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Hide-and-Seek in the Market: Placing and Detecting Hidden Orders*

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Abstract. This paper investigates why traders hide their orders and how other traders respond to hidden depth. Using a logit model, we provide empirical findings suggesting that traders use hidden orders to manage both exposure risk and picking off risk. Using probit models, we show that hidden depth increases order aggressiveness. Our interpretation of this empirical evidence is threefold. First, hidden depth detection is possible and frequent. Second, when traders detect hidden volume at the best opposite quote, they strategically adjust their order submission to seize the opportunity for depth improvement. Third, traders' response when hidden depth is detected suggests either that they do not associate hidden orders with informed trading or that the risk of trading with an informed trader is widely offset by the opportunity for depth improvement.

JEL Classification: G14, G10

1. Introduction

While most trading systems throughout the world have moved towards greater transparency, the use of hidden quantity is today a widespread practice. Despite few differences from one trading venue to another, market participants can use hidden quantity when trading on Euronext, the Toronto Stock Exchange, the Australian Stock Exchange, the Frankfurt Stock Exchange or Inet. Similarly,

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Nasdaq market makers and NYSE specialists, as well as MTS[1] market makers, have the ability to post additional depth in their quotes that is not visible to the marketplace.

Given the recent upswing in the use of hidden quantity, two relevant questions are why market participants use hidden volume and how the presence of hidden quantity affects traders' behavior. In the present paper, we investigate these two important issues on Euronext, an order-driven market where liquidity is provided through a limit order book, in which unfilled limit orders are stored, waiting for possible execution. In such a trading structure, hidden orders are specific limit orders that allow market participants to disclose only a part of the total quantity they want to buy or sell. The total order size is recorded in the order book but only the disclosed quantity is publicly displayed on the market screens.

Our first research question is about the decision of hiding. For traders, hiding part of one's limit order is a second stage decision after choosing between market and limit orders. A large body of literature has documented the risks that face traders when placing limit orders. The first is the risk that the order may fail to be executed. Indeed, the execution of limit orders depends on both order-specific characteristics (limit price, size) and market conditions (state of the order book, volatility).[2] Second, limit order traders risk being picked off. Buy (sell) limit orders are put (call) options for the market [Copeland and Galai (1983)]. Traders submitting limit orders can therefore bear adverse selection costs because their orders can become mispriced when new information arrives on the market. Foucault (1999) refers to the winner's curse problem because buy (sell) limit orders are more likely to be filled when they overestimate (underestimate) the asset value. The third risk is directly related to the market transparency level. When trading systems display their order book in real time, limit order traders run the so-called exposure risk [Harris (1997)]. The rationale behind this is that the display of an order can give a signal to the market and this signal can help other market participants to infer the trader's motive, the price impact of her trade or the free trading option underlying her order. In all these cases, limit order traders can be victims of front-running strategies.[3]

[1] MTS is the leading market in Europe for the electronic trading of fixed income securities.

[2] For more details on the determinants of the non-execution risk, see Biais et al. (1995), Parlour (1998), Foucault (1999), Lo et al. (2002) or Handa et al. (2003).

[3] Attempting to buy or sell securities ahead of an anticipated reaction to news or taking a position in order to benefit from an upcoming market-moving transaction are examples of front-running strategies.

Hidden orders are supposed to add an important dimension to limit order traders' strategies. For a given non-execution risk level, the decision to hide one's limit order should be affected by the picking off risk and/or the exposure risk. The extant literature, which is not extensive on this issue, provides some evidence. Harris (1996) and Aitken et al. (2001) find that liquidity suppliers use hidden quantity to reduce the option value of their orders. Tuttle (2005) and Pardo and Pascual (2005) suggest that liquidity providers prefer to submit undisclosed orders when the perceived risk of trading against informed traders is high. Since losses with informed traders increase with the order size, hidden limit orders may reduce the adverse selection costs.[4] Finally, Moinas (2004) suggests that some patient informed traders could be more willing to use hidden orders instead of large limit orders that could reveal their informational advantage.[5] Similarly, Anand and Weaver (2004) find evidence suggesting that informed traders use hidden limit orders to minimize price impact if the probability of non-execution is small.

To study the decision of placing hidden orders, we use a logit model to examine the trader's choice between hidden and usual limit orders. Specifically, we analyze how the current state of the order book as well as some characteristics of the order itself affect the decision of hiding. This analysis relies on several hypotheses related to the exposure risk and the picking off risk. While several models investigate the choice between limit and market orders [Harris and Hasbrouck (1996), Foucault (1999), Bae et al. (2003), Lo and Sapp (2005), Kaniel and Liu (2006)], to the best of our knowledge, no one has addressed the choice between hidden and usual limit orders. The main results of our model can be summarized as follows. Consistent with our hypothesis that exposure risk increases with order size, traders are more likely to hide part of their limit orders when the order size is large relative to the prevailing displayed depth. Next, traders tend to hide orders when the limit price is competitive, confirming that non marketable but competitive orders are really prone to exposure. We also find that traders are more likely to hide when they submit orders on the weak side of the book and show how this behavior is in line with the mitigation of picking off risk. Finally, the probability of hiding is higher for client orders that are more subject to both exposure risk and picking off risk. Market members who are used to better managing both risks through active order book monitoring have actually less

[4] If informed traders know only the displayed quantity available at prices where they can trade with profit, they may submit orders for fewer shares than they would if they could have seen the total quantity.

[5] Her model is based on Kaniel and Liu (2006), who argue that informed traders prefer to submit limit orders when their information is long lived or their valuation is close to the current market quotes.

incentive to hide. Hidden orders appear therefore as a real strategic tool, especially for non professional traders.

The second research question of the paper is how the presence of hidden depth at the best quote affects the submission of orders by other traders. As monitoring the limit order book can help traders to detect the presence of hidden orders, we can suspect that hidden depth affects traders' behavior over and above information directly observable from the limit order book, such as the bid–ask spread or the displayed depth. To address this issue, we estimate probit models by assuming that traders' aggressiveness is a function of several common variables (spread and displayed depth measures) and a new variable related to a signal indicating that there should be some hidden depth available. The latter is a dummy variable built upon our very rich dataset that includes information about hidden depth. We set this variable to 1 when limit order book changes may signal the presence of some hidden quantity at the best quote.

To date, almost all the empirical papers that analyze traders' behavior focus only on information directly observable in the limit order book [Biais et al. (1995), Griffiths et al. (2000), Bisière and Kamionka (2000), Ranaldo (2004), Beber and Caglio (2005), Pascual and Veredas (2004)]. Although Pardo and Pascual (2005) do not focus on traders' behavior, they are the only ones who document the impact of non-directly-observable information on the composition of the order flow. Using data from the Spanish stock exchange, they detect executed hidden orders by comparing the reported trade size with the associated change in the limit order book. The authors highlight a narrower spread and a more intensive buyer(seller)-initiated trading activity after a trade that discovers the presence of hidden volume on the ask (bid) side of the limit order book. Compared with Pardo and Pascual (2005), our paper relies on a very rich dataset that includes information on both the submission of hidden orders and their presence in the limit order book. First, this allows us to analyze the determinants of hidden order submission, while Pardo and Pascual (2005) focus only on hidden order execution. Second, our order aggressiveness analysis allows us to control other variables that are commonly used to explain traders' behavior.

In the present paper, we highlight that the detection of hidden depth at the best opposite quote significantly increases order aggressiveness. Our economic interpretation of this empirical evidence is threefold. First, hidden depth detection is possible and frequent on Euronext. This empirical result confirms what practitioners often claim about their ability to detect the presence of hidden orders. Second, when they observe a signal for hidden volume at the best opposite quote, traders adjust their order submission. This means that they behave strategically and seize the opportunity for depth improvement.

Adjusted order submission allows them to benefit from reduced implicit trading costs. Third, traders' response when hidden depth is detected suggests either that they do not associate hidden orders with informed trading or that the risk of trading with an informed trader is widely offset by the opportunity for depth improvement.

Summarizing all the findings reported in the paper, we can conclude that the use of hidden orders in a limit order book market is strongly related to the prevailing market conditions and, in turn, that the presence of hidden depth affects traders' behavior. At a time when traders' behavior is becoming more and more sophisticated, restricting the analysis of order placement to the impact of displayed market conditions could therefore result in misleading or incomplete conclusions.

