On the Hidden Side of Liquidity[*]

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ABSTRACT

This paper deals with the motives of traders that submit undisclosed limit orders, also known as hidden limit orders (HLO). In particular, we are aimed to discern whether HLO traders are information or liquidity-motivated. We use book and transaction data from the Spanish Stock Exchange and the sample of executed HLOs during the last six months of 2000. We contribute to the literature, first, by reconciling inconsistent findings in former related studies, and, second, providing brand new evidence on the behavior of HLO traders. Globally considered, our findings are more supportive of the notion that HLO traders are large liquidity traders.

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1. Introduction

Electronic order driven markets are usually held up as the paradigm of a highly pre-trade transparent market since limit order book (LOB) information is disseminated in real time to all market participants. Many of these markets, however, provide facilities that allow traders to submit partially or totally undisclosed limit orders, also known as iceberg orders or hidden limit orders (HLOs).[1] By submitting a HLO**,** the trader displays only a small fraction of the total amount of shares she wishes to buy or sell. As a consequence, market participants do not know the exact depth offered or demanded at the posted quotes. Hence, even in these transparent venues, liquidity is partially veiled.

From a market design point of view, HLOs represent a real trade-off between liquidity and transparency. By allowing HLOs, regulators encourage traders to provide liquidity when they might be reluctant to disclose their trading interests. On the negative side, regulators impose a certain degree of opacity in the trading mechanism. HLOs may therefore diminish the presumed benefits of a transparent LOB, such as low costs of market monitoring, real-time assessment of liquidity, less significant information asymmetries, and enhanced price efficiency (see Madhavan, 2000, and Bloomfield and O'Hara, 2000).

As far as we know, there is a lack of formal theoretical modeling regarding the rationale for HLO placement. Nonetheless, two basic tentative arguments have been proposed. The first widespread belief is that HLOs are used by large liquidity traders to reduce the option value of the limit orders, that is, their exposure risk (Copeland and Galai, 1983). Thus, limit order traders use HLOs as a self-protective strategy against either informed traders or parasitic traders. On the one hand, a limit order executing against an informed agent does it in the money, and the amount of the loss increases with the limit order size. Therefore, large buyers

[1] To name a few: Australian Stock Exchange, Copenhagen Stock Exchange, Deutsche Börse (XETRA), Euronext, NASDAQ ECNs, Milan Stock Exchange, Oslo Stock Exchange, Spanish Stock Exchange, Stockholm Stock Exchange, SWX Swiss Exchange, Toronto Stock Exchange, and Warsaw Stock Exchange.

and sellers facing adverse selection costs may choose to partially hide the size of their limit orders. If informed traders knew only the displayed depth at prices where they can profitably trade, they might submit smaller market orders than they would if they could also see the hidden volume. In this manner, HLO traders may reduce their adverse selection costs. On the other hand, parasitic traders seek to infer the security's ultimate value from the exposed liquidity. These traders use front-running and quote-matching strategies, jumping in front of the heavy side of the LOB and stealing price priority from the exposed limit orders (e.g., Harris and Panchapagesan, 2005). This activity benefits from a highly pre-trade transparent venue. HLO placement increases the trading risk born by parasitic traders by creating uncertainty over the total available depth on the LOB.[2]

As a second argument, some researchers postulate that HLOs are submitted by informed traders so as to obscure their positions and minimize the price impact of their trades. Informed traders are habitually characterized as impatient because, by assumption, their information advantage is perishable in the very short-term. Thus, it is typically assumed that these traders make use of orders that guarantee an immediate execution. Despite that, recent theoretical papers have shown that informed traders may use limit orders under certain circumstances. Thus, Harris (1998) concludes that informed traders facing wide spreads and distant deadlines, such as a market closure, are more likely to submit limit orders. Kaniel and Liu (2001) show that informed traders prefer to use limit orders when their information is long-lived or their valuation is close to the current market quotes.[3] In an experimental setting, Bloomflield et al. (2005) even show that informed traders use more limit orders than liquidity traders do. Intuitively, if the private information is substantial and it will not become public

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[2] Certainly, limit order traders might protect themselves from an elevated exposure risk using other strategies rather than submitting HLOs. For example, by breaking up their large orders into small ones and spreading them over time, the limit order trader may reduce both the probability of being front-run and the price impact of their orders. They can also cancel and modify orders more frequently or simply switch to market orders. These alternative strategies, however, might increase the trader's transaction costs.

[3] See also Seppi (1997) and Rindi (2003).

soon, informed traders may choose to trade less aggressively. In this case, they may prefer undisclosed instead of disclosed limit orders.

Until now, the question of whether HLO traders are liquidity or information motivated remains unsatisfactorily answered, largely because the scarce empirical evidence on this issue provides contradictory conclusions. Aitken et al. (2001) observe HLO traders in the Australian Stock Exchange (ASX) concentrating on the less frequently traded stocks, which they interpret as being supportive of the liquidity-motivated hypothesis. Anand and Weaver (2004), however, find the opposite pattern in the Toronto Stock Exchange (TSX). Moreover, while Aiken et al. (2001) conclude that a more restrictive undisclosed order regulation discourages liquidity-motivated HLO traders, Anand and Weaver (2004) determine that more permissive rules foster informed-motivated HLO traders.

It could be argued that these mixed findings might be due to microstructure and methodological disparities.[4,5] However, apart from these regulatory or technical issues, it seems more pertinent to emphasize that former studies do not base their conclusions on a direct test about the informativeness of HLOs. Some particularities of the ASX and TSX microstructures even suggest that these markets could be inadequate to implement such analyses. Their large minimum displayed volume units may discourage small HLO traders, if any. In addition, ASX HLOs are more exposed than similar orders in other electronic markets. ASX HLOs are signaled with specific marks, visible to all market participants. This may discourage informed traders from submitting HLOs since their presence would be revealed,

[4] To name a few, HLOs are remarkably more important in the ASX than in the TSX: 28% and 7% of the share volume submitted, and less than 4% and 1% of all orders submitted, respectively. ASX and TSX differ in the minimum displayed volume requirements for HLOs. In the ASX, the minimum displayed volume unit was $10,000 before October 1994, $25,000 between October 1994 and October 1996, and $100,000 afterwards. In the TSX, the displayed threshold for stocks trading for more than $1/share was set to 2,000 shares when HLOs were re-introduced in April 2002 (5,000 shares before 1996). This means that for a stock trading at $5, the ASX regulation was as permissive as the TSX regulation in 1996, but after 2002 the ASX regulation became more restrictive. Finally, HLOs lose time precedence in the TSX, but not in the ASX.

[5] Methodological implications are discussed later in section 2.

and the risk of non-execution would therefore increase as the market adjusts prices in the direction of their orders. In TSX, a similar kind of mark was removed in 2002.

In this paper, we use data from the electronic order-driven market of the Spanish Stock Exchange (SSE) to confront the two previous tentative hypotheses. In the SSE, traders are allowed to place hidden limit orders with a minimum displayed size of only 250 shares. Consequently, HLOs may be submitted more frequently than in the ASX and TSX markets. Furthermore, HLOs are not marked when submitted; therefore, the presence of undisclosed volume is only revealed when the undisclosed part of the HLO is totally or partially executed. Hence, the SSE may be a priori better suited for our purposes.

We use six months of displayed LOB and transaction data on a representative sample of 79 SSE-listed stocks. We do not have information on HLO submissions. However, we develop a reliable algorithm that identifies a HLO as soon as it is picked up by a market order or a marketable limit order.

With this information on *executed* HLOs, first we show that the apparently contradictory findings reported in previous studies can be reconciled. We group our stocks into portfolios of single-listed index stocks, dually-listed index stocks, and non-index stocks. As in Anand and Weaver (2004), we observe that HLOs are more common on the most actively traded stocks: the index stocks. However, when we split the index stocks into single-listed and cross-listed, we observe that HLO traders are detected more often among the single-listed, those index constituents that are less liquid and less active, which is consistent with the conclusions of Aiken et al. (2001). Hence, our findings indicate that HLO traders concentrate on index stocks, particularly among those with higher exposure risk. This evidence leads us to conjecture that HLOs may be concealing large liquidity traders, such as institutional investors, that concentrate their activity on index stocks. Our evidence, however, is not at all conclusive because a complementary intraday analysis reveals a significant increase in the use of HLOs right after the opening of the NYSE that is particularly dramatic for the cross-listed stocks, the most active and frequently traded.

Additional evidence supporting our conjecture is found in posterior analyses. We show that HLO traders mimic the institutional trading behavior reported in the literature (e.g., Griffin et al., 2003). We evidence that HLO traders are momentum traders and show herding behavior. This is intuitively incompatible with HLO traders being information motivated.

Finally, we perform a direct test on the informativeness of HLOs. We evaluate the information content of HLOs by studying the incidence of detecting hidden volume on the LOB on posterior stock returns and volatility. We also examine the influence of HLO detection on the traders' strategies by analyzing its impact on the composition of the order flow. We find that HLOs temporally increase the aggressiveness of traders when they are discovered, but just on the opposite side of the market. Moreover, hidden volume revelation has no relevant price impact. These findings strengthen our view that HLOs are submitted by large liquidity traders.

