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THE IMPACT OF LARGE ORDERS IN ELECTRONIC MARKETS

Luisella Bosetti
Pietro Gottardo
Maurizio Murgia
Andrea Pinna

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www.crenos.it
info@crenos.it

CRENoS – Cagliari
Via San Giorgio 12, I-09100 Cagliari, Italia
tel. +39-070-6756406; fax +39-070- 6756402

CRENoS - Sassari
Via Torre Tonda 34, I-07100 Sassari, Italia
tel. +39-079-213536; fax +39-079-213002

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The Impact of Large Orders in Electronic Markets

Luisella Bosetti[a], Pietro Gottardo[b], Maurizio Murgia[c], Andrea Pinna[d]

[a]*Borsa Italiana, London Stock Exchange Group*
[b]*University of Pavia, Department of Economics and Management*
[c]*Free University of Bolzano–Bozen, Faculty of Economics*
[d]*Free University of Bolzano–Bozen, Faculty of Economics and CRENoS*

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Abstract

We examine both displayed and non-displayed orders sent by all investors to the electronic central limit order book of the Italian stock exchange *Borsa Italiana* (BI) in 2005, after stocks recovered from the dot-com burst and before the run-up to the financial crisis. Extant literature relies on trades as basic level of observation for the lack of data. Our unique dataset enables us to reconstruct the evolution of the order book and trades over time. Trading costs are lower than in any other exchange analysed in the past. Rules on over-the-counter trading allow us to measure the economic impact of market fragmentation. Contrarily to the existing literature, we observe price impacts are lower in the electronic downstairs market than in the upstairs market. We explain our results in terms of exchange trading architecture.

Keywords: Large Orders, Electronic exchange, Upstairs market,

Block trading, Price Impact, Liquidity, Dark Pool.

JEL: G14, G15, G23.

1. Introduction

The execution of large orders affects prices and liquidity in markets with either limited participation or imperfect information. Such effect is temporary when it remunerates liquidity providers accommodating a short-run order imbalance, as in Kraus and Stoll (1972). It is permanent when the order reveals informational content, as explained by Scholes (1972). Obizhaeva and Wang (2013) show that liquidity similarly depends on investors' incentive to trade at the prevailing quotes after the execution of a large order.

This paper studies the reaction of the electronic Consolidated Limit Order Book (CLOB) to large orders sent by all investors in the Italian stock exchange (BI - *Borsa Italiana*). We use a unique dataset that collects all displayed and non-displayed orders placed by the whole population of investors participating to continuous trading sessions in 2005. Extant literature relies on either trade-level data or proprietary datasets because of little data availability. We have the opportunity to reconstruct the evolution of the order book and keep track of how quotes and depth evolve as trading takes place.

The largest orders in our dataset are blocks, which most exchanges allow to be executed in a parallel over-the-counter market "upstairs", in force of their specialness.[1] The architecture of BI allowed a parallel over-the-counter market – de facto a consortium-based dark pool – to coexist with the CLOB since 1992. The Italian exchange was therefore a fragmented market,

[1]In the period of observation the New York Stock Exchange defined as block trades those involving 10,000 shares or more. Block trades in the London Stock Exchange were trades 75 times the "Normal Market Size (NMS)" defined by the exchange, or 50 times NMS for securities with an NMS less than 2,000. Paris Bourse defined the minimum threshold value for a block of a fairly liquid stock as the maximum between one fortieth of its average daily turnover and 7.5 times the average depth of its inside quotes.

with no crossing rule, well before market liberalization was introduced by the MIFID directive.

We draw a clear distinction between the largest orders routed to different market venues. *Potential* blocks are the orders that investors decide to route through the CLOB, although these could be executed as *actual* blocks upstairs. We show that the price impact of potential block orders executed at BI is lower than in all exchanges considered in the extant literature. We explain that with the peculiar market structure of block trading at BI: the absence of a crossing rule, the delayed communication of upstairs trades and the full anonimity of counterparties induce investors to disseminate the most important pieces of information upstairs.

The reaction to potential block orders at BI is very different depending both on the type of stock – mid-cap or large-cap – and on what is happening in the actual upstairs market. The CLOB of any mid-cap stock is indirectly affected by upstairs trading, even before the latter becomes public information, for two reasons: on the one hand, the fact that an upstairs broker is working the block may subtract liquidity from the CLOB; on the other hand, we find evidence that the execution of an actual block is followed by highly informative potential block orders before the trade is disclosed.