The paper is organized as follows. Section 2 presents the institutional background of the study. Section 3 describes the data and the sample of stocks and orders. Section 4 investigates how traders choose between hidden and usual limit orders regarding order characteristics and market conditions. Section 5 deals with the impact of hidden depth on traders' behavior. The final section concludes the paper.

2. Institutional Background

Euronext is currently one of the most important trading venues in Europe[6] and relies on a homogeneous order-driven structure. Its platform is very transparent, since market participants have access to the whole order book and can immediately observe the last trades recorded by the system. However, two features reduce market transparency. First, orders and trades are anonymous since April 2001, which has reduced both pre trade transparency and post trade transparency. Second, hidden orders make it possible to disclose only a part of the order size to the marketplace. Before December 2003, only Euronext members had access to the whole limit order book, except for hidden quantities and members' identification codes (ID codes), while other traders could observe the best five limits of the order book. Today, the access to all the quotes in the order book has been extended to the entire marketplace.

[6] Euronext was created in September 2000 by the merger of the exchanges in Amsterdam, Brussels, and Paris. It became the first fully integrated, cross-border European market for equities, bonds, derivatives, and commodities. At present, Euronext includes the former exchanges of Amsterdam, Brussels, Lisbon, Porto, Paris, and also the London International Financial Futures and options Exchange (LIFFE).

The trading day for equities takes place in several stages. The market opens with a call auction following a pre opening phase. Then, the market switches over to continuous trading and closes with a call auction following a short pre closing period. Both opening and closing prices are set by crossing the supply and demand curves and selecting the price that maximizes the trading volume. The continuous trading system enforces a price time order priority rule to arrange trades. Incoming orders are partially or entirely filled if they hit the best quote on the opposite side of the order book. If no suitable counterpart exists, orders are recorded in the book according to their price and time priorities. Throughout the session, the trading system automatically feeds information into the electronic data dissemination network. The order book is continuously updated on traders' screens when orders are submitted, modified, or cancelled.

Traders can submit *limit orders* at any price on a pricing grid defined by a tick size. They can also submit *market-to-limit orders* that are executed at the best opposite quote. If the liquidity available at this best quote is insufficient to totally fill the order, the excess is converted into a limit order at that price. *Market orders* are orders that are immediately executed in full at any price. *Hidden orders*, also called *iceberg orders*, are limit orders specifying a hidden quantity. They are accepted both in the preopening/closing periods and during the continuous trading session. These orders allow traders to show other market participants only a part of the total quantity they want to buy or sell. The total order size is recorded in the order book but only the disclosed quantity is displayed on the market screens. Hidden limit orders are then placed in the order book according to their price and time priorities. When a hidden order is filled for its disclosed quantity, this quantity is automatically renewed and the order is positioned behind other orders at the same limit price.[7] The gradual disclosure of hidden quantity makes the limit order book different from what could be expected after a given trade. So, traders monitoring the limit order book are expected to infer the presence of hidden depth. This does not mean that they are able to guess how many shares are undisclosed.

Dual-trading is allowed on Euronext. Hence, market members are *brokers–dealers*. They can submit orders either for their own account (principal orders) or for the account of their clients (client orders). Besides, for small and mid-caps, market members may act as *liquidity providers*. As market specialists for their stocks, liquidity providers have a business agreement

[7] Hidden orders thus lose their time priority after execution of the displayed quantity. Concerning size modifications, only an increase of the visible quantity results in a loss of time precedence.

with Euronext whereby they undertake to quote two-way bid and ask prices in the limit order book, with a minimum volume and within a maximum spread.

3. Data and Sample

3.1 DATA DESCRIPTION

We use two datasets from the Euronext public database for the 40 stocks belonging to the CAC40 index over the three-month period from October 1 to December 31, 2002. The public trade data include the identification code of the stock, the date and time of the trade (with a precision to the second), the trade price, and the number of shares traded. The public order data contain the following information: the identification code of the stock, the date and time of order submission, the order direction (buy/sell), both total order size and disclosed quantity for hidden orders, the order type (limit order, market-to-limit order, market order), the limit price (if any), the date of order validity, and the state of the order at a particular date (totally executed, modified, cancelled, etc.). Two codes referenced both by day and by market member are also mentioned in this public order data set. They allow for linking records describing different states of a single order that has been modified.

In addition to publicly available data, Euronext provided us with additional information that is necessary to rebuild the limit order book,[8] that is, data about market members' ID codes for both orders and trades.[9] For orders, we have information about the time when an order disappears from the system (cancellation or full execution for example) and the date of the order modification, if any. As for trades, we have the date when both buy and sell orders triggering a given trade have been submitted (or last modified) and the sequence number of both orders included in the order file. This additional information allows us to identify which orders initiated a particular trade.

Another important piece of information available for each order referred in the database indicates for which account the market member submitted the order. As explained before, a market member on Euronext can act as a broker when he submits orders on behalf of a client (client orders), as a dealer when he submits orders for his own account (principal orders), or as a liquidity

[8] Given the organization of the different databases, rebuilding the order book was impossible with public data only. Several operations, such as order modifications, actually have to be related to the original order within the set of orders submitted by the same member.

[9] Actually, these ID codes are numerical in order to ensure market members' anonymity but allow us to isolate the whole set of orders or trades associated with a given member from the other orders and trades in the sample.

provider when he submits orders within the context of his business agreement with Euronext. Liquidity provider agreements do not exist for the CAC40 stocks. In this paper, we consider that client orders and principal orders are two different *order accounts*.

Based on both public and private data, we have developed a program allowing us to rebuild the limit order book second by second. Within this program,[10] the state of the order book is updated whenever a new order is submitted or a standing limit order is modified or cancelled. The output is accurate order book data including aggregate displayed and hidden quantities associated with each limit price. This new information set is very valuable because we not only know what Euronext members observe in real time on their computer screens at any given moment, but also the hidden quantities available at every quote on both bid and ask sides. Furthermore, ID codes allow us to know how many market members supply depth at a particular price as well as for which account they act.

3.2 SAMPLE PRESENTATION

The market value of the stocks included in sample is about € 619,211 million and the daily average trading volume is above € 3,000 million over the three-month period. The cross-sectional average daily return is about −0.1% over the same period. Table I gives additional information about activity and market capitalization for each CAC40 stock. Different statistics about the order book[11] as well as traditional liquidity measures are reported in Table II. To get meaningful cross-sectional liquidity measures, time-weighted depth is expressed in euro by multiplying the number of shares by the mid-quote. We can observe that all stocks have quite narrow spreads. Total depth at the best quotes represents slightly less than 20% of all aggregate volumes available at the best five quotes. On average, displayed depth at the best five quotes only accounts for less than 55% of the total depth available at these prices: more than 45% of depth at the best five quotes is hidden. These ratios are computed from all the order book states recorded during the continuous session, including those where no hidden depth is available at these quotes. It is worth noticing that the proportion of hidden depth rises to about 80% when only the order book states including some hidden depth at these quotes are

[10] The program rebuilds the limit order book by replicating Euronext market algorithm. We implement all the priority rules for the matching of orders. A note describing the methodology applied to build the limit order book from Euronext order and trade files is available on request.
[11] Due to their specific trading process, preauction periods have been dropped from our analysis.

Table I. Activity and market capitalization for CAC40 stocks

Stock is the stock identification code. *N* is the daily average number of trades. *Size* is the average trade size expressed in euro and *Volume* is the daily average volume expressed in millions of euro. *Capitalization* is the market capitalization (expressed in millions) computed at the beginning of our sample period. For the CAC40 row, *Size* is the simple arithmetic average of individual average trade sizes and the other variables show the sum of the individual results.