The paper proceeds as follows. Section 2 reviews former empirical studies on HLOs. Section 3 details the microstructure of the SSE. Section 4 describes the database and provides some statistics. Section 5 reports cross-sectional differences in the intraday distribution of HLOs. Section 6 studies the relationship between HLO trading and stock returns. Section 7 evaluates the information content of HLOs. Finally, we conclude in section 8.

2. Literature review

A recent group of papers make plain the relevance of HLOs in electronic order-driven systems. HLOs account for about 16% of the entire LOB of the Brussels CATS system (Degryse, 1999); 14% of all the limit orders submitted and 45% of the quoted depth at the Paris Euro-NM (D'Hondt et al., 2001); almost 12% of all order executions and shares transacted through the Island ECN (Hasbrouck and Saar, 2002); 22% of the inside depth of

Nasdaq stocks following the Super SOES implementation (Tuttle, 2002), and 50% of the book depth (five best levels) of the Euronext (D'Hondt et al., 2003).

The cross-sectional evidence at hand provides some insights on the motives for submitting HLOs. Harris (1996), Aitken et al. (2001), and D'Hondt et al. (2001) report that HLO submissions decrease with the relative tick size. As well, Aitken et al. (2001) find that HLOs are more common among the more volatile stocks. All these findings support the view that HLO traders manage the exposure costs of their limit orders, given that larger tick sizes make front-running strategies more difficult and expensive, and the option value of a limit order increases with volatility.

In some other cases, however, the empirical evidence is not conclusive. Aitken et al. (2001) find that the use of HLOs decreases with trading activity. Given that a higher non-execution risk enhances the option value of limit orders, the authors conclude that ASX HLOs are liquidity-motivated. Anand and Weaver (2004), however, report a positive relationship between HLO submissions and trading intensity. They argue that if informed traders were to make use of limit orders, they would probably choose stocks with a low non-execution risk. Hence, they conclude that TSX HLOs are information-driven.

Aiken et al. (2001) and Anand and Weaver (2004) also study the impact of disclosure regulation changes on market liquidity and activity. Once more, their conclusions are quite opposed. In October 1994, ASX regulators decided to enhance pre-trade transparency by increasing the minimum disclosed volume. Aitken et al. (2001) find that this decision caused a significant decline in trading volume. They conclude that, by tightening the undisclosed order regulation, ASX regulators discouraged primary liquidity suppliers. Similarly, Anand and Weaver (2004) analyze the decision by the TSX of abolishing HLOs in 1996, and then reintroducing them in 2002. These authors do not find a significant effect on trading activity. Nonetheless, they report an increase in the number of quote updates and an increase in total depth, both disclosed and undisclosed, after the 2002 reintroduction. Since this effect is particularly important among the active stocks, they conclude that the 2002 reintroduction encouraged informed traders to submit more HLOs.

Methodological differences might partly explain former inconsistencies. Thus, Aiken et al.'s (2001) evidence is based on a cross-sectional weighted regression of a proxy for HLO usage over a proxy for trading activity. The weights are the number of HLOs submitted for each stock. Even if HLOs were more important in relative terms among the inactive stocks, we would expect to observe more HLO submissions in absolute terms among the active and/or liquid stocks. If this were the case, the negative relationship reported by Aiken et al. might not be at odds with HLO traders focusing on liquid stocks and being more active in those of them with higher exposure risk.

Similarly, Anand and Weaver's (2004) standpoint is that informed traders are the most impatient type of traders. Hence, these traders balance the inherent non-execution risk of their limit orders by choosing stocks with the smallest non-execution risk. This argument is used to explain why, after the TSX reintroduction, there were more quote updates and limit order submissions were more aggressive among the most active stocks. Harris (1998) and Bloomfield et al. (2005), however, illustrate that aggressiveness is also agreeable with large liquidity traders facing a deadline to fulfill a target, such as rebalancing a portfolio. If these traders were to focus on frequently traded stocks, Anand and Weaver's findings would also be compatible with liquidity-motivated traders using HLOs aggressively to mitigate the risk of non-execution and, simultaneously, reducing the option value of their limit orders.

Taken as a whole, this methodological exposition suggests that making inference about the motivation of HLO traders based exclusively on cross-sectional statistics on HLO usage may be misleading. In the following sections, we show that Aiken et al.'s (2001) and Anand and Weaver's (2004) apparently contradictory findings may be reconciled by simply splitting frequently traded stocks into more explicit categories. Furthermore, Harris (1998), Foucault (1999), and Bloomfield et al. (2005) suggest that both informed and liquidity traders' relative use of limit orders may depend on variables such as the time to the market closure, the pricing error and its persistence, the quoted spread, the volatility, etc. All these variables may vary throughout the trading session and, consequently, so may the exposure-risk of liquidity traders and the information advantage of informed traders. Therefore, we expect HLOs usage to show concentration patterns as traders must decide not only how to trade but also when to trade. We investigate this possibility by splitting the SSE session into 30-minute intervals.

Finally, previous discussion makes prominent the need for a direct test of the information content of HLOs. Aiken et al. (2001) study the stock price behavior around HLO submissions by comparing matched samples of HLOs and disclosed limit orders (DLOs). They conclude that HLOs are not more informative than DLOs. In the ASX, however, HLOs are exposed to the market since the quantity field on the ASX-SEATS displays a "U" for undisclosed, visible for all market participants. Similarly, in the TSX a "flag" is displayed next to any quote that includes hidden volume. In both contexts, informed traders would be less willing to submit HLOs since the mark would signal the stock being wrongly priced, increasing the non-execution risk of the HLO. Therefore, the microstructure of these markets may not be appropriate for evaluating the relative attractiveness of HLOs for liquidity and informed traders. In the SSE, HLOs submissions are not marked, which means that the presence of undisclosed liquidity is only publicly revealed when HLOs are executed and effectively contribute to the trading process. Therefore, the SSE seems particularly well suited to implement a test on the price impact of HLOs. We will perform this test in a later section.

3. Institutional background

The Spanish Stock Exchange Interconnection System (SIBE) is a computer-assisted trading platform that holds all the SSE-listed stocks that achieve certain minimum levels of liquidity and trading activity.[6] The microstructure of the SIBE is that of a pure order-driven market. By "pure" we mean that there are no market makers, and liquidity is provided by an open LOB. Trading is continuous from 9:00 a.m. to 5:30 p.m., and is governed by a strict price-time priority rule. There is no floor trading and price improvements are impossible. Hence, all the orders are submitted through vendor feeds, and stored or matched electronically.[7] During the continuous trading session, orders are submitted, modified or cancelled, and a trade takes place whenever a counterpart order hits the quotes. Stocks are quoted in euros and the tick equals €0.01 for prices up to €50 and €0.05 for prices above €50. The SIBE is highly transparent, with information on both book and trade data provided in real time to all market participants through the Dissemination Information System (DIS).

There are three basic types of orders: market, market-to-limit and limit orders. Market orders are executed against the best prices on the opposite side of the book. They walk up or down the book until they are fulfilled. Market-to-limit orders are limited to the best opposite-side price on the book at the time of entry; the non-executed part is stored on the book as a limit order at that price. Limit orders are to be executed at the limit price or better. By default, orders expire at the end of the session. The maximum validity period is 90 calendar days and the minimum order size is one share. For every basic order type, special conditions are allowed, like "fill or kill", "execute or eliminate", "minimum execution", or "hidden volume".

The SIBE allows the submission of partially undisclosed limit orders. No mark indicates the condition of "hidden volume"; consequently only the supervisor of the SIBE and the broker that submits the order know of its presence. The investor chooses the "displayed

[6] Those stocks that do not comply with these requirements are assigned to a single-auction based market called "Fixing" where trades are only possible twice a day.

[7] Pre-arranged trades are possible, but only at the so-called Block Market and Off-Hours Market. The Block Market opens from 9:00 a.m. to 5:30 p.m., and the Off-Hours Market from 5:40 to 8:00 p.m. These segments allow market members to manage large volume orders, but under very rigid price and minimum size conditions. Data about these particular sections of the market are excluded from our database. There are also two daily call auctions that determine the official opening and closing prices that we do not consider either. In this paper, we concentrate exclusively on the continuous trading session.

volume unit" of the order, with a minimum of 250 shares. A new displayed volume unit emerges as soon as the current one is executed. The hidden part of the order loses, however, its time precedence.