Beside measuring the price impact of potential blocks, we track their effect on liquidity. To account for both resiliency and the fact that a block subtracts liquidity well beyond the prevailing quotes, we introduce a novel measure of illiquidity encompassing all orders seen by investors at a given time. Our analysis shows that large orders attract liquidity.

Understanding how large orders impact on the price and liquidity of a security is of primary importance to any institutional investor. Both temporary and permanent impacts, in fact, increase with the size of an order and go directly against the investor who initiates it. Moreover, since price impacts discourage trading in the first place and reduce market liquidity, studying their connection with market architecture is critical to the arrangement of orderly trading by exchanges and regulators.

Electronic order-driven exchanges have been indicated since Black (1971) path breaking paper, as the ideal setting to lower transaction costs and eliminate unnecessary brokers and intermediaries. Glosten (1994) formalizes the ideal conditions for an efficient electronic order driven market. Domowitz (2002) shows that electronic order-driven markets generally lower transaction costs, compared to quote-driven markets. Nonetheless, the extant literature on block trading advocate for quote-driven markets as the best venue to ensure a smooth clearance of large trades: Kraus and Stoll (1972) discuss the role specialists play when their inventory is used to lower temporary price impacts; Grossman (1992) argues that upstairs brokers have access to a pool of unexpressed liquidity that facilitates the clearing of a large order; Seppi (1990) points out that upstairs blocks shall be cheaper than downstairs, in terms of implicit costs, because they are certified as liquidity-driven by brokers who prefer dealing with noninformational orders.

We do not dispute Seppi (1990) theory *per se*, but we point out that its validity is specific to a given market design and that the latter may be suboptimal to uninformed traders. The market technology for block trading at BI turns the theory on block orders impact upside down: dual-capacity block dealers allow the execution of highly informative blocks over the counter. Far from constituting a heaven for noninformed investors inclined to give up some immediacy to get low execution costs, the upstairs market may become a netherworld where informed investors get suspicious orders executed. The cost of such trades is very high and benefits originator's counterparties. The identity of the latter is hidden and can be either the same broker who receives the order or a fellow broker, possibly trading for an agency account. We find that one fourth of block orders placed in the upstairs market could be executed at better price as a market order in the CLOB. The whole CLOB at any point in time can only be seen by brokers, whereas investors placing a block order upstairs see only five levels and are unable to assess the alternative cost of using its depth. This offers of course an arbitrage opportunity to their counterparties.

Potential blocks placed on the CLOB at BI are mostly on large-cap stocks whose ownership dispersion and liquidity allow trading large quantities at a low implicit cost. Moreover, high total impacts of informed trades upstairs permit the execution of noninformed potential block orders on midcaps without the stigma of being uncertified by an upstairs dealer. This enables the CLOB of BI to deal with potential block orders with relatively low price impacts, when the latter are compared with the extant literature.

In terms of policy recommendation, the short answer we can draw from our study is in line with the extant literature: an upstairs market benefits the execution of large orders. This is not the end of the story though, as price impacts suggest that such benefit is higher at BI where disruptive orders are taken out of the CLOB.

Departing from the extant empirical literature on block trading, we use orders as the basic unit of observation. Our dataset is unprecedented in terms of both accuracy and representativeness. We analyze the 778,166 orders greater than €150k posted on the BI electronic CLOB in 2005, when stocks had recovered from the dot-com burst and before the run-up to the financial crisis. Such orders account for 55% of the exchange annual turnover and originate 4.5% of annual trades.

The fact that we use order-level data of all investors makes our analysis ideal, as underlined by Bessembinder and Venkataraman (2004). In fact, differently from previous studies, our dataset includes large orders posted by all brokers and dealers taking part to both the downstairs and the upstairs market, on a broad range of firm capitalization.[2] Observing orders allows us to bypass the issue of trade direction, as well as the overestimation of block orders when the latter are split into many trades. Moreover, we avoid a problem that was not addressed in the previous literature and may have affected extant results: many orders of block size are posted to cross genuine blocks. In such a case, the direction of the block trade appears opposite to that of the order affecting the CLOB beforehand. Because we track orders in real time, spurious blocks do not affect our analysis. These effects are what we call the dark side of past block trading studies: both quantitative and qualitative conclusions are unwarranted, because most studies were not able to observe the true dynamics of order placement and trading outcomes.

