order size is a reduction in the option value provided by orders that do not execute immediately.

We also assess the relative costs and benefits of hiding order size. 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.

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 finding that traders submitting larger orders also elect to hide a larger portion of their orders suggest that hidden orders represent an important risk control tool for large traders. Thus, market centers may be more successful in attracting large orders if they allow for hidden 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 be useful guidance for 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.

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Figure 1

Figure 2 shows the empirical probabilities of full execution for orders characterized by whether a portion of the order size is not fully displayed. 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).

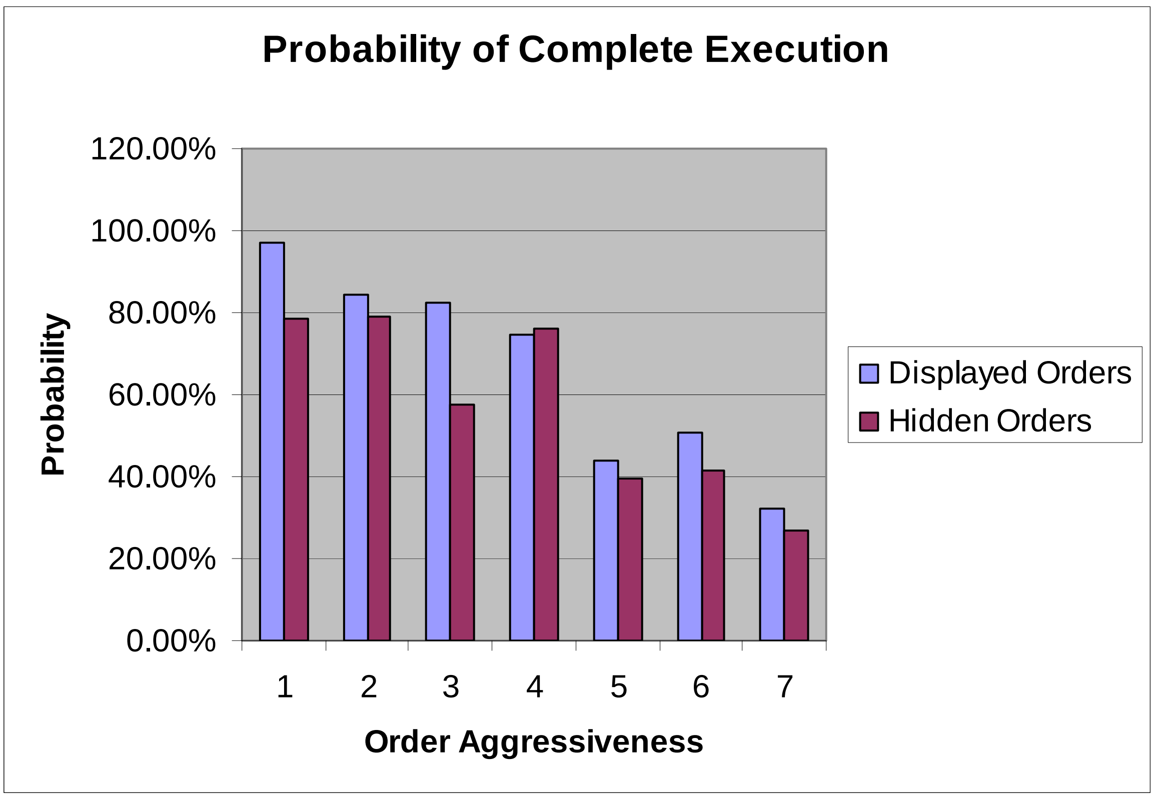

Table I
Descriptive Statistics on Sample

The average market capitalization, stock price, daily return volatility, monthly trading volume, trade and order size, and monthly trading activity in April 2003 are reported for the over all sample (in Panel A) and for each liquidity group (in Panel B). Based on the number of trades in April 2003, the sample firms are sorted into liquidity quintiles. We randomly select 20 firms from each liquidity quintile, resulting in the final sample of 100 firms. The data are obtained from the Base de Donnees de Marche (BDM) database from Euronext-Paris.