The most important indicator of how the SSE is performing is the IBEX-35 index. It is composed of the 35 most liquid and active SIBE securities during the most recent six-months control period. The composition is ordinarily revised twice a year, but extraordinary revisions are possible due to major events like mergers or new stock issues. The IBEX-35 is computed as a cross-stock average trade price weighted by market capitalization.[8]

4. Data

The database consist of 6 months of book and trade files, from July to December 2000 (124 trading days), on 79 SSE-listed common stocks. It includes all the information disseminated in real time through the DIS to every market member connected to the system. The LOB files contain the five best buy and sell positions, including quotes, (displayed) depth, and number of orders. These files are updated each time the book changes and are time-stamped at the nearest hundredth of a second. The trade files are updated each time the first level of the LOB changes. For each trade, they provide information about the marginal price of the last share traded, the trade size, and the broker/dealers codes.

Among the 79 stocks, 35 were included in the IBEX-35 index during 2000, and 6 of them were dually-listed: 5 NYSE-listed and 1 NASDAQ-listed ADRs. The 6 dually-listed stocks are the most frequently traded and liquid ones. They account for 53.19% of the market capitalization and 72.63% of the market activity in 2000. In contrast, all the IBEX-35 (non-IBEX) stocks represent 72.68% (5.07%) of the market capitalization and 84.83% (3.44%) of the trading activity. Table I provides some descriptive daily statistics on all the stocks grouped

[8] For more complete and detailed information on the SSE regulation, organization and trading procedures please visit http://www.sbolsas.es.

into three portfolios: single-listed IBEX-35 stocks, dually-listed IBEX-35 stocks, and non-IBEX-35 stocks. Table I evidences striking differences between these stocks and the non-index stocks in terms of liquidity, activity and volatility. Clearly, non-index stocks are infrequently traded.

[Table I]

Since HLOs are not marked as such on the SIBE DIS screens, we cannot directly identify all iceberg order submissions and cancellations. Nonetheless, we have developed a reliable algorithm that detects a HLO when it is totally or partially executed and its presence then revealed to the whole marketplace. The algorithm works in the following way. First, we match the book and the trade files. After that, it is straightforward to classify all the updates of the LOB into cancellations, modifications, market (or marketable limit) orders (trades), market-to-limit orders, and limit orders.[9] The classification of trades as buyer or seller initiated is very simple. There are no reporting lags like in the NYSE data. All trades involve a market or marketable limit order that matches with a limit order previously stored on the limit order book. Therefore, a trade that consumes liquidity on the bid (ask) side of the LOB it is classified as a seller (buyer) initiated trade. To infer about the presence of hidden volume, we compare the reported trade sizes (changes in the accumulated volume) with the corresponding updates on the LOB. In the SIBE, a deviation between these two quantities can

[9] Briefly, a cancellation produces no increase in the accumulated trading volume and cuts the number of orders on the LOB by 1 unit. A modification causes neither an increase in the accumulated trading volume nor a decrease in the number of orders on the LOB, but it changes the available depth. A limit order augments the accumulated depth on the LOB and the number of orders supporting the limit order price (by 1 unit), but does not have an effect on the accumulated trading volume. In this case, the increase in the accumulated depth is equal to the size of the limit order except when it is a HLO. Like the cancellation case, a market order may also reduce the number of orders stored on the LOB, but it increases the accumulated trading volume. The change in the accumulated trading volume is equal to the size of the market order. Finally, a market-to-limit order that demands fewer shares than available on the best opposite quote is undistinguishable from a market order. However, an aggressive market-to-limit order consumes the best opposite quote and the unexecuted part is stored on the LOB at the limit price.

only be explained by the presence of hidden volume.[10] We illustrate this procedure in Table II. It provides four typical examples of HLO detection.

[Table II]

With this algorithm, we identify *executed* HLOs whilst we ignore unexecuted HLOs that expire or are cancelled. These data impose some potential biases on the empirical analyses that follow. Namely, if an informed trader were to submit a limit order, she would choose a limit price equal to or better than the best quote on the LOB in order to minimize the risk of non-execution and reduce the expected time to execution. Indeed, Anand and Weaver (2004) observe that between 60% and 73% of the HLOs submitted to the TSX are placed at or inside the bid-ask spread.[11] Hence, we would expect our algorithm to detect most of the information-motivated HLOs, if any. If we further assume that liquidity traders uniformly distribute their HLOs throughout the LOB, this would lead us to the worst possible scenario as to reject the null hypothesis that HLOs are concealing informed traders. As a result, our analysis would be biased toward concluding that HLOs are information-motivated. Instead, it might be the case that liquidity HLO traders also prefer to place their orders at or inside the bid-ask spread.[12] In this case, the executed HLOs sub-sample would be more representative of the (executed plus unexecuted) HLO sample, and the previous bias would be alleviated.

[10] We have discussed the output of the algorithm with market members and supervisors, and all of them agree with us on this assertion. Other possible explanations are discarded. For example, two market orders cannot interact with each other except when the book is empty on one side (a very rare event). Besides, each update on the LOB corresponds to a single order, that is, two or more orders cannot be registered on the book simultaneously (recall that LOB updates are recorded at the nearest hundredth of a second). Therefore, a limit order and a market order cannot interact with each other before the limit order is stored on the LOB.

[11] In our case, roughly 60% of all trades involving HLOs were fulfilled when there was only the HLO supporting the best quote. Following backwards the evolution of these HLOs, it is possible to find the exact time of submission of 104,452 orders. Around 93% of these orders were placed inside the bid-ask spread. The median time to execution was 3 minutes.

[12] Notice that non-competitive limit order traders would have fewer motives to hide order sizes. Firstly, patient traders, by definition, are willing to accept longer times to execution. Therefore, parasitic trading would be a minor inconvenience. Secondly, the larger premiums/discounts associated with non-competitive limit order prices could compensate the higher adverse selection costs faced by large limit order traders.

5. Cross-sectional analysis

In section 2, we pointed out that the inconsistencies between Aiken et al. (2001) and Anand and Weaver (2004) might be resolved if undisclosed volume, either information-driven or liquidity-driven, were to concentrate on active and liquid stocks. Informed HLO traders having preference for active stocks could be explained by the lower non-execution risk of limit orders. Regarding liquidity-motivated HLO traders, we would expect them to be, for the most part, large investors, such as institutions, because HLOs are large-sized orders (e.g., Harris, 1996, and D'Hondt et al., 2003). Institutional investors' performance is usually evaluated in terms of whether they beat the market portfolio. Therefore, independently of whether they track the index or not, we should expect institutional portfolios to be mostly composed of index constituents (e.g., Cushing and Madhavan, 2000), which sensibly are the most liquid and active stocks in the market. In this section, we check if HLOs are more likely in index stocks ("index" hypothesis) by grouping the SSE stocks into portfolios of index stocks and non-index stocks.

Even if the index hypotheses were finally accepted, we would still expect different patterns in the use of HLOs depending on the traders' motivation. Only liquidity traders face the adverse selection risk; hence, they should be more sensitive than informed traders to the exposure-risk of limit orders. In contrast, informed traders need to trade so as to realize their information advantage; thus, they should be more sensitive than liquidity traders to the non-execution risk of limit orders. We would therefore expect more HLOs among the less active index stocks if HLOs were, for the most part, liquidity-driven; contrarily, we would expect more HLOs among the most active index stocks if HLOs were mainly information-driven. We test this "liquidity" hypothesis by further splitting the SSE index stocks into cross-listed and single-listed index stocks; this is tantamount to separating the most active index stocks from the least active index stocks (see Table 1).

Finally, we suggest that the use of HLOs may depend on the time of trading. Harris (1998) and Bloomfield et al. (2005) study the choice between market orders and limit orders by different types of traders. In Harris' (1998) model, liquidity traders need to meet a target by a certain deadline. They generally prefer limit orders. However, when the deadline approaches and their limit orders do not fill, liquidity traders eventually switch to more aggressive orders. Large liquidity traders in Bloomfield et al. (2005) behave accordingly. In Harris (1998), informed traders submit limit orders when the spread is wide and the deadline is distant; otherwise, they trade aggressively. This implies that informed traders are also less likely to submit limit orders as time passes. Bloomfield et al. (2005), however, report the opposite pattern.[13] According to these studies, we would expect liquidity-motivated HLOs to decrease towards the end of the session.[14] Regarding information-driven HLOs, however, the expected pattern is uncertain. We test for intraday patterns in undisclosed volume by splitting the SSE session into subintervals.

First, we test the "liquidity" and "index" hypotheses. We compute for each stock the percentage of trades involving hidden volume from July to December 2000. Then, we group the stocks into three portfolios of SSE stocks: 29 single-listed IBEX-35 stocks (SLI), 6 dually-listed IBEX-35 stocks (DLI), and 44 non-IBEX-35 stocks (NI). For each portfolio, we

[13] Bloomfield et al. (2005) observe that informed traders in their experiment trade aggressively at the beginning of the game. However, once their private information has been incorporated into prices, they change their behavior and begin acting as dealers. Since private information is revealed through trading, this switch in behavior happens towards the end of the game. In this period, they no longer submit market orders because the bid-ask spread encloses the efficient price; as a result, the probability of informed limit order submissions increases. In contrast to Harris (1998), Bloomfield et al. (2005) do not incorporate operative costs in their experiment. This detail might partly explain the opposite patterns reported for the informed traders. If prices are efficient and, consequently, any information advantage of informed traders is negligible, aggressive limit orders may no longer be profitable once operative costs have been taken into account. That is, in Bloomfield et al. (2005) informed traders do not stop trading because the execution of an informed limit order is always profitable.