Consistent with previous studies, we observe that both seller- and buyer-initiated trades experience statistically significant temporary and permanent price impacts. Our results depart from the extant literature in two important respects. Primarily, the asymmetries pointed out in the literature are confirmed by our estimates only in the case of mid-cap stocks.[3] In particular, the first potential block to sell in a day does not display permanent impacts. The first potential block to buy is, on average, the most informative order of the day.

Our explanation goes along the lines of Holthausen et al. (1990) and Allen and Gorton (1992): whereas a large buy order is likely based on information, investors are ready to consider

[2]Bessembinder and Venkataraman (2004) look at a dataset of trades. Keim and Madhavan (1996) draw their conclusion from a proprietary database, which is potentially biased by broker-specific trading strategies, and look at small firms only. Chan and Lakonishok (1995) look at packages of trades executed by a limited number of investment banks. Conrad et al. (2003) as well relies on proprietary data, Madhavan and Cheng (1997) focus on DJIA stocks, thus on very large cap stocks.

[3]See Holthausen et al. (1987) and Keim and Madhavan (1996) for empirical results on price impacts asymmetries and Saar (2001) for a theoretical explanation.

a sell order as resulting from liquidity needs. However, we see that the information content of the ensuing potential blocks to sell is comparable to that of buy orders. In days when a stock is not traded upstairs, potential blocks to sell exhibit price reversal and have a lower permanent impact than buy orders. In fact, the opposite happens in days when the stock is traded over the counter. Secondly, price impacts in Milan are consistently lower than in all exchanges analysed so far. We compare our results with the literature in the most direct way – i.e. by using the same metrics adopted in most published papers on block trading. Price impacts of potential blocks at BI are lower than in all other exchanges hitherto examined. By contrast, upstairs trading at BI is more expensive than in most other exchanges particularly in terms of temporary impact, and such efficiency gap led to a substantial demise of the upstairs market.

We investigate the determinant of price impacts and find that upstairs trading indeed explains much informative contents of a potential block order to buy. Sell orders contains much information independently of upstairs trading, but even in this case upstairs trading has a statistically significant effect on permanent impacts.

Finally, we introduce a measure of liquidity disruption in the CLOB and track how the latter reacts to potential block orders. We acknowledge the fact that book liquidity is not characterized by the bid-ask spread. The number of shares offered or demanded at the best quotes do not give the whole picture, particularly in the case of large orders that often walk the book. Thus, we propose to measure the average multi-level availability of liquidity in both the ask and the bid side of the limit orders book in a novel way. We confirm the result that illiquidity attracts liquidity. In fact, on average the book is replenished just 15 minutes after the execution of a potential block.

The rest of the paper is structured as follows. In section 2 we provide institutional details of the exchange and describe our dataset, providing descriptive statistics to give an overview of large trades at BI. Section 3 is a brief revision of different strands of finance literature that are related to our research. Section 4 provides results on the price impact of potential blocks in the limit order book. We compare our results to the previous literature and we analyse the impact of market structure. In Section 5 we introduce our multi-level measure of illiquidity and describe how the BI order book reacts to the passage of a large trade. Section 6 concludes.

2. Institutional Details and Sample Characteristics

2.1. Equity Trading in the Italian Stock Market

Italian listed stocks trade in an electronic market managed and supervised by BI.[4] We focus on the 161 large and medium capitalization stocks that trade in the Blue Chip and Star segments of the electronic market. Panel A of table 1 shows summary statistics for such firms, whose annual turnover approached 1€tn in 2005.

[PLACE TABLE 1 APPROXIMATELY HERE]

Limit and market orders are inserted into the electronic CLOB only by authorized exchange members, which operate in dual capacity (broker-dealer).[5] Trades are settled with both price and time priority.

[4]BI is a private company and manages the trading of several segments of the Italian financial market such as equity instruments, derivatives contracts, government bonds and fixed income securities, exchange traded funds and other indexed products. BI merged in 2007 with London Stock Exchange and since then is part of LSE Group.

[5]BI has designated specialists with mandatory market making obligations who assist the trading only for the 72 mid-caps that are included in the Star segment of our sample.

The daily trading session is organized into three main phases: opening auction, continuous trading, and closing auction. Orders of a relevant size can be executed both in the electronic market (downstairs) and in the special "block market"(upstairs), which is a bilateral over-the-counter market. Details on market design of BI and block trading rules during our sample period are reported in Appendix A.