	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 relevant statistic is calculated for each firm during April 2003 and the table reports the (cross-sectional) average across sample firms. Based on the number of trades in April 2003, the sample firms are sorted into liquidity quintiles. 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. The data are obtained from the Base de Donnees de Marche (BDM) database from Euronext-Paris.

		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 Categories

The table presents descriptive statistics on hidden order usage in April 2003 by Price Aggressiveness and Order Size groups. 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). The data are obtained from the Base de Donnees de Marche (BDM) database from Euronext-Paris.

		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 (survival analysis model) for a sample of 100 Euronext stocks in April 2003. The explanatory variables describe order characteristics and market conditions and are similar to Lo et al. Specifically, we include the distance in basis points of the order's limit price from the quote mid point as a measure of price aggressiveness (Limit Price- MidQuote); a buy 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, normalized (Same side depth); the square of the previous measure to account for non-linearity in the relation (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); and the number of trades in the last hour (Trade frequency); We also include an indicator valuable that equals one if the order has hidden size and equals zero otherwise (Hidden Order Indicator). We report on average results across firms, including the aggregate mean coefficient 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. To measure execution costs, we rely on the implementation shortfall approach proposed by Perold (1988) and define three measures: Price Impact, Opportunity Cost and Implementation Shortfall as the sum of the two aforementioned costs. 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 costs measure the costs of non-execution and 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 stock characteristics, i.e., price aggressiveness, size, buyer-initiated order indicator and hidden order indicator, and two market condition variables, i.e. trading frequency in the last hour before order submission and return volatility. For Price Impact and Opportunity Costs we also report regression results conditional on either partial or full order execution (Price Impact ≠ 0, column 3), or partial or full non-execution (Opportunity Cost ≠ 0, column 5). We calculate time series coefficient estimates on a firm by firm basis and report on average results across firms, including the aggregate mean coefficient and the t-statistics of the mean, using the Bayesian framework of DuMouchel (1994).

	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
Order 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
Volatility	0.0115	0.81	-0.0124	-2.68	0.1670	7.73	0.0202	1.52	0.0146	0.81

Table VI
Simultaneous Equation Model of Price Aggressiveness, Order Exposure and Order Size

Column (1) reports on the coefficients of a simultaneous equation model of limit order traders' price aggressiveness, order exposure and order size decision, employing two-stage least squares estimation that allows for endogeneity. Specifically, we model the following set of simultaneous equations on a firm by firm basis and report on average results across firms, including the aggregate mean coefficient and the t-statistics of the mean, using the Bayesian framework of DuMouchel (1994).

$$Aggressive_{it} = \alpha_0 + \alpha_1 PctHidden_{it} + \alpha_2 OrderSize_{it} + \alpha_3 Volatil_{it} + \alpha_4 Aggressive_{it-1} + \alpha_5 DepthSame_{it} + \alpha_6 DepthOpp_{it} + \alpha_7 Spread_{it} + \alpha_8 Rel.TradFreq_{it-1} + \alpha_9 HiddenSameSide_{it-1} + \alpha_{10} HiddenOppSide_{it-1} + \alpha_{11} Ind.Volatility_{it-1} + \alpha_{12} MktVolatility_{it-1} + \alpha_{13} LastHour_{it} + \varepsilon_{it} \quad (1)$$

$$PctHidden_{it} = \gamma_0 + \gamma_{1,1} D_1 Aggressive_{it} + \gamma_{1,2} D_2 Aggressive_{it} + \gamma_{1,3} D_3 Aggressive_{it} + \gamma_2 OrderSize_{it} + \gamma_3 Volatil_{it} + \gamma_4 WaitTime_{it} + \gamma_5 Rel.TradFreq_{it-1} + \gamma_6 HiddenSameSide_{it-1} + \gamma_7 HiddenOppSide_{it-1} + \gamma_8 Ind.Volatility_{it-1} + \gamma_9 MktVolatility_{it-1} + \gamma_{10} LastHour_{it} + \eta_{it} \quad (2a)$$