[14] Harris (1998) also finds that a wide spread encourages liquidity traders to submit more limit orders (see also Foucault, 1999). He also suggests that low volatility allows liquidity traders to place limit orders aggressively without giving up too much option value. This incentive, however, fades away when traders face a near deadline and the non-execution risk increases. It is very well known that market liquidity and volatility show L or U-shaped intraday patterns. Moreover, HLOs are more attractive than DLOs when volatility is high and spreads are wide because the option value of DLOs increases. If the deadline effect dominates, a U or L-shaped pattern in volatility may reinforce the predicted decreasing intraday pattern in uninformed HLOs.

compute the average percentage and standard deviation across stocks for trades executed against hidden volume.

For the 79 stocks in the sample, we find that 14.4% of all trades executed involved a HLO. This percentage changes to a significantly lower 10.36% for NI stocks, and it increases to 15.55% for the index constituents, but this increase is not statistically significant at the 1% level. Differences between index constituents and NI stocks are more striking as we further separate SLI from DLI stocks. The percentage for the cross-listed stocks is 13.15%, which is not statistically below the average 14.4%, but it is statistically above the NI percentage. For the SLI stocks, the percentage jumps to 17%, which is statistically higher than the mean and, consequently, it is also above the percentage for the other portfolios. These findings support the "index" hypothesis, since HLOs are more frequent in index constituents. Moreover, we find favorable evidence for the "liquidity" hypothesis, since HLOs are far more relevant in those index stocks that are less frequently traded.

In order to gain insight on the use of HLOs, we consider next the intraday distribution of HLOs. We break up the continuous trading session into seventeen 30-minute intervals. For each half-hour interval, we compute the percentage of trades involving HLOs, HLO_{it} hereafter. This is the dependent variable in the following cross-sectional time-series linear model, that we estimate using FGLS,

$$HLO_{it} = \sum_{h=1}^{17} \lambda_h^{sli} \left(H_{it}^h \times SLI_i \right) + \sum_{h=1}^{17} \lambda_h^{dli} \left(H_{it}^h \times DLI_i \right) + \sum_{h=1}^{17} \lambda_h^{ni} \left(H_{it}^h \times NI_i \right) + \varepsilon_{it}. \qquad [1]$$

The model is unbalanced since certain NI-stocks do not trade on all the 124 trading days considered. The explanatory variables are:

- SLI_i : Equals 1 if the *i*th stock is a SLI-stock and 0 otherwise.
- DLI_i : Equals 1 if the *i*th stock is a DLI-stock and 0 otherwise.
- NI_i : Equals 1 if the *i*th stock is not an index stock and 0 otherwise.

- H_{it}^{h}: Equals 1 if the observation corresponds to the *h*th half-hour interval and 0 otherwise.
- ε_{it}: The noise term. We allow ε_{it} being heteroskedastic across and autocorrelated within panels.

We plot the estimated intraday coefficients for the three portfolios and their mean in Figure 1. Standard Wald tests on the coefficients of model [1], not reported, evidence statistically significant differences (at the 1% level) in the intraday-patterns of the three portfolios. Figure 1 provides additional support to the "index" hypothesis. HLOs are more often involved in the trading activity of IBEX-35 stocks than in the trading activity of NI stocks during all the session. Indeed, NI stocks are systematically below the mean. With the exception of the first half-hour interval, the estimated coefficients for the SLI stocks are always above those estimated for the DLI stocks, with a maximum difference of 6% between 13:00 and 13:30. Moreover, SLI stocks are systematically above the mean. These findings corroborate the "liquidity" hypothesis.

[Figure 1]

Regarding the intraday distribution of HLOs, Figure 1 depicts a pattern that is more complex than Harris (1998) and Bloomfield et al. (2005) would suggest. During the first half of the session, HLO_{it} smoothly decreases for the DLI stocks while it increases for NI and SLI stocks. From 14:30 on, the detection of HLOs accelerates in all portfolios. This variation is particularly dramatic for the DLI stocks: from 14:30 to 16:00, HLO_{it} increases 64% for the DLI stocks versus 21% for the SLI and NI stocks.

The sharp increase in the use of HLOs is probably connected with the opening of the NYSE (15:30 Spanish time).[15] As the US market opening approaches, the SSE trading process

[15] Public announcements and international macro-indicators are frequently disseminated around the opening of the NYSE (15:30). In particular, our data comprise 29 announcements at 14:30 and 10 announcements at 16:00.

changes in many dimensions other than the use of HLOs.[16] The sudden increase in the average trade size of index stocks occurring from 15:00 on may be particularly relevant to understand the HLO pattern depicted in Figure 1. Up to 15:00, the trade size in the SSE is stable for all stocks. From 15:00 to 16:00 the average trade size increases 166% for SLI stocks and 194% for DLI; then, it stabilizes at these high averages. This pattern indicates that many large traders in the SSE wait for the opening of the NYSE to initiate their trading activity.

This concentration pattern by large traders may have several explanations. First, large liquidity traders may be looking for a low adverse selection risk period. By waiting until the NYSE opens, they may expect to find more efficient prices, as the uncertainty associated with the opening in the US is finally resolved. As well, they may delay trading in the hopes of finding another liquidity trader on the other side (Admati and Pfleiderer, 1988). Second, some institutional investors may be willing to operate near the close so as to minimize the tracking error. In addition, they can offset individual inflows and outflows occurring during the day, reducing the required amount of trading, and thereby their trading costs (e.g., Harford and Kaul, 1998). Finally, a concentration of liquidity-motivated traders also attracts informed traders. Admati and Pfleiderer (1988) demonstrate, however, that competition between informed traders intensifies the forces leading to the concentration of liquidity traders.

In accordance with Harris (1998) and Bloomfield et al. (2005), we should expect large liquidity traders to switch from limit orders to market orders as the market closure (their deadline) approaches. Figure 1 reveals the use of HLOs on IBEX-35 stocks to progressively decrease a total 10% for DLI stocks and 9% for SLI stocks the last one and a half hours.

We have included in model [1] dummy variables so as to control for public disclosures. Our conclusion is that these announcements cannot explain the increase in HLO use before the NYSE opening. Indeed, we only find a significant increase of 1.7% in HLO detection between 14:30 and 15:00 on announcement days.

[16] During our sample period, the trading activity, either measured by the number of trades or the share volume, the bid-ask spread, and the mid-quote volatility of the SSE experience a similar break point right before the opening of the NYSE. Volatility and trading activity decrease up to 15:00. From that moment on, both of them sharply increase. The bid ask spread accelerates its overall decreasing pattern right after the opening of the US market, achieving its minimum at the end of the trading session. These intraday patterns are not reported because of space limitations, but they are available upon request from the authors.

However, several patterns depicted in Figure 1 prevent us from concluding without question that HLOs are liquidity-motivated. A first issue is the smooth increasing pattern observed for the NI stocks during the last two hours. This behavior might suggest that investors submitting HLOs in these stocks either do not face a deadline or their deadline is distant, for example traders with long-lived private information. A second issue is the different behavior observed for cross-listed stocks and single-listed stocks during the first six and a half hours of trading, which suggests traders with different motivations or trading interests using HLOs. A final issue is the larger increase in HLO use for DLI stocks around the opening of the NYSE. Following Anand and Weaver (2004), this finding could signal informed HLO traders focusing on stocks with the lowest expected non-execution risk. This explanation, however, would be hard to reconcile with the decreasing pattern in HLO_{it} observed afterwards. As we have previously noted, these cross-listed stocks account for 70% of the IBEX-35 capitalization. Therefore, institutions tracking the index might just need these stocks so as to replicate the index. Furthermore, cross-listed stocks may concentrate the interest of the non-Spanish institutional investors.

In summary, our findings show that HLO traders prefer to trade index constituents, supporting our "index" hypothesis. Moreover, they submit more orders among those index stocks with higher exposure-risk, in accordance with our "liquidity" hypothesis. These findings may reconcile the contradictory findings in previous studies. The intraday analysis, however, shows a complex pattern that is not totally supported by the theoretical predictions. Although the behavior observed is consistent with the deadline effect suggested by Harris (1998) and Bloomfield et al. (2005) for large liquidity traders, we need further evidence to corroborate this point. In the next section, we check whether HLO traders behave as institutions.

6. HLOs and stock returns

Several studies have analyzed the trading behavior of institutional investors using quarterly and yearly data.[17] They document that institutions are momentum investors, also known as trend chasers or positive feedback traders. These traders tend to follow past returns, buying tomorrow in response to an increase in today's price. They also find a strong contemporaneous relationship between institutional buy-sell imbalances and stock returns. Finally, mutual funds sometimes tend to move together or engage in herding behavior.