Block trades upstairs are arranged in an intermediate way (direct phone-negotiated), and can be executed only when the order size is equal or greater than a minimum threshold. Block thresholds are computed on the basis of stock turnover. During the time period covered by our research, block trade thresholds were between euros 150,000 and 1.5 million.

Differently from the exchanges studied in the extant literature, the block market at BI does not have any interaction rule and upstairs trades do not have to be crossed downstairs. Exchange members can complete a block trade upstairs at any price and have the sole obligation to report all trade details to BI within 15 minutes. A summary of the block trade contract is disclosed to the market through Network Information System (NIS) after further 45 minutes.

2.2. *Sample characteristics*

Our sample comprises all orders posted in 2005 on 161 listed firms which represent about 90% of market capitalization and 95% of total trading volume.[6] Order and trade data in the downstairs market for year 2005 are obtained by the BI electronic market database which we describe in Appendix B.

We construct our sample by first selecting all orders of relevant size, *i.e.* all orders greater than the minimum block trade threshold of €150,000 that may allow trading in the upstairs market. This results in 778,166 orders, of which 207,688 are to

[6]BI was ranked in 2005 as the 7th exchange in the world by trading volume.

sell and 570,478 are to buy.

We create two subsamples. The first contains all potential blocks that had the opportunity to be placed upstairs as per regulation. The second collects what we define large orders – *i.e.* orders larger than €150,000 that were not allowed to be traded upstairs.

[PLACE TABLE 2 APPROXIMATELY HERE]

Panel A of Table 2 presents summary statistics on orders placed on the CLOB. Our focus is on potential blocks, of which only 1.7% are market orders. The 9.5% of potential block size expressed as limit orders were iceberg orders. Although iceberg orders display by definition only a fraction of their true size in the order book, and disclose another fraction of the iceberg only when the previous one is executed, we have information on their total size from the time they are placed. We find more iceberg orders among potential block orders to sell than to buy.

The average size of potential block orders to buy and sell have similar magnitudes of €1,297,920 and €1,561,127, respectively. Median values depend heavily on order direction: a value of €1,606,500 for buy orders contrasts with a value of €551,100 in the case of potential blocks to sell. Sell orders are then composed of many relatively small orders and few larger ones, when compared to buy orders. Such asymmetry reflects on the number of trades per order, that are on average 18.5 in case of buy and only 12 in the case of sell orders.

Panel B contains detailed information on trades in our dataset. These are in the range of 5 millions downstairs, whereas only 3,760 blocks were traded upstairs. The dataset of upstairs block trading is obtained from the Italian Securities and Exchange Commission (CONSOB). Although blocks account for a negligible portion of overall trades and trading volume, their size is huge when compared to what is placed in the CLOB downstairs. On average, the size of upstairs block is about 5 times that of downstairs potential block.[7] Since trade size is considered a proxy for informational content, the fact that block trades are disclosed to all market participants only 60 minutes after execution introduces a strong asymmetry among investors.

Actual blocks are evenly split between principal and agency account, whereas broker-dealers originate only one fifth of potential blocks. Moreover, in the case of potential block orders to sell, the median size of trades on principal account is three time that of clients.

Panels C-E show the distribution of both large orders and potential blocks on the CLOB, and that of upstairs blocks. Orders size and details on their execution are provided for the different capitalizations, accounts, and order types.

3. Related Literature

Easley and O'Hara (1987) show that trade size may proxy for the amount of information. As a consequence, counterparts in a large trade shall require price concessions in compensation for providing liquidity to a potentially informed investor. The prediction that trade price impact is an increasing function of order size is confirmed empirically for all common market structures: hybrid exchanges, crossing networks, and electronic limit order markets.[8]

In an attempt to lower explicit and implicit trading costs, exchange regulators in many economies allowed for the existence of fragmented markets where the same stock could be traded at the lowest implicit cost. Upstairs markets have been studied and compared with centralized markets, to find out whether the latter needed in fact a parallel market. Results are diverse in size,

[7] Bessembinder and Venkataraman (2004) find a similar value in the case of *Paris Bourse*.

[8] See Madhavan and Cheng (1997), Fong et al. (2004), and Bessembinder and Venkataraman (2004), respectively.

but the extant financial literature claims de facto unanimously that upstairs markets improve the functioning of an exchange by allowing execution of large liquidity-driven orders outside the main trading venue (CLOB or floor).