Stock	Company	N	Size	Volume	Capitalization
1	AGF	1213	10615	12.87	4829
2	TF1	1585	17142	27.17	4585
3	AIR LIQUIDE	2450	20696	50.71	12652
4	CARREFOUR	3935	25427	100.05	29158
5	SANOFI SYNTHELABO	3052	37705	115.08	41808
6	TOTAL FINA ELF	5930	71831	425.99	94969
7	OREAL	3316	31300	103.77	49623
8	ACCOR	1676	19399	32.51	5976
9	BOUYGUES	1690	18752	31.68	8938
10	SUEZ	4415	16747	73.93	16764
11	LAFARGE	2738	24511	67.12	10845
12	AXA	6069	24083	146.17	16748
13	GROUPE DANONE	2369	36668	86.85	17350
14	LVMH MOET VUITTON	3055	23293	71.17	18079
15	SODEXHO ALLIANCE	1163	12950	15.07	3106
16	MICHELIN	1238	14823	18.35	3852
17	THALES	1356	12351	16.75	4535
18	VIVENDI UNIVERSAL	6699	20003	134.01	12519
19	PINAULT PRINTEMPS	1915	21245	40.68	7772
20	PEUGEOT	1844	23898	44.06	9774
21	SCHNEIDER ELECTRIC	1658	23612	39.15	10622
22	SAINT-GOBAIN	3095	19757	61.16	7748
23	CAP GEMINI	2664	16627	44.3	2026
24	VINCI	1386	16472	22.82	5213
25	CASINO GUICHARD	1052	16361	17.22	6190
26	ALCATEL A	9247	9893	91.48	2924
27	LAGARDERE	1400	14699	20.57	5420
28	SOCIETE GENERALE A	3958	30355	120.14	18679
29	AVENTIS	4120	40487	166.82	42492
30	BNP PARIBAS	6270	35008	219.49	29720
31	RENAULT	2071	23783	49.26	12295
32	STMICROELECTRONICS	5625	26467	148.88	12155
33	FRANCE TELECOM	8298	14903	123.67	8584
34	CREDIT LYONNAIS	4542	19020	86.39	11529
35	THOMSON MULTIMEDIA	2700	12780	34.51	4428
36	DEXIA	1710	16686	28.53	10529
37	EADS	1966	11087	21.79	8747
38	VIVENDI ENVIRON.	1369	14984	20.51	8243
39	ORANGE	3044	14481	44.08	22628
40	CREDIT AGRICOLE	2346	11212	26.3	15157
	CAC40	126228	21803	3001.06	619211

Table II. Order book statistics for CAC40 stocks

Stock is the stock identification code. N is the number of order book states observed for a particular stock. *Relative Spread* is the time-weighted quoted spread divided by the mid-quote and $Depth_{1/5}$ is the time-weighted depth at the first limit (1) or at the best five limits (5). *Full Depth* aggregates displayed and hidden depths. Depth measures are obtained by multiplying the number of shares by the mid-quote in order to allow comparisons across stocks. Results for the CAC40 row are simple arithmetic averages.

Stock	N	Relative Spread	Displayed $Depth_1$	Full $Depth_1$	Displayed $Depth_5$	Full $Depth_5$
1	247132	0.34	41146	79889	207084	384665
2	208830	0.24	55726	153671	287169	753148
3	267043	0.21	106729	218638	572378	1074045
4	397222	0.16	92016	204771	507441	957356
5	291415	0.17	212634	386899	1222299	2029604
6	487968	0.11	494388	739020	3591722	4959217
7	304077	0.17	160467	316260	944776	1622328
8	259226	0.21	56248	142682	321537	723769
9	201458	0.22	52867	143170	306454	680859
10	393186	0.21	68563	144281	377249	699281
11	288795	0.19	116572	256684	651822	1266824
12	495369	0.18	106254	236731	655698	1201712
13	245432	0.16	220238	418569	1533608	2773609
14	364639	0.19	71046	184664	405865	967059
15	193941	0.33	35326	87829	183981	472046
16	216467	0.26	57512	126177	260508	547518
17	185809	0.26	38626	118429	215656	516632
18	442225	0.2	87581	229372	567738	1148033
19	209308	0.23	79409	196653	468212	996949
20	243549	0.19	74758	169721	387197	815891
21	230486	0.22	67643	171954	362964	827067
22	316605	0.21	72295	196951	401891	919151
23	281609	0.27	44397	152335	259902	699016
24	150995	0.2	98878	240766	541901	1207806
25	162572	0.26	74417	162191	370063	753663
26	501891	0.29	170439	293260	1127954	1569554
27	195910	0.23	57626	123240	287559	578952
28	364896	0.18	153487	323352	909686	1615145
29	384379	0.16	264842	449333	1550119	2427575
30	531236	0.13	121362	287903	724405	1402624
31	253285	0.19	77162	210311	426568	1003665
32	712705	0.12	143325	234199	1017118	1299809
33	477582	0.19	89038	221360	609207	1095269
34	267627	0.2	193856	973366	1292024	3619315
35	273796	0.25	52101	159010	291856	734248
36	211001	0.25	62758	150370	376478	702471
37	206814	0.29	43434	122880	236043	583261
38	177317	0.29	49568	128758	272960	618331
39	253946	0.26	105884	233384	625065	1142962
40	218091	0.29	55789	138326	277932	600480
CAC40		0.22	105660	238184	640752	1199773

considered. Therefore, when available, hidden depth is much larger than the corresponding displayed depth.

To characterize traders' behavior, we shall rely on the notion of aggressiveness of orders. The latter can be viewed as a measure of the extent to which orders consume or supply liquidity. The order aggressiveness classification that we will use includes five categories depending on how the order arrival affects the prevailing visible liquidity. The first two categories contain orders consuming liquidity and are the most aggressive ones. They consume all the depth displayed at the best opposite quote (category 1) or part of it (category 2). Categories 3 and 4 contain less aggressive orders, which increase liquidity by improving the best quote on the same side of the market (category 3) or by raising the depth available at the existing best quote (category 4). All other orders fall into the fifth category and increase the overall depth in the order book without affecting the best limit in terms of either price or quantity.[12] Cancellations and modifications are not classified.

Table III presents the results of our aggressiveness classification for the whole sample of orders, according to both their direction (buy/sell) and account (principal/client). For both client and principal orders, we can see that the most frequent events are orders of the fifth category, whatever the direction. Next, the proportion of orders that consume liquidity is respectively about 32.63% (36.87%) for client buy (sell) orders and 38.07% (39.95%) for principal buy (sell) orders. Although the fraction of these orders is only slightly higher for principal orders, the distribution of orders across the first two categories (aggressive orders) as well as the last three categories (passive orders) differs much more.

As for aggressive orders, market members submit more orders consuming all the visible depth at the best opposite quote than their clients do. This suggests a better monitoring by market members when they trade as principal. When they observe an attractive quote on the opposite side, they seize the opportunity and submit an order consuming the depth available at that quote. This behavior is also consistent with an active search for hidden volume, allowing them to benefit from depth improvement. In this case, market members need to place aggressive orders for a quantity equal to or larger than the disclosed depth available at the best opposite quote. Concerning passive orders, principal orders are more competitive than client orders. This reveals again a better market monitoring for market members who are actively involved in the mitigation of the risk of non-execution. Further examination

[12] The aggressiveness classification of orders resulting in immediate execution (categories 1 and 2) is based on the opposite quote as well as on the visible depth available at that quote. For other orders, the aggressiveness classification relies on the best quote on the same side as the order.

Table III. Order aggressiveness for the whole sample

Unconditional frequencies of aggressiveness categories are reported for the whole sample of orders regarding both their direction (buy/sell) and account (principal/client). Category 1 contains orders consuming all the visible depth at the best opposite quote. Category 2 refers to orders consuming part of the visible depth at the best opposite quote. Category 3 contains buy (sell) orders improving the best bid (ask). Category 4 refers to buy (sell) orders submitted at the prevailing best bid (ask). All other orders fall into the fifth category. Frequencies are expressed in percentage.

Aggressiveness Category	Client orders	Principal orders
Panel A: Buy orders		
1	12.35	21.98
2	20.28	16.09
3	10.90	18.87
4	18.60	19.19
5	37.86	23.85
Panel B: Sell orders		
1	11.81	23.19
2	25.06	16.76
3	9.49	19.56
4	16.63	17.25
5	36.99	23.23

of order aggressiveness through the continuous session reveals no intraday seasonality.

The first research objective is to characterize the trading strategies that involve hidden limit orders, as opposed to usual limit orders whose total size is disclosed. Intuitively, hidden orders should typically be less aggressive than usual limit orders: the exposure risk and/or the picking off risk really exist for standing limit orders that are not immediately filled in full. There is no reason for hiding part of a very aggressive limit order that will be immediately executed in full. However, although not very aggressive, hidden orders will also generally be quite competitive limit orders. Otherwise, their would be little scope for hiding part of the order size.