Recently, Griffin et al. (2003) have studied the relationship between institutional buy-sell imbalances and stock returns in the Nasdaq market using intraday data. Their findings support former research. They also show that the strong contemporaneous relationship between daily stock returns and institutional ownership reported in previous studies is primarily explained by the intraday trend chasing behavior of institutions. Next, we use intraday data on HLO imbalances and stock returns to check whether the HLO traders in index stocks behave as institutions.

We estimate the dynamic panel-data models in equations [2] and [3] for the 35 index stocks, both SLI and DLI stocks. We compute the time series of continuously compounded quote midpoint returns (R_{it}) and a proxy for the changes on HLO traders' inventories (NH_{it}) in every 30-minute interval. We obtain R_{it} using the first and the last quote midpoint in each interval. We define NH_{it} as the difference between executed HLOs to sell minus executed HLOs to buy. We standardize both R_{it} and NH_{it} per stock and half-hour interval.

$$NH_{it} = \sum_{j=1}^{k} \alpha_{t-j} NH_{it-j} + \sum_{j=1}^{k} \beta_{t-j} R_{it-j} + \varepsilon_{it} \qquad [2]$$

$$R_{it} = \sum_{j=1}^{k} \lambda_{t-j} NH_{it-j} + \sum_{j=1}^{k} \gamma_{t-j} R_{it-j} + \xi_{it} \qquad [3]$$

[17] See Grinblatt et al (1995), Odean (1998), Wermers (1999), and Grinblatt and Keloharju (2000).

Equation [2] involves the linear projection of net HLO trading on its own lagged values and the lagged returns. If HLO traders were to rely on momentum, we would expect negative β coefficients. Moreover, if HLO traders were to engage in herding behavior, we would anticipate positive α coefficients. Equation [3] involves the linear projection of returns on its own lagged values and the lagged net HLO trading. This equation is used to test for predictability of stock returns by HLOs imbalances. Note that, a priori, negative λ coefficients would be inconsistent with HLOs being liquidity traders.

Table III provides the FGLS estimates of equations [2] and [3], truncated at lag 5, for all the index constituents, DLI plus SLI, and for the DLI stocks alone. No overnight return has been considered, and no lag reaches back to the previous day. We control for heteroskedasticity across panels and first-order autocorrelation within panels.

[Table III]

Table III shows that NH_{it} is positively autocorrelated, implying persistence in the trading positions of HLO traders at the intraday level. If we assume that HLO trading in a stock is not dominated by any particular HLO trader, persistence in NH_{it} is consistent with herding behavior (Griffin et al., 2003). Moreover, HLO-trading largely follows past stock returns. HLOs to buy (sell) are more frequent than HLOs to sell (buy) for those stocks with positive (negative) returns in preceding intervals. Consequently, HLO traders are engaged in trend chasing. These patterns are particularly strong for the SLI stocks, consistent with the "liquidity effect" reported in the previous section.

Table III provides several statistical tests on the β coefficients in equation [2]. The sum of the β coefficients is statistically different from zero at the 1% level for the SLI stocks and at the 5% level for the DLI stocks. Moreover, these coefficients are globally statistically significant at the 1% level.

In summary, the estimation of equation [2] agrees with those supporting the idea that HLOs conceal liquidity-motivated institutional investors. The results from equation [3] in Table III, however, cast some doubt on it. We find evidence of a statistically significant short-term return predictability of net HLO trading on stock returns. Posterior intraday returns tend to move in the same direction as precedent HLO imbalances. Certainly, this return predictability seems to be weak, with most of the coefficients only statistically significant at the 10% level and with the first lag of NH_{it} being not statistically significant. Statistical tests reported in Table III, however, indicate that this effect can not be disregarded. Nonetheless, information is not the only possible explanation for this finding. Keim and Madhavan (1995) argue that institutions that pursue a technical trading strategy, e.g., a momentum strategy, may exacerbate price movements. Griffin et al. (2003) report a similar finding in their analysis of institutional trading, and they conclude that it is due to temporary overreaction to the activity of these investors. In the next section, we perform a trade-by-trade analysis that seeks to clarify if there is any statistically relevant intraday informative effect of HLO trading.

7. The information content of hidden orders

So far, our study has been inconclusive regarding what motivates traders to submit HLOs. However, none of the analyses previously reported, however, represent a direct test on the information content of HLOs. Next, we perform such a test. In the SSE, HLO traders are exposed to the marketplace when their orders are executed. Hence, we can evaluate the motivation of HLOs by examining how stock returns and price volatility react when HLOs are unveiled. If HLO traders were information-motivated, we would expect prices to move in the direction of the disclosed HLO. Namely, prices would tend to increase (decrease) when HLOs are detected on the bid (ask) side of the LOB. In addition, the disclosure of these orders would increase volatility in the short-term as prices would adjust to the new information.

We look for additional insights on the motives of HLO traders by studying their influence on other traders' behavior. In particular, we assess the effect of discovering HLOs on the liquidity provision and the order flow composition. If HLOs were information-motivated, we would expect liquidity to deteriorate once the presence hidden volume has been revealed, because of the increase in adverse selection costs. Moreover, if HLO traders were to provide some new information, we would expect other traders to mimic them. Namely, we would predict more buyer (seller)-initiated trades when HLO buyers (sellers) are exposed to the market. Moreover, we would expect imitators to trade aggressively so as to make profits before the new information is totally incorporated into prices.

The experiment is designed as follows. We construct two samples of matched trades. The first sample includes trades revealing the presence of HLOs on either side of the LOB (henceforth, TH trades). The second sample includes matched "ordinary" trades, that is, trades that do not involve hidden volume (henceforth, TO trades). A TH trade and a TO trade match if both are either buyer or seller-initiated, equally-sized, and executed under similar market conditions. We use these matched samples to test for statistically significant differences in terms of post-trade stock returns, volatility, liquidity, trading activity, and order flow composition. Since trades match in every aspect except the revelation of hidden volume, any post-trade difference should be attributed to the HLOs involved in the TH trades. Notice that buyer (seller)-initiated TH trades reveal HLOs on the ask (bid) side of the LOB, that is, HLOs to sell (buy). Next, we summarize the details of the matching procedure.

For each stock, we separate buyer from seller-initiated trades (henceforth, BITs and SITs respectively). We eliminate any TH trade preceded by some other TH trade within a 5-minute interval. In this manner, we only pick up those TH trades that were the first in revealing the presence of undisclosed volume on a given quote. Similarly, we discard every TO trade preceded or followed by a TH trade within a 5-minute interval. With this filter, we seek to minimize the risk of market conditions near ordinary trades being contaminated by TH trades.

For each trade remaining, we compute the post-trade quote midpoint returns (QR_t) and volatility (QV_t) as,

$$QR_t = \log(Q_\tau / Q_t), \qquad [4]$$

$$QV_t = \left(\log(\overline{Q}_t^\tau) / \log(\underline{Q}_t^\tau)\right) - 1, \qquad [5]$$

where τ > t defines 4 different time intervals (τ - t): 5, 10 and 30 minutes, and until the end of the trading session; Q is the quote midpoint, and $\overline{Q}_t^\tau$ ($\underline{Q}_t^\tau$) is the maximum (minimum) of Q in the interval (t ,τ]. We standardize these variables per half-hour interval.

In addition, for each minute in a five-minute window before and after each trade, we compute and standardize the following variables:

- Returns (R_t): As in [4], but with Q at the end and at the beginning of each minute.
- Volatility (VLT_t): As in [5], but using the maximum and minimum of Q in each minute.
- Bid-ask spread (SPR_t): Average number of ticks between the best offer and bid quotes weighted by time.
- Net depth (ND_t): Average difference between the displayed shares on both sides of the LOB weighted by time.
- Net trades (NT_t): Difference between the number of buyer-initiated and seller-initiated trades (market orders or marketable limit orders).
- Net volume (NV_t): Difference between the buyer-initiated volume and the seller-initiated volume in shares.
- Net limit orders (NLO_t): Difference between limit orders to buy and limit orders to sell submitted.

BITs and SITs are further partitioned into seven trade-size categories each, henceforth S1 to S7. These categories are defined by the 25%, 50%, 75%, 90%, 95%, and 99% sign and stock-specific percentiles of the empirical distribution of trade sizes. We group all trades across stocks by size category, from S1 to S7. Then, for each category, we compute the 10%, 30%, 50%, 70%, and 90% percentiles of the pre-trade empirical distribution of the control variables R_t, VLT_t, SPR_t, ND_t, NT_t, NV_t, and NLO_t. These percentiles are used as thresholds to define 6 value-intervals, henceforth L1 to L6, which will typify the level of each control variable in the pre-trade matching period. Different matching periods have been considered, from 1 to 5 minutes. Our main findings are independent of the matching interval considered. Thus, we will only report the results for the 5-minute pre-trade matching interval.

For each TH trade, we look for a TO trade with the same sign, the same size category, and with perfectly matching pre-trade market conditions, i.e., the same level in each control variable. When no matching occurs, the TH trade is eliminated. When multiple matching occurs, we choose the TO trade that minimizes the sum of the absolute deviations in prior market conditions with respect to the TH trade of reference.