$$OrderSize_{it} = \delta_0 + \delta_1 PctHidden_{it} + \delta_2 Aggressive_{it} + \delta_3 DepthSame_{it} + \delta_4 DepthOpp_{it} + \delta_5 Volatil_{it} + \delta_6 Rel.TradFreq_{it-1} + \delta_7 TradesHour_{it} + \delta_8 TradesSize_{it-1} + \delta_9 HiddenSameSide_{it-1} + \delta_{10} HiddenOppSide_{it-1} + \delta_{11} Ind.Volatility_{it-1} + \delta_{12} MktVolatility_{it-1} + \delta_{13} LastHour_{it} + \nu_{it} \quad (3)$$

where Aggressive is a continuous measure of price aggressiveness, defined as the distance in basis points of the order's limit price from the opposite quote price (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); PctHidden is the percentage of total order size that is hidden; Volatil is the standard deviation of quote midpoint returns over the preceding hour; DepthSame is the displayed depth at the best bid (ask) for a buy (sell) order; DepthOpp is the displayed depth at the best ask (bid) for a buy (sell) order; spread is the percentage bid-ask spread; OrderSize is the total (exposed plus hidden) size of the order; WaitTime is the average elapsed time between the prior three order arrivals on the same side; HiddenSameSide is the size of hidden orders revealed by the last transactions for orders on the same side as the current order; HiddenOppSide is the size of hidden orders revealed in the last transaction for orders in the opposite side of the current order; TradesHour is the number of trades in the last hour; Rel.TradFreq is the number of Trades in the last half hour divided by the number of orders in the last hour; TradesSize is the size of the last trade; Last Hour is an indicator variable that equals one for orders submitted in the last hour of the trading day and is zero otherwise; Ind.Volatility is the volatility of a portfolio of stocks in the same industry during the prior hour; Mkt.Volatility is the volatility of the CAC40 Index during the prior hour; and the subscript "i,t" refers to the time t order in stock i. D_1 is an indicator variable that equals one for limit orders priced outside the best same-side quote (aggressiveness categories 6 and 7) 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, and D_3 is an indicator variable that equals one for limit orders priced beyond the opposite side quote and zero otherwise. Column (2) reports on the coefficient estimates for the new set of simultaneous equations.