Table IV provides the results of aggressiveness classification for the sample of limit orders only, regarding respectively their type (hidden/usual), direction (buy/sell), and account (principal/client). As expected, hidden orders are overall less aggressive than usual limit orders: about 23% of client usual limit orders consume liquidity on the bid side while it only amounts to 16% for the corresponding hidden orders. This difference is even more pronounced for

Table IV. Order aggressiveness for the limit order sample

Unconditional frequencies of aggressiveness categories are reported for the whole sample of limit orders regarding their type (hidden/usual), direction (buy/sell) and account (principal/client). Category 1 contains orders consuming all the visible depth at the best opposite quote. Category 2 refers to orders consuming part of the visible depth at the best opposite quote. Category 3 contains buy (sell) orders improving the best bid (ask). Category 4 refers to buy (sell) orders submitted at the prevailing best bid (ask). All other orders fall into the fifth category. *Usual* (*Hidden*) refers to usual (hidden) limit orders. For each subsample of orders, the *average size* in euro amounts (the number of shares multiplied by the limit price) as well as the *average hidden part* (the hidden size divided by the total size) are given. Frequencies are expressed in percentage.

	Client orders		Principal orders	
Aggressiveness Category	Usual	Hidden	Usual	Hidden
Panel A: Buy orders				
1	10.68	14.45	22.40	12.06
2	12.48	1.13	16.36	4.8
3	11.90	22.58	18.68	25.11
4	21.38	20.20	18.87	27.97
5	43.55	41.63	23.69	29.99
average size	29 630	218 424	30 357	153 054
average hidden part		0.79		0.72
Panel B: Sell orders				
1	10.54	14.95	23.58	13.58
2	13.03	1.20	16.83	5.8
3	10.90	22.74	19.50	24.11
4	20.24	20.16	17.04	24.85
5	45.28	40.95	23.04	31.61
average size	29 140	218 959	30 725	165 221
average hidden part		0.78		0.72

principal orders, where about 39% of usual limit orders and only 17% of hidden orders are aggressive. Results are similar on the sell side. The findings that about 17% of hidden orders are aggressive may appear surprising. A further investigation reveals that on average only about 3% of them are immediately filled in full. Indeed, most of the aggressive hidden orders are executed only partially at the time of their submission. As their unfilled part becomes the best quote on their market side, these orders end up providing liquidity to the market. This strategy is close to the submission of orders within the spread or at the best quote.

Descriptive statistics about order size and hidden part are also reported in Table IV. Whatever the order direction, we can see that the average order size is much larger for hidden orders. On average, client (principal) hidden orders are seven (five) times larger than corresponding usual limit orders. As for the hidden size relative to the total order size, traders tend to hide on average 75% of their orders.

4. Hidden Orders versus Usual Limit Orders

For traders, hiding part of one's limit order is a second stage decision after choosing between limit and market orders. To investigate how traders choose between usual limit and hidden orders, we will focus on order characteristics and market conditions around submission. From hypotheses derived from the extant literature, we will assess through a logit model the influence of the prevailing order book and some order characteristics on the decision to hide part of one's limit order or not. This analysis will be performed on a stock by stock basis, for buy and sell orders separately.

Both the literature and the statistics reported in Section 3.2 reveal that only large traders cope with the decision to hide. Exposure risk and picking off risk are relevant mainly for large orders. Our analysis will therefore focus on large limit orders. To define the sample of large limit orders for a given stock, we first compute the median size across all the hidden orders submitted for that stock. We then include in the sample all hidden orders and all usual limit orders with a size at least equal to this median size.

Although this selection enables us to focus on large limit orders, it does not solve the large imbalance between the number of hidden orders and the number of usual limit orders. Overall, hidden orders account only for about 5% of all limit orders. Even if this imbalance is less dramatic when only large limit orders are considered, it remains strong enough to cause estimation problems for our logit model. Consequently, a specific sample of orders for each stock is built to better estimate the logit model: it contains all the large hidden orders as well as an equal number of usual limit orders that are randomly selected among all the large usual limit orders. As explained later, our results are not sensitive to these sample selection criteria.

4.1 HYPOTHESES

Several papers in the extant literature provide evidence that hidden orders are used by traders to manage exposure risk [Harris (1996), Aitken et al. (2001), Anand and Weaver (2004)]. This risk exists when the display of an order can give a signal to the market about the trader's motive, the price impact of her trade or the value of the option associated with her order. Order size plays an important role: the larger the order, the stronger the signal. However, for a given order size, the signal is stronger if the displayed depth is small at the order submission time. Our first assumption is that *traders are more likely to hide part of their limit orders when the prevailing displayed depth is small relative to their order size*.

The other motivation in the literature for using non-displayed quantity is the mitigation of picking off risk [Pardo and Pascual (2005) and Tuttle (2005)]. Traders face a higher risk of being picked off when an adverse price movement is more likely to occur. According to Kavajecz and Odders-White (2004), it is likely that limit order books, which synthesize the order placement strategies of both informed and uninformed traders into supply and demand functions for the stock, contain information relevant for future prices. An asymmetric order book may reflect the presence of informed traders[13] or the likely direction of future price changes.[14] In both cases, traders who place orders on the weak side of the limit order book will perceive a higher probability of being picked off. Consistent with this, Pardo and Pascual (2005) find that limit order traders hide more volume on the ask (bid) side when the order book is heavier on the bid (ask) side. Our second hypothesis is consequently that *buyers (sellers) are more likely to hide part of their limit orders when the visible ask (bid) depth is larger than the visible bid (ask) depth*.

Pardo and Pascual (2005) suggest that the risk of exposure is not uniform over the continuous session. They report that the effective contribution of hidden volume to trading activity increases towards the end of the session. Hidden order traders can benefit from clustered trading before the close: the presence of hidden quantities can be harder to infer when both order submission and trading are heavy. In line with this argument, we put forward the following hypothesis: *traders are more likely to hide part of their limit orders when the market close approaches*.

Anand and Weaver (2004) report that hidden quantity can be used to reduce price impact if the probability of non-execution is small. Pardo and Pascual (2005) show that execution of hidden volume increases in periods of

[13] Informed traders' preference for limit orders evidenced by Bloomfield et al. (2005) and Kaniel and Liu (2006) should result in a market imbalance.

[14] Other papers evidence the positive relationship between market imbalance and future price movements but do not relate this to informed trading. Harris and Panchapagesan (2005) examine whether the limit order book is informative about future prices changes. They characterize information in the book through asymmetry between buys and sells and use the asymmetry in the option values provided by limit orders standing in the book. They found that a book heavy on the buy-side (ask-side) forecasts future price increases (decreases). Cao et al. (2004) examine whether order book information is associated with future returns. They find that imbalance between demand and supply from the best 10 quotes provides additional power in explaining future short-term returns.

intense trading activity. On order-driven trading venues, trades are triggered by marketable[15] orders which hit the opposite side of the order book. Periods of heavy trading are thus periods where aggressive orders are clustered. To minimize the non-execution risk, hidden order traders can wait for a higher trading aggressiveness on the opposite side of the market. By placing hidden orders when the counterpart appears more willing to trade, traders could reduce implicit trading costs and find faster trading executions. This allows us to propose a fourth hypothesis: *buyers (sellers) are more likely to hide part of their limit orders when sellers (buyers) submit aggressive orders*.

Limit orders are sitting ducks that tend to be adversely hit when information reaches the market. Hidden orders should help traders to cope with the picking off risk because they are less likely to be hit by opportunistic traders than usual limit orders. By monitoring the market actively, market members reduce their risk of being picked off [Foucault et al. (2003)] and should have less incentive to hide. Furthermore, the risk of being front-run varies with trader types. According to Anand and Weaver (2004), traders who monitor the market more actively are less likely to be front-run. Once again, market members should have less incentive to hide. Finally, as argued by Esser and Monch (2005), hidden orders facilitate the splitting of large orders by executing this strategy automatically. When a trader monitors the market, his needs for hidden orders are weaker. Consequently, our fifth hypothesis is that *market members are less likely to hide part of their limit orders than clients*.