After all this process, we end up with 14 matched samples, 2 for each of the 7 trade-size categories, 7 for BITs, and 7 for SITs. Table IV provides some details on the resulting matched samples. The percentage of matched TH trades is high, with an average success of 98.5% for BITs and 97% for SITs. Table IV also shows that there are no remarkable trade size differences between the matched samples.

[Table IV]

We check for differences in post-trade market conditions between TH and TO trades using the non-parametric Wilcoxon test of equality of medians (H_0: TH=TO). We consider different alternative hypotheses for this test: the medians are different (H_1: TH≠TO); the median for TH trades is larger than the median for TO trades (H_1: TH>TO); and the median for TH trades is smaller than the median for TO trades (H_1: TH<TO).[18] Rejections of the null would be

[18] We only report the findings for the first two alternatives. The third alternative (H1: TH < TO) is redundant

attributed to the effect of disclosing hidden volume. To get more robust findings, tests are performed over 1000 subsamples of 1000 trades each, randomly selected with replacement from the S1 to S7 samples described in Table IV.

Tables V and VI summarize our main findings. For each particular variable, we report the percentage of cases for which the null (H_0: TH=TO) is rejected at the 1% level. We distinguish between TH trades revealing HLOs on the ask side the LOB, and TH trades revealing HLOs on the bid side of the LOB.

Table V focuses on the impact of hidden volume disclosure on liquidity and order flow. We consider the 10-minute interval centered on the time stamp of each trade (*t* in the table). Due to the limited space, we only report the findings when HLOs are revealed by medium-sized (S4) TH trades. The results for the other trade-size categories are similar and available upon request from the authors.

[Table V]

The pre-trade interval t-5 to t in Table V is the 5-minute matching interval. The results for this particular period support the null hypothesis of equality of medians for all the variables, with percentages of rejection close or equal to zero. This simply proves the precision of the matching process. Regarding the post-trade interval, from t to t+5, our findings do not support the notion HLOs are information-motivated. First, liquidity does not deteriorate following the HLO detection. The null of equal bid-ask spreads is never rejected against the alternative that the spread after TH trades is wider than after TO trades. Regarding the net LOB depth (ND_t), the null hypothesis is strongly supported. Therefore, our evidence does not concord with an increase in adverse selection costs when the presence of HLOs is revealed to the marketplace.

Second, the aggressiveness of traders suddenly increases at least one minute after a HLO is detected. The discovery of hidden volume fosters the trading activity. In 85% (83%) of the

given the results for the other two. In any case, the results are available upon request from the authors.

subsamples, we reject the null of equal NV_t one minute after a HLO is unveiled on the offer (bid) side of the LOB. However, these incoming traders do not mimic HLO traders. We observe negative (positive) net trading when HLOs to buy (sell) are exposed to the market. A similar, but weak, pattern is observed for the net number of trades (NT_t), with percentages of rejection of 26% and 27.9% respectively. Regarding the submission of limit orders, the equality of NLO_t is rejected less frequently, with percentages of only 9.6% and 3.7% respectively. Globally, these findings indicate that HLO detection encourages large market-order traders on the opposite side of the market. Intuitively, the possibility of buying or selling larger quantities at the same cost induces traders to submit more aggressive orders to consume the hidden part of the available liquidity. All these effects, however, dissipate quickly.

In Table VI, we provide the results for the post-trade mid-quote returns (QR_t) and the mid-quote volatility (QV_t). We report the findings for three trade-size categories: small trades (S1), medium-sized trades (S4), and large-sized trades (S7). If HLO traders were information-motivated, we would expect QR_t to increase (decrease) when hidden volume is revealed on the bid (ask) side of the LOB. Our findings, however, show no remarkable differences in stock returns. Almost all the percentages of rejection of the null hypothesis are below 10%, independently of the time horizon and trade-size category considered. Regarding volatility, if HLOs were informative we would expect volatility to increase as soon as the presence of HLO traders becomes public knowledge. However, we observe that volatility is slightly lower after TH trades than after TO trades on both small and medium-sized trades. Thus, the null of equal volatility in the first post-trade 5 minutes is rejected for 24.1% (34.80%) of the S1 (S4) subsamples. No relevant incidence is observed on the largest trade-size category. Nonetheless, this volatility effect dissipates in 5 to10 minutes.

[Table VI]

In summary, our findings suggest that HLOs induce traders on the opposite side of the market to act more aggressively in the very short-term. These same traders, however, do not consider the hidden side of liquidity to be informative about the true value of the stock. Consequently, neither volatility nor stock returns are affected by the disclosure of hidden volume.

8. Conclusions

This paper has studied what motivates those traders that choose to hide their trading interests by using hidden limit orders (HLOs). A first tentative hypothesis suggests they are liquidity-motivated traders trying to manage their exposure risks. A second tentative hypothesis postulates that they are information-motivated traders that want to minimize the price impact of their trades. We have analyzed the case of the HLO traders that operate in the continuous electronic order-driven market of the Spanish Stock Exchange (SSE). In the SSE, HLOs have a relatively small displayed volume unit (250 shares); as a consequence, they are more frequently used than in other markets. Moreover, HLOs are less exposed than in other markets, since they are only detected if they are either totally or partially executed. Our database consists of six months of book and trade files on 79 stocks, which we have used to get a large sample of *executed* HLOs.

The contribution of this paper is twofold. First, we show that the contradictory findings reported in previous related studies may be reconciled. Namely, we evidence that HLO traders in the SSE focus on index constituents, but they are particularly active on those with higher exposure risk. These findings may settle the apparently contradictory findings in Aiken et al. (2001) and Anand and Weaver (2004) regarding HLO traders in the Australian and Toronto Stock Exchanges. We show that HLO traders may concentrate on active stocks and still behave consistently as liquidity-motivated traders.

Second, we provide brand new evidence on the behavior of HLO traders. We observe that the use of HLOs sharply increases right before the opening of the NYSE, two hours before the SSE closure. From that moment on, the use of HLOs progressively decreases for index stocks. The decreasing pattern in the use of HLOs towards the end of the session is consistent with theoretical predictions in Harris' (1998) model regarding the behavior of large liquidity traders facing a deadline (i.e., the market closure). Furthermore, we report that HLO traders behave like the literature has shown institutional investors do. They are trend chasers and engage in herding.

Although all this evidence suggests that HLO traders may be large liquidity traders, these preliminary analyses can not be considered as conclusive. Among other intriguing findings, we find some degree of predictability of stock returns by preceding HLOs buy-sell imbalances; opposite regularities in the use of HLOs during the first half of the SSE session between cross-listed stocks (decreasing use) and the rest of the sample (increasing use), and a slow but increasing pattern in the use of HLOs from the opening of the NYSE to the closure of the SSE for the non-index stocks.

So as to get more conclusive evidence, we have also implemented a direct test on the informativeness of HLOs using trade-by-trade data. We look at stock returns and volatility immediately after the disclosure of HLOs, which happens when a market order is executed against a HLO stored on the limit order book. We also analyze other traders' responses when the presence of HLO traders is revealed. We find that, when the strategy of a HLO trader is disclosed, the other traders do not act as copycats. They become more aggressive, but on the opposite side of the market. Moreover, neither liquidity deteriorates nor volatility increases, and, more importantly, the detection of HLOs has no relevant price impact.

Considering the big picture, our evidence is more favorable to the notion that HLO trading is for the most part liquidity-motivated, and very probably due to large liquidity institutional traders. Therefore, market regulators could draw two basic implications from the SSE experience. First, the main motive of submitting HLO in the SSE is to manage the option value of the limit orders. Second, iceberg orders in the SSE do not have distorting effects either on prices or on volatility.

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TABLE I
Daily Statistics

This table contains daily average statistics for the 79 SSE-listed stocks in the sample, from July to December 2000. We group the stocks into three portfolios: single-listed index-constituent stocks (29), dually-listed index-constituent stocks (6), and (single-listed) non-index stocks (44). The table contains the median for each variable on the 124 trading days in the sample. “Volume” is the number of shares traded each day. “Trades” are the number of trades completed each day. “Midpoint volatility” is the difference between the daily maximum and minimum of the quote midpoint divided by its median. “LOB updates” are the number of changes in the 5 best levels of the LOB in a given day. “Limit orders submitted” are the number of buyer and seller-initiated limit orders submitted each day. “Relative spread” is the bid-ask spread divided by the quote midpoint (averaged weighting by time). “Book depth” is the mean of the accumulated displayed shares stored at the 5 best ask and bid quotes on the LOB (averaged weighting by time).