In particular, Seppi (1990) suggests that brokerage houses may act as principal in the upstairs market. They screen information investors and build with clients an implicit commitment rule not to trade again in the stock until the desk has traded off its block position. In equilibrium, blocks are therefore traded upstairs for uninformative balancing reasons and receive better execution than they would receive downstairs. Grossman (1992) claims that intermediaries play a fundamental additional role as repositories of information about unexpressed demand. This implies that execution costs in the upstairs market will be lower, because additional information will increase the effective liquidity and reduce dealers risk upstairs. Under such circumstances, one would expect no large order to be channeled downstairs for liquidity reason. Thus, no large order would be executed downstairs, unless we believe noise investors who populate theoretical models take part to actual transactions.

However, Burdett and O'Hara (1987) and Keim and Madhavan (1996) stress the additional temporary costs upstairs block trades imply due to search costs and information leakage, respectively. Therefore, the benefits occurring from an upstairs market depend on participation and confidentiality. These are indeed the main levers regulators used when setting up the operation of upstairs markets.[9]

Kyle (1985) suggests that informed investors would make many smaller trades rather than a large one, to hide their information. However, this comes with costs in terms of both time-

[9]Upstairs orders are usually subject to execution rules in terms of both eligibility – i.e. order size – and disclosure – i.e. the time window before they are disclosed downstairs.

liness and execution costs. Barclay and Warner (1993) finds that the relationship between size and price impact is not linear. Because of the possibility of informed trading, they predict medium size transactions have higher price impacts. Seppi (1990) shows that liquidity investors may actually prefer posting large orders rather than many smaller trades, if they can signal their type. In his model and in Easley and O'Hara (1987) this happens through a reputation effect that, thanks to the certification role played by block brokers, allows liquidity investors to distinguish themselves from the pool of informed investors to reduce adverse selection costs.

By focusing on the measurement of implicit costs of large transactions in the downstairs market at BI, we contribute to the literature on block trading. Madhavan and Cheng (1997) study block trading in Dow Jones Industrial Average stocks. They find that most block trades are executed downstairs and do not find any significant difference between execution costs of block trades handled down- or upstairs. The NYSE is a hybrid electronic-broker market, and this may allow the downstairs market to exhibit some of the advantages that are usually attributed to upstairs brokers. Biases of the dataset in terms of both securities – that are among the most liquid one may conceive –, and proprietary trading – the sample is restricted to few large investment firms –, may explain the unusual result.

The fact that observations are limited to a set of investors or a category of firms is a flaw that is common to most researches on block trading. Some investment strategies affect price impacts, both because of different investors' time horizon and because of different price elasticity of demand. On the latter point, Mikkelson and Partch (1985) suggest that demand for a firm's shares is less elastic for smaller, less traded, and less researched stocks. Our paper is the first, to the best of our knowledge, to focus on the overall set of orders in markets whose size is comparable to the BI.

Keim and Madhavan (1996) measure price impacts in the NYSE, across different investment strategies. The fact that they find sizable differences among trading styles confirms that any dataset that does not contain the whole range of market participants may lead to draw inaccurate results. We adopt their measure of trading costs to allow comparison and find that trading costs in the CLOB of BI are four times smaller than in the far more liquid NYSE, both for buyer– and seller–initiated orders. Keim and Madhavan (1996) find an asymmetric impact of buy and sell orders, a feature that is common to the literature on block trading (See Saar (2001) for an explanation). Allen and Gorton (1992) give a plausible explanation in terms of asymmetry between liquidity purchase and liquidity sales: it is difficult for the market to believe that a investor needs to buy a security immediately for liquidity reason, whereas it makes sense that she wants to sell because of liquidity needs. We find asymmetric results for buyer and seller initiated blocks, but the direction of such asymmetries depend on the type of order we consider.

Fong et al. (2004) study blocks executed on the Australian stocks to compare price impacts in three different trading venues. The authors have a dataset of orders that, although spanning over six years (1993-1998), contains only around 70k trades. The small sample size is due to the ASX allowing only huge orders, independently on a stock capitalization, to be traded upstairs. Results on the Australian Stock Exchange (ASX) limit order book are similar to Madhavan and Cheng (1997) and in strong contrast with the findings by Bessembinder and Venkataraman (2004) that upstairs trades have little information content.