As explained before, there is no rationale for hiding part of a very aggressive limit order that will be immediately executed in full. Marketable orders are thus less likely to be hidden. However, as already explained, hidden orders are bound to be competitive limit orders: only orders submitted within the best 5 quotes are really prone to exposure. Pardo and Pascual (2005) report that 93% of hidden orders in their sample were placed inside the best quotes. Anand and Weaver (2004) also report that hidden orders are frequently submitted either at the quote or within the spread. This leads to our sixth hypothesis, that *traders are more likely to hide part of their limit orders when they submit non marketable but competitive orders*.

Finally, one could wonder whether the bid–ask spread plays any role in the choice between hidden orders and usual limit orders. If the bid–ask spread

[15] Marketable orders result in immediate execution. The unexecuted part, if any, is generally converted into a limit order. Any order that does not generate an immediate trade when it enters the market is defined as non marketable. Non marketable orders are stored in the limit order book until they are hit by marketable orders. On Euronext, only limit orders that do not hit the best opposite quote are non marketable. The other limit orders, market orders and market-to-limit orders are classified as marketable.

can be viewed as a proxy for adverse selection costs,[16] the inclination to hide part of one's limit order should be positively related to the spread size. Furthermore, a large spread makes front-running strategies more profitable. We can then expect that traders will hide more volume when the spread is large because the probability of being front-run increases. Consequently, our final hypothesis is that *traders are more likely to hide part of their limit orders when the contemporaneous spread is large*.

4.2 MODEL SPECIFICATION

To test the above hypotheses, we analyze the probability of placing hidden orders using a logit model. The dependent variable, Y_t, is the choice indicator, which equals one if the order submitted at time t contains a hidden part and zero otherwise. The probability of placing a hidden order conditioned on a set of regressors, X, is $Prob[Y = 1|X] = \wedge(x\prime b)$, where $\wedge(.)$ is the logistic cumulative distribution function. The set of regressors includes six variables describing the prevailing market conditions at time t, two variables related to order characteristics and an intercept.

$Spread_t$ denotes the prevailing bid-ask spread at time t, expressed in number of ticks.[17] $OrderSize/Depth_t^S$ or $OrderSize/Depth_t^O$ refers to the total order size divided by the aggregate number of shares displayed at time t at the best five limits on the same market side (S) as the incoming order or on the opposite side (O). MI_t refers to the visible market imbalance at the best 5 quotes at time t, which is defined as the visible bid size divided by the sum of visible bid and ask sizes. $TimeClose_t$ represents at time t the pending time (expressed in hours) to the next market close. $OppAggr_t$ is a variable related to the aggressiveness level of the last five orders submitted on the opposite market side. For buy (sell) orders, it refers to the last five sell (buy) orders submitted before the incoming order. The value of this variable is actually the sum of aggressiveness indexes of the last five orders of opposite direction. According to the classification described in Section 3.2, the most aggressive orders get an index of 1 while the least aggressive orders get an index of 5.

To assess whether a given limit order is competitive or not, we follow the methodology applied by Harris (1996) and Al-Suhaibani and Kryzanowski (2000). We measure relative price aggressiveness, $PriceAggr_t$, by $1 - 2(A - P)/(A - B)$ for buy orders and $-(1 - 2(A - P)/(A - B))$ for

[16] Lots of studies use the spread as a proxy for adverse selection costs. An example is Grammig et al. (2001), who show that the probability of informed trading is positively related to the bid-ask spread for 30 German stocks.

[17] Using the relative bid–ask spread leads to similar results.

sell orders. $A(B)$ denotes the contemporaneous best ask (bid) and P is the order price. This measure assigns a positive (negative) value to buy orders specifying a price higher (lower) than the mid-quote and a positive (negative) value to sell orders specifying a price lower (higher) than the mid-quote. Finally, we construct a dummy variable, $Principal_t$, equal to one when the order is submitted by a market member for his own account, and zero otherwise.

For each market side, the logit model is estimated stock by stock for the sample of large limit orders described at the beginning of Section 4. In Section 3.2, we show that usual limit orders include more aggressive orders than hidden orders. To check whether this phenomenon biases the results, we also estimate the logit model by using another sample of large limit orders whose selection process is the same, except that the sample of limit orders is restricted to non marketable orders. This second estimation is thus achieved on a sample of large non marketable orders only.

4.3 RESULTS

Since logistic regressions estimate the probability of success (the event occurs) over the probability of failure (the event does not occur), the results of the analysis are reported in odds ratios.[18] Table V presents the results for buy and sell orders. In Panel A, the model is estimated for samples of orders containing both marketable and non marketable orders. In Panel B, the model is estimated for samples of orders restricted to non marketable orders only. For each panel, the table exhibits the cross-sectional median of the estimated coefficients as well as the number of stocks presenting significant negative and positive coefficients at the 5% level. The cross-sectional median of the relevant odds ratios and the corresponding 95% confidence intervals are also reported.

From Panel A, we observe that the signs of the estimated coefficients are mostly in line with our hypotheses. First, the impact of the displayed depth and the influence of order account are consistent with our expectations for a very large proportion of stocks. $OrderSize/Depth^S$ and $OrderSize/Depth^O$ are clearly positively related to the decision of hiding. The corresponding median odds ratios are both significantly larger than one. For example, the cross-sectional median odds ratio for $OrderSize/Depth^S$ equals 1.161 for buy

[18] Odds ratios are common statistics used to assess the risk of a particular outcome if a certain factor is present. In a logit model, the odds ratio for a given explanatory variable is the exponential of its estimated coefficient. When the independent variable is continuous, the odds ratio measures how the probability of success changes if the variable increases by one unit (from x to $x + 1$). For a binary variable, the odds ratio assesses how the probability that the event will occur changes when the variable goes from zero to one. If the odds are greater (lower) than one, then the event is more (less) likely to happen.

Table V. Results of the logit model

This table presents the results of the logit model described in Section 4 and estimated stock by stock for buy and sell orders. Panel A reports the findings when the model is estimated for a sample of orders containing both marketable and non marketable orders. Panel B reports the results when the model is estimated for a sample of orders restricted to non marketable orders only. For each panel, the table exhibits the cross-sectional median of the estimated coefficients (Estimate), the number of stocks (out of 40) presenting a significant negative (Negative) or positive (Positive) coefficient at the 5%. The cross-sectional median of the relevant odds ratios and the corresponding 95% confidence intervals are also reported. Both are computed only across stocks presenting the strongest effect. For example, 1.054 at the first row is the median of the odds ratios computed across the 30 stocks presenting a positive and significant estimate for the spread. Lower CL (Upper CL) is the lower (upper) limit of the confidence interval. $Spread$ denotes the prevailing spread in number of ticks. $OrderSize/Depth^S$ and $OrderSize/Depth^O$ refers to the total order size divided by the aggregate number of shares displayed at the prevailing best 5 limits on the same market side (S) as the incoming order or on the opposite side (O). MI is the visible market imbalance at the best 5 quotes, defined as the visible bid size divided by the sum of visible bid and ask sizes. $TimeClose$ represents the pending time (in hours) to the next market close. $OppAggr$ is a variable related to the aggressiveness level of the last 5 orders submitted on the opposite market side. The value of this variable is actually the sum of aggressiveness indexes of the last 5 orders of opposite direction. $PriceAggr$ represents relative price aggressiveness and is defined as $1 - 2(A - P)/(A - B)$ for buy orders and $-(1 - 2(A - P)/(A - B))$ for sell orders. A (B) denotes the contemporaneous best ask (bid) and P is the order price. $Principal$ is a dummy variable equalling one when the order is submitted by a market member for his own account, and zero otherwise.