	Index-constituent Stocks		
	Single-listed	Dually-listed	Non-Index Stocks
Volume (Shares)	259450	5489858	27417
Trades	323	2216	36
Midpoint Volatility	0.0091	0.0087	0.0071
LOB updates	762	3981	101
Limit orders submitted	297	1286	44
Relative Spread	0.0011	0.0003	0.0035
Book (5 best) Depth (shares)	5467	34975	4658

TABLE II
Examples of HLO detection

This table reports 4 illustrative examples of HLO detection. For each case, the table reports the 3 best levels of the LOB before and after a trade took place. Case #1: It seems that a market-to-limit order consumes the 1931 shares available at the best ask (9.75€). The unexecuted part of the order is stored at that price on the bid side of the book. The trade file, however, reports a trade size of 3063 shares. Thus, the algorithm reveals that the actual size of the market-to-limit order was 6000 (2937+3063) shares and that the limit order supporting the best ask was a HLO (Stock: ACR, 7-4-2000, 1:53:11 p.m.). Case #2: It seems that a market order (or equivalent) consumes 1853 shares at the best bid (9.8€) and, as a consequence, one limit order is totally executed. The trade file reports a trade size of 3000 shares. In this case, the algorithm reveals that at least one of the three orders supporting the best bid was a HLO (Stock: ACR, 7-4-2000, 2:56:12 p.m.). Case #3: Apparently, a market order (or equivalent) consumes the best bid (22.63€), 4391 shares. The trade file, however, reports a trade size of 26391 shares. The algorithm reveals a HLO at 22.63€ with 22000 shares hidden. The arriving order is, probably, a market order with an "execute or eliminate" condition for a size larger than 26391 shares (Stock: TEF, 7-3-2000, 9:16:44 a.m.). Case #4: It seems that a market order (or equivalent) of 457 shares reduces the quoted depth at 22.64€ from 824 shares to 367 shares. The trade file, however, reports a trade size of 5457 shares. The algorithm reveals a HLO at 22.64€ with displayed volume unit 5000 shares: 824 (displayed) – 5457 (demanded) + 5000 (displayed volume unit) = 367 (Stock: TEF, 7-3-2000, 9:13:46 a.m.).

Case #1: Before the trade			After the trade		
Quote	Depth	Orders	Quote	Depth	Orders
9.79	1700	2	9.8	3400	3
9.78	1300	2	9.79	1700	2
9.75	1931	3	9.78	1300	2
9.72	1833	2	9.75	2937	1
9.71	588	3	9.72	1833	2
9.7	10833	14	9.71	588	3

Case #2: Before the trade			After the trade		
Quote	Depth	Orders	Quote	Depth	Orders
9.84	2300	2	9.84	2300	2
9.83	2219	2	9.83	2219	2
9.82	847	1	9.82	847	1
9.8	3152	3	9.8	1299	2
9.79	3000	2	9.79	3000	2
9.77	1000	1	9.77	1000	1

Case #3: Before the trade			After the trade		
Quote	Depth	Orders	Quote	Depth	Orders
22.68	2696	1	22.68	2696	1
22.67	145	1	22.67	145	1
22.65	2718	2	22.65	2718	2
22.63	4391	2	22.61	3443	3
22.61	3443	3	22.6	4626	13
22.6	4626	13	22.56	500	1

Case #4: Before the trade			After the trade		
Quote	Depth	Orders	Quote	Depth	Orders
22.67	145	1	22.67	145	1
22.66	1500	1	22.66	1500	1
22.65	5578	2	22.65	5578	2
22.64	824	1	22.64	367	1
22.63	4000	2	22.63	4000	2
22.61	3443	3	22.61	3443	3

TABLE III
HLO trading and stock returns

This table reports the FGLS estimated coefficients of two panel-data models,

$$NH_{it} = \sum_{j=1}^{k} \alpha_{t-j} NH_{it-j} + \sum_{j=1}^{k} \beta_{t-j} R_{it-j} + \varepsilon_{it} ,$$

$$R_{it} = \sum_{j=1}^{k} \lambda_{t-j} NH_{it-j} + \sum_{j=1}^{k} \gamma_{t-j} R_{it-j} + \xi_{it} .$$

The two dependent variables are (a) continuously compounded quote midpoint returns (R_t), and (b) changes on HLO traders' inventories (NH_t). We compute NH_t as the difference between executed HLOs to sell minus executed HLOs to buy. They are computed in 30-minute intervals. No overnight returns are allowed and no lag reaches back to the previous day. All the variables are standardized per stock and half-hour interval. We provide the estimation results for the 35 index constituents (single plus dually listed) and for just the 6 dually-listed index stocks. We also report four statistical tests: (a) a Wald test on the global significance of all the coefficients of the model; (b) a Wald test on the null that the sum of the β (λ) coefficients in the first (second) equation is zero; (c) a Wald test on the null that each model can be reduced to the autoregressive structure; that is, β_{t-j} =0 (λ_{t-j} =0) ∀j in the first (second) equation; (d) a likelihood ratio test on the same null as in the (c) test. P-values appear in parenthesis.

	Index stocks		Dually-listed index stocks	
	NH_{it}	R_{it}	NH_{it}	R_{it}
NH_{it-1}	0.2005 *	-0.0017	0.3055 *	-0.0049
NH_{it-2}	0.0814 *	-0.0045	0.0785 *	-0.0201 ***
NH_{it-3}	0.0490 *	-0.0091 ***	0.0642 *	0.0151
NH_{it-4}	0.0456 *	-0.0086 ***	0.0457 *	-0.0222 ***
NH_{it-5}	0.0409 *	-0.0152 *	0.0305 *	-0.0289 **
R_{it-1}	-0.0175 *	0.0281 *	-0.0507 *	0.0048
R_{it-2}	-0.0322 *	-0.0105 **	-0.0150	-0.0118
R_{it-3}	-0.0242 *	0.0054	-0.0144	-0.0124
R_{it-4}	-0.0163 *	0.0101 **	0.0219 **	0.0270 **
R_{it-5}	-0.0093 **	-0.0058	0.0092	-0.0066
Obs.	51816	51784	8910	8910
Stocks	35	35	6	6
Log Lklhd.	-71128.69	-73183.89	-11883.24	-12587.82
Tests on the coefficients				
(a) Wald $\chi^2(10)$	4225.18	86.66	1572.64	29.1
	(0.0000)	(0.0000)	(0.0000)	(0.0012)
(b) Wald $\chi^2(1)$	115.75	27.01	5.12	13.41
	(0.0000)	(0.0000)	(0.0236)	(0.0002)
(c) Wald $\chi^2(5)$	133.58	32.14	36.86	20.47
	(0.0000)	(0.0000)	(0.0000)	(0.0009)
(d) LR-Test $\chi^2(5)$	761.28	32.07	48.81	20.4
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

* Statistically significant at the 1% level.
** Statistically significant at the 5% level.
*** Statistically significant at the 10% level.

TABLE IV
Matched Samples

This table provides descriptive statistics on matched samples of ordinary trades or TO trades (reported as "No Hidden") and trades involving hidden volume or TH trades (reported as "Hidden"). We construct separate sub-samples for buyer-initiated trades (BIT) and for seller-initiated trades (SIT). We further separate BIT and SIT into 7 trade-size categories, S1 to S7. S1 includes the smallest trades and S7 the largest ones. These 7 categories are defined using the 25, 50, 75, 90, 95, and 99% percentiles of the empirical distribution of the trade-size per stock and trade-sign (BIT versus SIT). The market conditions preceding each trade are characterized in terms of liquidity (bid-ask spread, depth and limit orders submitted), volatility of the quote midpoint, activity (share volume and number of trades) and midpoint returns. For each of these variables we define 6 value-levels (L1 to L6) using as thresholds the 10, 30, 50, 70, and 90% percentiles of its pre-trade empirical distribution. We consider a 5-minute pre-trade matching interval. Two trades are matched if they are both either BIT or SIT, belong to the same trade-size category (from S1 to S7), and are preceded by similar market conditions (L1 to L6), for every dimension, in the pre-trade matching interval. For each sample, the table reports the average trade size (standard deviation in parenthesis), and the number of TH trades finally matched, both in absolute terms and in relative terms (in parenthesis).