Bessembinder and Venkataraman (2004) is the work that is most easily comparable to ours. This is due to the similarities between *Paris Bourse* and the BI. Both exchanges moved to electronic trading around the turn of the 1990s, shifting from daily auction floor-trading to continuous trading with an electronic centralized limit order book.[10] Large orders are allowed to be executed upstairs depending on their size, whereas the downstairs market is informed of such trades only with some delay. Bessembinder and Venkataraman (2004) look at blocks above roughly €90,000, finding that both temporary and permanent effects are higher downstairs than upstairs. This shall not come as a surprise, given that around two thirds of overall eligible blocks volume of the French exchange is cleared upstairs. The fact that results in terms of downstairs price impacts are so different between the two exchanges is particularly striking because of the aforementioned similarities. We suggest that differences between the crossing rule may be the explanation.

Smith et al. (2001) and Booth et al. (2002) are other examples of papers that study price impacts in order driven markets, with parallel upstairs markets that clear most of large trades volume. The first studies large orders executed on the order driven Toronto Stock Exchange (TSE), finding that upstairs market complements downstairs market, providing liquidity and allowing transactions to be executed with price impact that would be about 20 times larger downstairs. The latter measures price impacts in the Helsinki Stock Exchange (HSE). Again, price impacts are almost ten times larger than at BI.

Gregoriou (2008) studies the asimmetry of price impacts in the London Stock Exchange (LSE) and finds impacts considerably higher than those we find at BI. His estimates are of particular importance to the present paper, since the time windows of the two studies overlap. In fact, that allows to neglect the possibility of low price impacts driven by technological improvement.

[10] Both exchanges adopted a modified version of the old CATS (Computerized Assisted Trading System), first implemented at Toronto Stock Exchange. For an empirical analysis of the unique market architecture of BI before the milestone reform of 1991 see Amihud et al. (1990), whereas Steil (1996) presents an in depth cross-country analysis of the evolution of European securities markets after a decade of reforms and trading systems innovation.

We can then compare implicit trading costs at BI and the LSE focusing only on differences in their market architecture.

4. Price Impact of Block Orders

Following previous research on the price impact of block trades, we distinguish between temporary and permanent components of the price change around a block transaction. Orders of relevant size enter the market with the stigma of either positive or negative information on the value of assets, depending on whether their direction is to buy or sell. Investors spotting a potentially informational large order revise their assessment of the stock intrinsic value and update their bid or ask price. Easley and O'Hara (1987) and Holthausen et al. (1987) provide theoretical ground and empirical evidence to the intuition that such informative effect is more pronounced for larger orders, when size is compared to the amount of shares investors consider normal to trade. A large order has therefore a greater impact on the stock price. Such impact is permanent, since it lasts until a new relevant event changes investors' information set.

Beside any informational content, stock prices are expected to react to large orders if it is difficult to readily find liquidity on the other side of the market. Kraus and Stoll (1972) suggest that large buy orders are settled at prices above stocks intrinsic value for this reason, whereas the opposite happens for sales. The fact that a large order walks the book to find sufficient liquidity determines a price change that adds to the permantent one and goes in its same direction. Such liquidity effect depends on size, since limit orders standing at lower levels of the book must be hit to fulfill larger quantities. The impact is temporary and fades away as liquidity in the CLOB is restored, determining a price reversal towards the stock equilibrium price.

We label respectively as P_b, P_{b-1}, P_{b+1} and $r_{m^{(t,t')}}$ the average execution price of a large order, the stock price before its placement, that after its execution, and market return between two points in time t and t'. Accordingly, we measure the permanent effect of an order as

$$\pi = \ln P_{b+1} - \ln P_{b-1} - \ln r_{m^{(b-1,b+1)}}; \tag{1}$$

whereas the temporary effect is

$$\tau = \ln P_{b+1} - \ln P_{b} - \ln r_{m^{(b,b+1)}}. \tag{2}$$

Therefore, the total effect of a large order is found as the difference between permanent and temporary effect:

$$T = \pi - \tau = \ln P_{b} - \ln P_{b-1} - \ln r_{m^{(b-1,b)}}. \tag{3}$$

Block orders to buy are expected to display positive permanent impacts when they have informational content. In the case of short-run order imbalances, the price reversal shall result in negative temporary impacts for buy orders. The opposite reasoning applies to block orders to sell.

4.1. A Cross-Exchange Comparison of Price Impacts

To clarify how relevant the peculiar market architecture of BI is for trading costs, we provide a direct comparison between the price impacts in both CLOB and upstairs market of BI and the results reported in extant literature.