Variable	OLS (1)	tValue	2SLS (2)	tValue	2SLS (3)	tValue
	Firm-By-Firm Regressions					
Dependent Variable is Order Aggressiveness						
Intercept	-0.021	-14.67	-0.014	-12.80	-0.017	-13.02
Percentage Hidden (Endo)	-0.001	-0.66	-0.003	-1.71	-0.003	-2.38
Normalized Order Size (Endo)	-0.037	-2.66	0.000	-0.06	0.001	0.35
Volatility	-0.003	-6.19	-0.004	-6.10	-0.003	-6.27
WaitingTime	-0.012	-2.32	-0.013	-2.57	-0.008	-2.57
Last Trade Size (Norm)	-0.001	-0.42	0.000	0.00	-0.002	-1.47
Trade freq (previous hour)	0.002	9.60	0.001	8.35	0.002	8.80
Bid-ask spread (norm)	-0.570	-25.46	-0.585	-21.56	-0.572	-22.62
Same side depth (norm)	0.000	1.74	0.000	1.75	0.000	1.61
Opposite side depth (norm)	0.000	-1.18	0.000	-0.06	0.000	-0.33
HiddenSameSide (norm)	-0.011	-2.74	-0.016	-3.15		
HiddenOppSide (norm)	0.011	3.58	0.009	2.08	0.013	3.61
Book Order Imbalance (norm)	0.000	-0.19	0.000	-1.54	0.000	-1.47
Traded Share Imbalance (previous hour)	0.004	5.34	0.004	4.06	0.004	4.86
Lag (Order Agg)	0.089	7.23	0.080	6.10	0.081	6.48
Lag (Prc Hidden)	0.000	-0.40				
Lag (Order Size)	0.000	1.41				
Market Volatility (previous hour)	0.000	0.34	0.000	-0.65	0.000	-0.53
Industry Volatility (previous hour)	0.000	-1.78	0.000	-1.72	0.000	-1.62
Last Trading Hour Indicator	0.001	3.95	0.000	1.32	0.000	1.73
Dependent Variable is Percentage of Order Hidden						
Intercept	0.049	8.08	0.076	6.89	0.072	7.05
Order Aggressiveness * D1 (Endo)	-0.090	-2.04	-1.015	-2.29	-0.963	-2.54
Order Aggressiveness * D2 (Endo)	-0.801	-3.70	0.739	2.15	0.543	1.95
Order Aggressiveness * D3 (Endo)	-5.312	-5.84	4.667	8.25	4.096	8.29
Normalized Order Size (Endo)	6.032	4.07	0.285	5.44	0.294	6.52
Volatility	-0.002	-0.57	0.007	0.91	0.001	0.34
WaitingTime	0.093	3.57	0.060	2.72	0.043	2.65
Last Trade Size (Norm)	-0.320	-3.18	0.116	2.43	0.008	0.41
Trade freq (last hour)	-0.003	-2.60	-0.002	-0.79	-0.001	-0.74
Bid-ask spread (norm)	0.156	0.84	0.749	3.31	0.616	3.32
Same side depth (norm)	-0.003	-7.98	-0.001	-2.67	-0.001	-3.11
Opposite side depth (norm)	-0.001	-1.47	0.000	-0.59	0.000	-0.38
HiddenSameSide (norm)	1.127	5.33	0.260	2.50	0.243	4.74
HiddenOppSide (norm)	0.057	0.56	-0.032	-0.42		
Book Order Imbalance (norm)	-0.005	-1.62	-0.002	-0.40	-0.004	-0.93
Traded Share Imbalance (previous hour)	-0.010	-1.66	-0.005	-0.52	-0.006	-0.63
Lag (Order Agg)	0.000	0.43				
Lag (Prc Hidden)	0.094	15.19	0.089	12.78	0.090	14.22
Lag (Order Size)	-0.395	-3.82				
Market Volatility (previous hour)	-0.001	-5.17	-0.001	-4.00	-0.001	-3.98
Industry Volatility (previous hour)	-0.001	-4.80	-0.001	-3.81	-0.001	-3.89
Last Trading Hour Indicator	-0.001	-0.77	0.001	0.59	0.003	1.07
Dependent Variable is Order Size						
Intercept	0.007	3.35	0.003	3.68	0.004	4.31
Percentage Hidden (Endo)	0.973	6.63	0.007	1.56	0.078	3.53
Order Aggressiveness (Endo)	-0.008	-2.23	-0.033	-1.58	-0.023	-1.28
Volatility	0.001	5.25	0.001	3.16	0.001	3.80
WaitingTime	0.002	0.95	0.007	3.21	0.009	3.56
Last Trade Size (Norm)	0.192	13.05	0.224	10.95	0.144	10.19
Trade freq (last hour)	0.000	0.38	0.000	1.75	0.000	1.86
Bid-ask spread (norm)	-0.008	-0.60	0.019	0.94	0.033	1.86
Same side depth (norm)	0.000	3.57	0.000	1.64	0.000	2.29
Opposite side depth (norm)	0.000	3.51	0.000	3.57	0.000	3.98
HiddenSameSide (norm)	-0.202	-10.42	-0.186	-6.48		
HiddenOppSide (norm)	0.117	3.01	0.051	2.01	0.169	5.75
Book Order Imbalance (norm)	0.000	3.27	0.000	1.56	0.000	1.24
Traded Share Imbalance (previous hour)	0.001	0.42	-0.001	-0.57	0.000	-0.03
Lag (Order Agg)	0.000	-0.05				
Lag (Prc Hidden)	-0.014	-5.51				
Lag (Order Size)	0.091	11.90	0.097	9.51	0.090	9.94
Market Volatility (previous hour)	0.000	0.92	0.000	-0.86	0.000	-0.37
Industry Volatility (previous hour)	0.000	-1.89	0.000	-1.90	0.000	-1.63
Last Trading Hour Indicator	0.001	2.70	0.001	2.63	0.001	2.72