	Buy orders						Sell orders					
Variable	Estimate	Negative	Positive	OR	Lower CL	Upper CL	Estimate	Negative	Positive	OR	Lower CL	Upper CL
Panel A: Unrestricted Sample												
$Spread$	0.036	3	30	1.054	1.036	1.071	0.033	3	26	1.048	1.031	1.066
$OrderSize/Depth^S$	0.143	0	34	1.161	1.096	1.228	0.175	1	34	1.219	1.143	1.308
$OrderSize/Depth^O$	0.207	0	39	1.231	1.181	1.358	0.203	0	39	1.231	1.140	1.329
MI	−0.406	20	2	0.502	0.330	0.723	0.286	2	16	2.081	1.489	3.192
$TimeClose$	0.024	0	23	1.034	1.012	1.059	0.021	2	23	1.030	1.006	1.056
$OppAggr$	−0.014	20	3	0.976	0.965	0.990	−0.012	19	0	0.977	0.965	0.988
$Principal$	−0.307	34	2	0.715	0.649	0.781	−0.401	31	4	0.649	0.589	0.717
$PriceAggr$	−0.0004	14	3	0.992	0.988	0.996	−0.0002	11	2	0.995	0.992	0.998
Panel B: Restricted Sample												
$Spread$	−0.015	23	4	0.967	0.952	0.983	−0.020	24	2	0.966	0.958	0.982
$OrderSize/Depth^S$	0.151	1	30	1.266	1.135	1.358	0.207	3	35	1.245	1.115	1.348
$OrderSize/Depth^O$	0.211	1	34	1.251	1.171	1.340	0.227	0	37	1.271	1.168	1.353
MI	−0.540	22	2	0.331	0.206	0.536	0.422	1	19	2.818	1.933	4.028
$TimeClose$	0.034	0	27	1.046	1.024	1.069	0.032	3	25	1.040	1.018	1.062
$OppAggr$	0.001	7	10	1.029	1.010	1.048	−0.002	9	7	0.978	0.965	0.989
$Principal$	−0.503	37	0	0.581	0.518	0.646	−0.597	33	4	0.504	0.446	0.575
$PriceAggr$	0.006	0	32	1.006	1.003	1.010	0.004	0	33	1.005	1.003	1.008

orders: when $OrderSize/Depth^S$ is one unit higher, the probability of hiding increases by about 16%, all other things being equal. As for the $Principal$ dummy variable, we find the expected negative impact, suggesting that clients are more likely to hide their limit orders than market members. This confirms that hidden orders are used to reduce the risk of being picked off or front-run. Second, findings related to the visible market imbalance and the aggressiveness on the opposite market side are also consistent with our hypotheses for about half the stocks in our sample. About 20 (16) stocks exhibit a significant negative (positive) influence of the market imbalance (MI) on the probability of hiding for buyers (sellers). Concerning the $OppAggr$ variable, we find for 20 stocks that buyers choose to hide their limit orders when sellers are aggressive. On the sell side, the result is significant for 19 stocks.

As for the relative price aggressiveness ($PriceAggr$), our results reveal that traders tend to hide their orders when they submit less aggressive orders. This finding is consistent with our sixth hypothesis and reveals that, when considering both marketable and non marketable orders together, hidden orders are mainly non marketable orders. In order to fully confirm the sixth hypothesis, we need to observe the opposite relationship in Panel B, where the sample is restricted to non marketable orders only. Indeed, among these non marketable orders, competitive orders will be the most aggressive ones.

Results about the $TimeClose$ variable in Panel A reject our third hypothesis. Twenty three stocks exhibit on both market sides significant odds ratios larger than one. This suggests that traders do not trade more with hidden quantity towards the end of the continuous session. If anything, the probability of hidden order submission appears larger towards the beginning of the session.

Finally, we find a positive impact of the spread on the probability of placing a hidden order for most of the stocks. Traders tend to hide their orders when the spread is large. However, this result could be related to the sample composition. Marketable orders are more likely when the spread is narrow while non marketable orders are more likely when the spread is large. The findings might be biased because most hidden orders are non marketable. If this result is linked to the sample selection, it should differ in Panel B based on the restricted sample.

In Panel B, most results remain unchanged compared with those of Panel A. Only three variables exhibit a different impact on the probability of hiding. First, as expected, the $PriceAggr$ variable has now a positive impact on the decision of trading with hidden volume. Its coefficient is significant at the 5% level for 32 (33) stocks on the bid (sell) side. This is in line with the hypothesis that traders tend to hide when they submit non marketable but competitive orders. Next, the spread is now negatively related to the probability of choosing hidden orders. This negative relationship is reported for 23 (24) stocks on the bid (ask) side. This finding confirms that the coefficients reported in Panel A were biased due to the sample composition. Finally, the impact of the aggressiveness on the opposite market side is now more ambiguous. For buy (sell) orders, 7 (9) stocks present a negative coefficient and an odds ratio lower than one while 10 (7) stocks exhibit the opposite results. Based on this evidence, it is not easy to identify the real impact that the aggressiveness on the opposite market side has on the decision to hide.

In order to check the sensitivity of our results to the sample selection criteria, we estimate the logit model using all the large usual limit orders instead of a random sample of equal size to that of the hidden orders. All the results survive and lead to the same conclusions.

5. Hidden Depth and Traders' Behavior

It seems quite natural to assume that traders base their order placement upon information observable in the limit order book [Biais et al. (1995), Griffiths et al. (2000), Ranaldo (2004) and Pascual and Veredas (2004)]. In addition, monitoring the limit order book may help practitioners to detect the presence of hidden orders, so that order submission can be affected by hidden depth. This issue appears even more relevant as the presence of hidden orders at the best quote often implies quite a large additional depth. When present, average hidden depth is 4 or 5 times greater than average displayed depth.

The presence of hidden depth at the best quotes is directly observable from our order book data and we build a dummy variable ($Presence$) for each market side indicating whether some hidden depth is really available at the best quote ($Presence = 1$) or not ($Presence = 0$). However, this dummy variable does not appear as the most relevant since market participants have no access to such data. In practice, when monitoring order book changes, traders are able to detect only a signal indicating that there should probably be some hidden depth available. Therefore, we propose to base our analysis on this signal through another dummy variable ($Signal$) rather than on the true presence or absence of hidden depth.

For traders, this signal is generated by the following sequence of events: (i) a trade occurs and consumes some liquidity, (ii) traders observe an unexpected change in the order book due to the renewal of the displayed size of a hidden order.[19] This signal starts at the first renewal of the displayed size of the hidden order and ends when the order disappears from the limit order book.

[19] When a hidden order is filled for its disclosed quantity, this quantity is automatically renewed and the order looses its time priority.

Accordingly, we use our order book data to build our *Signal* variable and, for each order book state, we check whether the best quote contains a hidden order whose displayed quantity has already been renewed. We set the *Signal* variable to one in this case and to zero otherwise. This dummy variable is defined for each market side.

For the relevance of our research question, the signal must be reliable and long enough to affect traders' behavior. The reliability is checked through a comparison of the signal (*Signal*) with the actual presence of hidden depth at the best quote (*Presence*). For the 40 stocks in our sample, Table VI shows the relative frequencies for the combinations of both dummies for each order book side. On average, *Presence* and *Signal* dummies are identical in 88% of the cases. In about 10% of the cases, there is no signal while there is actually some hidden depth at the best quote. This happens when the displayed part of the hidden order at the best quote has not been fully executed yet. In less than 2% of the cases, the signal is wrong because the remaining size of a hidden order is fully disclosed. Table VII reports statistics about the durations associated with the actual presence of hidden depth and the signal. No difference appears between market sides. When focusing on the signal, the key result is that durations are long enough to allow traders to change their order placement. For example, when the signal indicates that there is probably hidden depth at the best quote, traders have about 1 minute to adjust their order submission. All these results confirm the relevance of our research question.

5.1 METHODOLOGY

In order to analyze the effect of the signal, we estimate an ordered probit model. We assume that traders' aggressiveness is a function of several elements, such as spread, displayed depth measures, and the signal. Traders' aggressiveness (A_t) at time t is assumed to be explained as follows:

$$\begin{aligned} A_t &= \beta_1 * Spread_t + \beta_2 * Depth^S_{1,t} + \beta_3 * Depth^O_{1,t} + \beta_4 * Depth^S_{+,t} \\ &\quad + \beta_5 * Depth^O_{+,t} + \beta_6 * Signal^S_t + \beta_7 * Signal^O_t + \epsilon_t \\ &= X_t + \epsilon_t, \epsilon_t \sim N(0, \sigma^2_t) \end{aligned} \tag{1}$$

Most of these explanatory variables are easily observed in the limit order book prevailing at time t. $Spread_t$ denotes the prevailing absolute bid-ask spread when the order is submitted at time t. $Depth^{S/O}_{1/+,t}$ is the number of shares displayed at the first limit (1) or at the four next ones (+) on the same side (S) as the incoming order or on the opposite side (O) at time t. $Signal^{S/O}_t$ are dummy variables which are equal to 1 if, at time t, traders can observe

Table VI. Hidden orders: Presence versus Signal

Stock is the stock identification code. P and S refer to *Presence* and *Signal* dummies. The figures are relative frequencies for the four different possible cases. $P = 0$ And $S = 0$ refers to order books without hidden orders at the best limit and no signal. $P = 0$ And $S = 1$ refers to the absence of hidden orders at the best quote when there is a signal for hidden depth. $P = 1$ And $S = 0$ refers to the non-signalled presence of hidden orders at the best limit. $P = 1$ And $S = 1$ indicates that there are hidden orders at the best quote and they are signalled. The last row is the average of these frequencies across stocks.