[PLACE TABLE 3 APPROXIMATELY HERE]

Table 3 shows the price impacts reported in some prominent papers on block trading and those we find at BI when we use the same definition of price impact. Only the use of such diverse set of metrics allows direct comparison among different exchanges. Moreover, direct comparison shows that low trading costs of the ensuing analysis on the CLOB are robust to the choice of metrics and that results do not depend on a deliberate choice of time windows.

Panel A shows that total price impacts of potential block orders placed in the CLOB of BI are lower than those recorded in all other exchanges. Such result is driven by permanent impacts. Our dataset displays price impacts that are two-thirds those measured by Chiyachantana et al. (2004) in a broad worldwide basket of exchanges. Even when compared to single order-driven exchanges that share the same architecture of electronic trading, such as the Helsinky Stock Exchange, *Paris Bourse*, and the London Stock Exchange, BI has the cheapest CLOB. This result is not driven by the use of a dataset that is relatively recent in comparison with most studies that are available for comparison. In fact, Gregoriou (2008) reports significantly higher estimates, for the fairly liquid London Stock Exchange, over a time window that encompasses that of our dataset.

Panel B shows that, on the contrary, price impacts at BI are relatively high in the upstairs market. This result is driven by temporary price impacts. It is worth specifying that temporary impacts in the upstairs market at BI do not necessarily correspond to a market reaction in terms of liquidity. Differently from all other exchanges, an upstairs broker at BI is free to set the trading price to any level accepted by the client. No crossing rule was in place at BI during the observation period, and upstairs trading was disclosed with a delay of 60 minutes.

Such market fragmentation makes the interaction between parallel markets at BI unique. We then focus on market architecture to explain the surprisingly low price impacts of orders in the CLOB. Our results show that the Seppi (1990) theory of certification by brokers in the over-the-counter upstairs market does not apply to BI. According to such theory, potential blocks are the most suspicious orders the CLOB can display. Thus they shall result in high permanent and total impacts.

4.2. Incentives and certification in the upstairs market

Under the certification theory, upstairs brokers accept only liquidity-driven orders to protect their reputation and, in case of order flow internalization, their own capital. We show that such theory does not fit to BI.

Since brokers do not need to price stocks inside the prevailing quotes in the CLOB, they can charge investors any mark-up. Whenever the price charged upstairs is higher than the weighted average execution prices available in the CLOB, the broker is facing an arbitrage opportunity. In force of delayed communication, brokers' strategy does not imply the banned practice of front-running. Thus, upstairs brokers at BI have no incentive to avoid dealing with informed investors as long as the latter are able to pay for such service.

[PLACE TABLE 4 APPROXIMATELY HERE]

Table 4 shows that, net of brokerage fees, about 22% of sell orders and 31% of buy orders executed in the upstairs market would find sufficient liquidity downstairs and get better weighted-average prices if they were placed as market orders in the CLOB. Conditional to the presence of sufficient liquidity on the CLOB, almost 38% of buy and more than 36% of sell actual blocks would find better execution downstairs.

A similar exercise is performed by Bessembinder and Venkataraman (2004) on a dataset of trades at *Paris Bourse*. Among the few stocks that are allowed to trade without crossing rule in Paris, only 6% of upstairs trades could be executed downstairs at a better price. The authors define such finding an apparent puzzle, and explain it through a bias of their dataset in favour of the CLOB.

Since we look at order-level data, we are immune from the bias acknowledged by Bessembinder and Venkataraman (2004) and do not risk overstating the depth of the CLOB. The result that $22 - 31\%$ of blocks executed in the upstairs market at BI would be executed at better prices downstairs is a fact, and it is not a puzzle: block brokers are free to execute trades at the price they wish, as far as their clients agree. Since investors cannot monitor all quotes in the CLOB, the high mark-up they pay to brokers is not surprising.

Implications for the certification role of upstairs brokers are self-evident. The informational advantage of an informed trader can be translated into profits and gives brokers the wrong incentives in terms of certification.

The weight of upstairs blocks at BI declined from 22% of the exchange turnover in 1992 to a mere 7% in 2005. High mark-ups in the guise of temporary impacts seem a good motivation for the demise of the upstairs market. The absence of any crossing rule suggests that the upstairs market may be too expensive for liquidity-driven investors to choose such venue, unless the size of an order is too large to allow its execution downstairs.