			Size cathegory						
			S1	S2	S3	S4	S5	S6	S7
Hidden	BIT	Avg. Size	114.79	352.01	994.32	2657.85	5271.91	10859.10	46247.31
			(66.8)	(233.0)	(838.8)	(2303.3)	(3871.9)	(9030.2)	(109688.6)
No Hidden	BIT	Avg. Size	91.61	303.24	831.63	2397.86	5256.29	10905.91	92795.30
			(63.7)	(218.8)	(757.9)	(2194.3)	(3988.0)	(9247.2)	(328943.0)
		Obs.	5711	14521	31856	38630	17441	18923	4025
		% matched	(99.7)	(99.7)	(99.6)	(99.5)	(98.4)	(98.0)	(94.4)
Hidden	SIT	Avg. Size	98.77	258.31	674.07	2051.07	4666.59	10353.14	46042.97
			(59.1)	(134.8)	(428.3)	(1494.8)	(3046.6)	(7472.0)	(125460.3)
No Hidden	SIT	Avg. Size	79.85	223.72	616.47	2036.86	4956.41	10577.84	87180.25
			(54.3)	(124.1)	(409.9)	(1492.2)	(3150.2)	(7360.0)	(261565.5)
		Obs.	5211	11199	26722	36255	19024	19634	3964
		% matched	(90.4)	(99.7)	(99.7)	(99.5)	(98.7)	(97.7)	(93.7)

TABLE V
Liquidity and order flow

This table provides evidence on the impact of the disclosure of hidden limit orders (HLOs) on both liquidity and the composition of the order flow. Liquidity is measured by the bid-ask spread (*SPR*) and the net depth on the limit order book (ask minus bid depth) (*ND*). The net (buyer minus seller-initiated) share volume (*NV*), the net number of trades (*NT*) and the net number of limit orders submitted (*NLO*) stand for the order flow composition. We standardize all these variables per stock and intraday time interval. We consider two types of trades: (a) TH trades reveal the presence of HLOs on a given side of the limit order book; (b) TO trades are "ordinary trades", in the sense that they do not reveal the presence of HLOs. All trades are separated into buyer-initiated and seller-initiated, and further split into 7 trade-size categories (S1 to S7). We report the results for the medium-sized (S4) trades only, that is, those with size between the 75% and 90% percentiles of the trade-size empirical distribution of the corresponding stock. We construct 1000 subsamples with 1000 matched TH and TO trades each. Two trades are matched if they have a similar size, the same sign (buyer / seller-initiated), and are preceded by similar market conditions. To test the null of equality of medians (TH=TO), we use the non-parametric Wilcoxon test. This table provides the percentage of subsamples for which the null is rejected against the alternative (a) the medians are different (TH≠TO) or (b) the median for the TH trades is bigger than for the matched TO trades (TH>TO). We consider the 10-minute interval centered on the execution of the trades (t), and execute the test minute by minute from t-5 to t+5 (with t-5 to t-1 being the matching interval).

		Percentage of Rejections at the 1% level (H0: Equality of medians)																			
		Ask side of the book										Bid side of the book									
		Pre-trade 1-minute intervals					Post-trade 1-minute intervals					Pre-trade 1-minute intervals					Post-trade 1-minute intervals				
Variable	Test (H1)	t-5	t-4	t-3	t-2	t-1	t+1	t+2	t+3	t+4	t+5	t-5	t-4	t-3	t-2	t-1	t+1	t+2	t+3	t+4	t+5
SPR_t																					
	TH ≠ TO	0.00	0.00	0.00	0.00	0.00	18.10	9.10	2.90	2.40	0.90	0.00	0.00	0.00	0.00	0.00	10.00	7.60	3.40	3.20	3.10
	TH > TO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
ND_t																					
	TH ≠ TO	0.00	0.00	0.00	0.00	0.10	0.00	0.20	0.30	0.20	0.80	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.30	0.90	0.30
	TH > TO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.10	0.20	0.90	0.30
NV_t																					
	TH ≠ TO	0.50	0.50	0.20	0.60	10.60	85.90	1.50	1.30	0.90	1.20	0.80	0.80	2.00	0.30	0.70	83.30	3.20	1.00	1.20	1.40
	TH > TO	0.30	0.50	0.20	0.60	0.00	85.90	1.50	1.10	0.90	1.00	0.00	0.00	0.00	0.00	0.60	0.00	0.00	0.00	0.10	0.00
NT_t																					
	TH ≠ TO	0.70	0.50	1.10	0.60	0.40	26.10	5.12	2.81	3.40	4.41	0.10	0.30	0.50	0.20	0.20	27.90	2.91	2.21	0.40	1.20
	TH > TO	0.60	0.50	1.10	0.60	0.00	26.10	5.12	2.81	3.40	4.41	0.10	0.00	0.00	0.00	0.20	0.00	0.20	0.00	0.00	0.00
NLO_t																					
	TH ≠ TO	0.60	1.21	0.71	1.50	2.11	9.63	3.62	1.81	1.31	1.01	0.60	0.61	0.30	0.20	13.03	3.73	1.01	0.90	2.81	0.60
	TH > TO	0.10	0.00	0.00	0.00	2.11	0.00	0.00	0.00	0.00	0.10	0.60	0.20	0.10	0.00	0.00	3.63	0.40	0.10	0.10	0.20

TABLE VI
Returns and volatility

This table summarizes the impact of hidden volume on stock returns and volatility when it is revealed. For each trade, we compute the post-trade mid-quote returns (QR_t) and the mid-quote volatility (QV_t) as,

$$QR_t = \log(Q_\tau / Q_t) ,$$
$$QV_t = \left(\log(\overline{Q}_t^\tau) / \log(\underline{Q}_t^\tau)\right) - 1 ,$$

where τ > t defines 4 different time intervals (τ - t): 5, 10 and 30 minutes and until the end of the trading session; Q is the quote midpoint, and $\overline{Q}_t^\tau$ ($\underline{Q}_t^\tau$) is the maximum (minimum) of Q in the interval (t,τ]. We standardize these variables per stock and half-hour interval of the trading session. We consider two types of trades: (a) TH trades reveal the presence of HLOs on a given side of the limit order book; (b) TO trades are "ordinary trades", in the sense that they do not reveal the presence of HLOs. All trades are separated into buyer-initiated and seller-initiated, and further split into 7 trade-size categories (S1 to S7). We report the results for the small (S1), medium-sized (S4), and large (S7) trades. We construct 1000 subsamples with 1000 matched TH and TO trades each. Two trades are matched if they have a similar size, the same sign (buyer / seller-initiated), and are preceded by similar market conditions in a 5-minute window before their time stamp. To test the null of equality of medians (TH=TO), we use the non-parametric Wilcoxon test. This table provides the percentage of subsamples for which the null is rejected at the 1% level against the alternative (a) the medians are different (TH≠TO) or (b) the median for the TH trades is bigger than for the matched TO trades (TH>TO).

Panel A: Returns	Percentage of Rejections at the 1% level (H0: Equality of medians)								
Trade-size category	Test (H1)	Ask side of the book				Bid side of the book			
		t+5	t+10	t+30	Closing	t+5	t+10	t+30	Closing
S1 (Small)	TH ≠ TO	2.40	0.80	1.10	2.30	0.91	0.80	0.60	4.30
	TH > TO	0.00	0.00	0.10	0.10	0.91	0.80	0.20	4.30
S4 (Medium-sized)	TH ≠ TO	3.80	4.40	3.80	7.90	7.62	10.11	10.00	10.60
	TH > TO	0.00	0.00	0.00	0.00	7.62	10.11	10.00	10.60
S7 (Large)	TH ≠ TO	8.12	11.30	2.10	7.20	3.03	1.51	1.40	5.02
	TH > TO	0.00	0.00	0.00	0.00	0.00	0.10	1.30	4.91

Panel B: Volatility	Percentage of Rejections at the 1% level (H0: Equality of medians)								
Trade-size category	Test (H1)	Ask side of the book				Bid side of the book			
		t+5	t+10	t+30	Closing	t+5	t+10	t+30	Closing
S1 (Small)	TH ≠ TO	24.10	2.50	1.00	0.50	9.80	2.80	1.30	13.70
	TH > TO	0.00	0.00	0.00	0.00	0.00	0.00	0.00	13.70
S4 (Medium-sized)	TH ≠ TO	34.80	20.60	4.00	0.90	34.40	13.70	5.01	2.60
	TH > TO	0.00	0.00	0.00	0.20	0.00	0.00	0.00	2.60
S7 (Large)	TH ≠ TO	3.50	0.50	0.60	1.00	0.60	1.20	3.90	5.70
	TH > TO	3.50	0.50	0.60	0.90	0.50	1.20	3.90	5.70

FIGURE 1
Proportion of trades involving hidden volume

This figure provides, for all the 79 SSE stocks in our sample, the intraday distribution of executed hidden limit orders. The stocks are grouped into three portfolios: Single-listed index-constituent stocks (SLI), dually-listed index-constituent stocks (DLI), and (single-listed) non-index stocks (NI). The intraday patterns are estimated using the following panel-data model:

$$HLO_{it} = \sum_{h=1}^{17} \lambda_h^{sli}\left(H_{it}^h \times SLI_i\right) + \sum_{h=1}^{17} \lambda_h^{dli}\left(H_{it}^h \times DLI_i\right) + \sum_{h=1}^{17} \lambda_h^{ni}\left(H_{it}^h \times NI_i\right) + \varepsilon_{it} \,,$$

where SLI_i equals 1 if the *i*th stock is a SLI stock and 0 otherwise; DLI_i equals 1 if the *i*th stock is a DLI stock and 0 otherwise; NI_i equals 1 if the *i*th stock is not a NI stock and 0 otherwise, and H_{it}^h equals 1 if the observation corresponds to the *h*th half-hour interval and 0 otherwise. We split the SSE trading session (from 9:00 a.m. to 17:30 p.m.) into seventeen 30-minutes intervals. "AVG" is the mean of the estimated coefficients of the three portfolios.