Stock	$P = 0$ And $S = 0$		$P = 0$ And $S = 1$		$P = 1$ And $S = 0$		$P = 1$ And $S = 1$	
	Bid	Ask	Bid	Ask	Bid	Ask	Bid	Ask
1	79.77	80.84	1.37	1.49	9.96	8.54	8.89	9.13
2	71.05	70.72	1.68	1.62	11.2	11	16.06	16.66
3	76.5	75.91	2.13	2.18	9.56	9.88	11.81	12.03
4	73.26	74.26	1.75	1.73	9.95	9.71	15.03	14.3
5	73.39	74.66	1.98	1.84	9.92	9.35	14.71	14.16
6	78.7	78.35	1.96	2.01	8.92	9.04	10.42	10.6
7	71.87	73.56	2.13	2.23	10.57	10.47	15.43	13.75
8	72.75	74.36	1.56	1.58	10.29	10.05	15.4	14
9	70.05	71.29	1.98	1.94	11.86	10.44	16.12	16.33
10	74.7	73.95	1.77	1.77	9.13	9.1	14.39	15.18
11	75.2	71.12	2.14	2.01	9.95	9.92	12.71	16.95
12	68.14	71.34	2.36	2.13	10.58	9.5	18.92	17.02
13	68.15	70.59	2.39	2.29	13.68	11.77	15.78	15.34
14	72.72	72.18	1.84	1.86	9.99	10.61	15.44	15.35
15	73.51	74.32	1.65	1.46	10.95	11.49	13.89	12.73
16	73.54	77.02	1.7	1.31	11.24	9.15	13.52	12.51
17	72.52	74.19	1.66	1.37	9.89	9.9	15.93	14.54
18	70.85	71.57	2.05	1.82	9.5	9.07	17.6	17.54
19	71.78	69.67	2.27	2.1	11.44	11.46	14.5	16.78
20	72.48	71.95	1.82	1.95	11.46	10.88	14.25	15.22
21	70.53	71.93	1.97	1.85	11.74	10.85	15.76	15.38
22	71.11	68.84	1.84	1.86	11.38	10.58	15.68	18.73
23	69.3	71.03	1.73	1.46	10.91	9.78	18.06	17.73
24	67.44	66.47	2.43	2.44	10.67	12.86	19.46	18.23
25	71.8	76.05	2.02	1.77	11.48	9.99	14.69	12.18
26	73.86	73.71	2.05	2.04	8.96	8.17	15.14	16.08
27	78.07	75.21	1.46	1.62	9.1	10.1	11.36	13.06
28	70.64	71.46	2.23	2.09	10.92	10.51	16.21	15.94
29	71.55	73.15	2.1	2.18	10.49	10.15	15.86	14.53
30	69.6	69.98	1.86	1.93	12.41	10.85	16.13	17.25
31	71.26	71.7	1.71	1.7	10.84	10.5	16.18	16.1
32	85.02	86.94	1.12	0.9	5.28	4.62	8.59	7.55
33	73.67	76.32	1.76	1.72	8.1	7.47	16.47	14.49
34	58.71	71.04	1.78	2.26	9.48	11.56	30.03	15.14
35	71.32	73.83	1.58	1.34	10.2	8.84	16.9	15.99
36	70.31	70.57	2.14	2.03	11.2	11.15	16.34	16.24
37	70.74	70.39	1.61	1.64	10.3	9.99	17.35	17.98
38	72.31	69.7	1.6	1.72	12.13	13.21	13.96	15.37
39	69.08	69.16	2.28	2.12	10.46	11.14	18.17	17.58
40	72	68.83	1.64	1.59	11.37	11.86	14.99	17.72
	72.23	72.95	1.88	1.82	10.44	10.14	15.45	15.08

Table VII. Hidden depth at the best quotes

$HO_{Bid/Ask}$ is the proportion of time in continuous trading when hidden depth is present/signalled at the best *Bid/Ask*. $Dur_{0/1}^{Bid/Ask}$ is the mean duration for presence/signal (1) or absence/non signal (0) of hidden depth at the best *Bid/Ask*. Duration is measured in number of order book states and the corresponding time expressed in minutes and seconds is given between brackets. Figures presented are sample averages.

Event	HO_{Bid}	HO_{Ask}	Dur_0^{Bid}	Dur_1^{Bid}	Dur_0^{Ask}	Dur_1^{Ask}
Presence	28.53	27.94	23.3 (2:27)	8.7 (0:58)	24.5 (2:31)	8.7 (0:59)
Signal	18.85	18.48	40.8 (4:23)	9.0 (1:00)	42.7 (4:33)	9.1 (1:01)

a signal indicating that some hidden depth is probably available at the best quote (same side or opposite side). ϵ_t represents the independent but not identically distributed residual. In order to avoid correlations across displayed depth measures, we replace $Depth_{+,t}^{S/O}$ by the residuals of an OLS regression of $Depth_{+,t}^{S/O}$ on $Depth_{1,t}^{S/O}$.

As traders' aggressiveness is not directly observable, we can consider Equation (1) as a latent one. However, the order submitted by a trader at time t can inform us about the trader's aggressiveness. Applying the order classification described previously, we get an observable discrete variable Cat_t linked to the latent variable A_t. The relationship between the latent variable and the ordered response is expressed as follows :

$$Cat_t = \begin{cases} 1 & if\, A_t \leq \gamma_1 \\ m & if\, \gamma_{m-1} < A_t \leq \gamma_m, m = 2, 3 \text{ or } 4 \\ 5 & if\, A_t > \gamma_4 \end{cases} \tag{2}$$

Equations (1) and (2) form an ordered probit model of which parameters β_k and γ_j can be estimated. Actually, the γ_j's are thresholds that determine what value of Cat_t a given value of A_t will map into.

The existing literature provides some priors for the signs of the parameters associated with displayed market conditions. First, order aggressiveness should be negatively correlated with spread since it is more difficult to execute orders when the spread is large. Next, observable depth on the same side (i.e., bid for buy orders and ask for sell orders) should encourage traders to be more aggressive in their order placement. Indeed, a new non marketable order has a lower time priority than other orders already into the system. So, one needs to improve the order's limit price to gain priority. The literature refers to this behavior as the competition effect. Conversely, order aggressiveness should be negatively correlated with depth observable on the opposite side because traders are more confident about order execution. Many orders available at the opposite quotes are likely to match their own order. In the literature, this is known as the strategic effect.

Expectations about parameters associated with the *Signal* dummies can be built upon both economic intuition and the extant literature. Except if hidden orders are associated with informed trading, traders are expected to be more aggressive when there is hidden depth at the best opposite quote because they can benefit from depth improvement. Indeed, this additional non-displayed depth gives them the opportunity to trade a larger amount at the best quote.

As for hidden depth on the same market side, two conflicting hypotheses can be put forward. The first one stems from the assumption previously made for the opposite side. If hidden depth reinforces order aggressiveness on the opposite side, traders on the same side as hidden depth can benefit from this and wait for their passive orders to be executed more quickly. This results in a strategic behavior involving less aggressive orders: traders will place non marketable orders instead of marketable orders. The second hypothesis builds upon the existing literature and is consistent with the competition effect. According to this, the hidden depth at the best bid (ask) should encourage buyers (sellers) to submit more aggressive orders to gain priority over this hidden depth.

Since the information set used by buyers and sellers could be different, the model is estimated separately for buy and sell orders. Moreover, market members may be affected differently by market conditions whether they act for a client or for their own account. Therefore, we repeat the analysis described above while discriminating for these two different order accounts.

5.2 RESULTS

A summary of the results for the whole sample is given in Table VIII.[20] Parameter estimates often exhibit the expected sign at the 1% significance level. For example, our results confirm those of Griffiths et al. (2000) and Ranaldo (2004) showing that aggressive orders are more frequent when bid–ask spreads are narrow and when displayed depth at the best quote on

[20] We conduct the same analysis for each of the three months of our sample period. The cross-sectional average daily return is 0.23% for October, 0.11% for November and −0.75% for December. The results obtained for each month are totally consistent with those presented here for the whole sample.