Table VII
Cross-Sectional Regressions of Price Aggressiveness, Order Size and Order Exposure on Firm Characteristics

The table reports regression coefficients (and t-values) of price aggressiveness (Panel A), percentage hidden (Panel B) and order size (Panel C) respectively on firm characteristics after controlling for time series variation in market conditions. Relative Tick size is the tick size divided by stock price; market capitalization is the market size and volatility is the return volatility during the sample period. Market maker is an indicator variable that equals one if the stock had a designated market maker assigned by the exchange, and zero otherwise. The dependent variables are the intercepts obtained from firm-by-firm simultaneous regressions of price aggressiveness, order exposure and order size on market conditions and order characteristics, after normalizing every individual explanatory variable. Specifically, each variable on the right side of equations (1), (2), and (3) is normalized by deducting the full sample mean of the explanatory variable. Reported are the average results across firms, including the aggregate mean coefficient and the t-statistics of the mean, using the Bayesian framework of DuMouchel (1994).

Variables	Coefficient (1)	tValue	Coefficient (2)	tValue	Coefficient (3)	tValue	Coefficient (4)	tValue	Coefficient (5)	tValue
Panel A: Dependent Variable is the (firm-by-firm) Intercept From OrderAggressiveness Regressions										
Intercept	-0.0046	-0.52	-0.0052	-0.54	0.0247	1.29	-0.0125	-1.14	-0.0162	0.82
Relative Tick Size	-9.6198	-3.36	-9.5809	-3.32	-7.1440	-2.26	-10.1284	-3.53	-7.1631	-2.27
Market Capitalization			0.0002	0.15					0.0006	0.59
Market Maker							0.0273	1.59	0.0351	2.01
Volatility					-0.0131	-1.73			-0.0152	-2.02
R-Square	0.12		0.13		0.16		0.16		0.20	
Panel B: Dependent Variable is the (firm-by-firm) Intercept From Hidden Percentage Regressions										
Intercept	0.0744	3.35	0.0689	2.87	0.0856	1.78	0.0887	3.22	0.0897	1.78
Relative Tick Size	-16.7153	-2.33	-16.3364	-2.31	-15.7722	-2.10	-16.9614	-2.32	-16.0393	-2.10
Market Capitalization			0.0016	0.63					0.0012	0.46
Market Maker							-0.0311	-0.71	-0.0249	-0.18
Volatility					-0.0050	-0.26			-0.0034	-0.18
R-Square	0.07		0.07		0.07		0.07		0.08	
Panel C: Dependent Variable is the (firm-by-firm) Intercept From Order Size Regressions										
Intercept	0.0711	0.86	0.0880	0.99	0.4256	2.45	0.0586	0.57	0.4162	2.27
Relative Tick Size	40.2932	1.53	39.0532	1.47	70.1769	2.44	40.9898	1.53	69.6207	2.37
Market Capitalization			-0.0049	-0.52					-0.0046	-0.49
Market Maker							0.0127	0.08	0.0486	0.30
Volatility					-0.1579	-2.31			-0.1600	-2.30
R-Square	0.03		0.03		0.05		0.03		0.10	