Table VIII. Results of the ordered probit model

For each explanatory variable, the mean parameter and the mean p-value across stocks are given. The next line gives the numbers of stocks with respectively negative and positive estimates at a 1% significance level. The results are presented for all orders (*All*), for client orders (*Client*) and for principal orders (*Principal*). *Spread* denotes the prevailing absolute bid-ask spread, $Depth^{S/O}_{1/+}$ is the number of displayed shares at the first limit (1) or at the four next ones (+) on the same side (S) as the incoming order or on the opposite side (O). $Signal^{S/O}$ are dummy variables indicating the signal for hidden depth at the best quote on the same side or on the opposite side. LR is the likelihood ratio resulting from the comparison of the general model with the model without both dummies indicating the signal for hidden depth. AIC is the level of the Akaike Information Criterion. For LR, the table also reports the number of stocks for which the model with dummies must be preferred. For AIC, the table indicates how many times the model with dummies related to the signal for hidden depth must be preferred to the model with the actual presence of hidden depth.

Account	$Spread$		$Depth^S_1$		$Depth^O_1$		$Depth^S_+$		$Depth^O_+$		$Signal^S$		$Signal^O$		LR		AIC
Panel A : Buy orders																	
All	−3.648	0	0.087	0	−0.079	0	0.018	0.03	−0.042	0.006	−0.037	0.096	0.219	0	1093.823	0	446527.945
All	40	0	0	40	40	0	2	30	37	2	29	1	0	40	40		40
Client	−2.086	0	0.092	0	−0.048	0	0.011	0.118	−0.013	0.182	0.022	0.291	0.125	0	154.916	0	212547.854
Client	40	0	0	40	40	0	6	23	16	6	1	16	0	40	40		36
Principal	−5.502	0	0.08	0	−0.102	0	0.025	0.042	−0.071	0	−0.072	0.041	0.273	0	964.044	0	223877.579
Principal	40	0	0	40	40	0	3	26	40	0	31	0	0	40	40		40
Panel B : Sell orders																	
All	−3.413	0	0.081	0	−0.086	0	0.016	0.067	−0.051	0.011	−0.045	0.093	0.221	0	1153.346	0	466452.756
All	40	0	0	40	40	0	2	28	38	1	26	2	0	40	40		40
Client	−1.741	0	0.083	0	−0.051	0.001	0.01	0.148	−0.018	0.187	0.021	0.182	0.12	0	142.206	0	226637.934
Client	39	1	0	40	39	0	5	18	20	4	5	14	0	40	40		35
Principal	−5.513	0	0.078	0	−0.114	0	0.02	0.128	−0.082	0	−0.083	0.015	0.28	0	1009.376	0	226687.613
Principal	40	0	0	40	40	0	2	23	40	0	35	0	0	40	40		40

the same (opposite) side of the limit order book is large (small). When splitting orders according to their account (client or principal), our findings for $Spread$ and $Depth_1^{S/O}$ are consistent with those obtained for the whole sample. Our results about disclosed depth at the next quotes[21] are consistent with Pascual and Veredas (2004), who show that next quotes affect traders' behavior, even if this effect is less significant. Furthermore, it is worth noticing that our estimates for $Depth_+^S$ and $Depth_+^O$ are more often significant for principal orders. This phenomenon could be explained by larger size and/or better market monitoring.

The most innovative finding is the positive and very significant estimate for the signal for hidden depth at the best opposite quote. Consistent with our assumption, when there is a signal for hidden depth at the best opposite quote, traders tend to be significantly more aggressive. They behave strategically and seize the opportunity for depth improvement. These results remain valid whatever the order account.[22]

As for the signal for hidden depth at the best quote on the same side, the results are less significant and give some validation to both conflicting assumptions. The competition effect appears to be stronger for client orders while the strategic effect is mainly present for principal orders. When focusing on principal orders, buyers (sellers) seem to be aware that sellers (buyers) will be more aggressive when a signal for hidden depth at the best bid (ask) is observed. Consequently, traders are more confident about the execution of their own non marketable orders and are less aggressive. For more than 30 stocks, the signal for hidden depth at the best bid (ask) results in less aggressive buy (sell) orders. However, the other assumption based on the competition effect seems to better suit client orders. When significant, the parameter estimate is often positive, indicating that the signalled hidden depth at the best bid (ask) makes client buy (sell) orders more aggressive.

When we test for the joint significance of the $Signal$ dummies, we obtain a Likelihood Ratio which is always significant at the 1% level, indicating that a regression omitting the signal for hidden depth would be misspecified. Furthermore, we do not include the $Signal$ dummy variables together with the $Presence$ dummies because they are highly correlated, as we have previously shown. This correlation makes it very difficult to interpret the results since the effects of hidden depth are spread over two variables. Nevertheless, we perform a robustness check of the results by replacing both $Signal$ dummy

[21] The computation of this depth uses the number of shares displayed from the second to the fifth quotes. However, we specify that these depth measures have been replaced by OLS residuals.

[22] A further examination of trades involving hidden orders reveals that market members are not used to submitting aggressive orders to hit hidden orders they have placed.

variables in Equation (1) by the *Presence* dummies indicating the actual presence or absence of hidden orders at the best quote. Since *Signal* and *Presence* variables often present the same values, the same relationships are expected but the explanation power should be somewhat weaker. Indeed, in some specific cases, traders' behavior may not be affected by the presence of hidden orders at the best quote because this presence is not signalled. As these models are not nested, we compute the Akaike Information Criterion (AIC) for both models in order to compare their relevance. We obtain a higher value for the AIC when using *Presence* rather than *Signal* dummies, indicating a better explanatory power with the latter dummies.[23] Therefore, all our results show that traders detect the signal for hidden depth at the best quotes and that this signal significantly affects their order placement strategy.

6. Conclusion

Using a logit model to investigate the decision to hide, we show that traders are more likely to hide part of their limit orders when the order size is large relative to the prevailing displayed depth, the price limit is competitive and the spread is narrow. To the extent that it is measured by the visible market imbalance, a higher perceived risk of being picked off also seems to increase the use of hidden orders. Besides, the probability of hiding is higher for client orders than for principal ones. As for the relationship between the decision of hiding and the order aggressiveness on the opposite market side, results are ambiguous. We do not find any support for the hypothesis suggesting that hidden order traders wait for a higher aggressiveness on the opposite market side to minimize their non-execution risk. All these empirical findings suggest that traders use hidden quantity to manage both exposure risk and picking off risk. Furthermore, market members who are used to better managing both risks through active order book monitoring are less likely to hide their limit orders. Hidden orders appear therefore as a real strategic tool, especially for non-professional traders.

Using ordered probit models, we highlight that the signal for hidden depth at the best opposite quote significantly increases order aggressiveness. The economic interpretation of this result is threefold. First, the detection of hidden depth is possible and frequent on Euronext. This empirical result is consistent with practitioners who argue that they can detect the presence of hidden orders. Second, when there is a signal for hidden volume at the best opposite quote, traders adjust their order submission. They behave strategically and seize the opportunity for depth improvement. This allows them to benefit

[23] Except for 4 or 5 stocks when focusing on client orders.

from reduced implicit trading costs. Third, traders' response when a signal for hidden depth is detected suggests either that they do not associate hidden orders with informed trading or that the risk of trading with an informed trader is widely offset by the opportunity for depth improvement.

When some hidden depth is signalled on the same market side, our empirical findings are more ambiguous. Traders also adjust their order submission but adjustments seems to depend on the order account. Consistent with the competition effect, client orders become more aggressive to gain priority over hidden volume. Conversely, when some hidden depth is signalled, principal orders on the same market side tend to be less aggressive. This could suggest that market members are more aware of the interactions between market conditions and traders' behavior. Consistent with the strategic effect, they adjust their behavior to reduce their implicit trading costs.

Summarizing all the findings, we can conclude that the use of hidden quantity in a limit order book market is strongly related to the prevailing market conditions, and in turn, that the presence of hidden depth affects traders' behavior. Consequently, order submission strategies appear to be more and more sophisticated, and focusing only on displayed market conditions to analyze traders' behavior could result in misleading or incomplete conclusions.

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