This is a first evidence supporting the hypothesis that the upstairs market at BI does not act as a screening device. The selection of orders that remains in the CLOB at BI is then pretty different from that of other exchanges. Unexpectedly low price impacts at BI are explained by the interaction between the two parallel markets, the CLOB and the upstairs. We find additional evidence on the peculiarities of informational content in the two parallel markets when we zoom on price impacts.

4.3. Price Impact of Potential Blocks (CLOB)

We select intervals of five minutes pre- and post-block execution as the most appropriate measure of price impact in the fully electronic and fairly liquid CLOB of BI.[11]

[PLACE TABLE 5 APPROXIMATELY HERE]

[11] We tried different time intervals, ranging from one minute to one trading day. We select the five-minute interval to trade off the fact that no order is posted on illiquid stocks over very short intervals with the possibility that many blocks and pieces of information mingle in one time window. The speed of information flow makes the measurement of price impacts over different trading days anachronistic in modern markets.

Table 5 shows estimates of price impacts in the CLOB, measured in basis points and broken down by stock capitalization. Trading costs are statistically significant, but they are economically negligible. The highest total impact is just 46bp, for buy orders on mid-caps. Results on the whole sample confirm the standard findings, first explained by Holthausen et al. (1987), that buy orders have a higher permanent impact whereas sell orders have higher temporary effect. Total impacts of buy and sell potential blocks are of the same magnitude.

When we estimate costs separately for stock capitalization, a more nuanced story becomes apparent. The usual price asymmetry is noticeable in the case of mid-caps, where buy orders are more informative and sell orders face statistically significant liquidity costs. Buy and sell orders are instead equally informative in the case of large-cap stocks, where permanent impacts are remarkably low.

The main differences between the way large orders are dealt with at BI and in other exchanges such as NYSE, London, Paris, Toronto or Helsinki consist in the architecture of the upstairs market and its interaction with the CLOB. Therefore, we turn our focus to the price impact of block orders executed over-the-counter and to their effect on block trading downstairs.

4.4. Price Impacts of Actual Blocks (Upstairs)

The upstairs market at BI worked similarly to modern consortium-based dark pools since its introduction in 1992. Investors can contact dual-capacity brokers to trade any block of shares above some thresholds (see Appendix A for institutional details).

Since trade execution is disclosed with a one-hour delay, we cannot use for actual blocks the same five-minute intervals we adopted in the analysis of impacts in the CLOB. On the one hand, such piece of information is not incorporated into trades and resulting prices in the CLOB until investors are informed of the trade executed in the upstairs market. On the other hand, the fact that an actual block is being worked upstairs may affect liquidity in the CLOB before its execution. The efficiency of the CLOB at BI is testified by its comparison with the book of other exchanges and we do not need a direct comparison with the upstairs market. Therefore, we can change the time window of our impact measure and use the stock price one-hour before as pretrade price to capture the effect of delayed *disclosure*. The stock price just after disclosure is taken as new equilibrium value.

Panel B of Table 5 shows our estimates of implicit trading costs in the upstairs market at BI. These are driven by temporary impacts. Thus, the finding that normally liquidity-driven sell orders are more expensive than relatively more information-driven buy ones comes with no surprise.

Potential blocks display the same permanent impacts as those of block orders executed upstairs. Although one might think *prima facie* that permanent impacts of potential and actual blocks are not directly comparable because of different order size, both theory and empirical evidence suggest the opposite is true. On the empirical side, Bessembinder and Venkataraman (2004) show that trades downstairs have a higher permanent impact than actual blocks albeit the latter are about 5 times larger on average. In terms of theoretical explanation, and differently from liquidity effects, what matters to the market is that a potentially informed trader received a relevant piece of information and whether that news is positive or negative.

Although the figures in Panel B suggest there is little information in actual blocks, such result arises because the largest liquidity-driven orders on mid-caps are forced to go upstairs for lack of liquidity in the CLOB. This fact is evident in Table 4, which shows that about 53% of actual blocks to buy and 69% to sell could not be executed in the CLOB. This self-selection dilutes the informative effect of actual blocks, but we detect informative content by tracking subsequent potential blocks routed to the CLOB.

4.5. Interaction Between CLOB and the Upstairs Market

We demonstrate that upstairs brokers improve average block execution in the CLOB by taking informed investors upstairs, leaving an advantageous selection of liquidity trades downstairs. We believe such interaction between upstairs market and CLOB brings down average trading costs of potential blocks.

We split the sample of potential blocks between those posted in days when there is no upstairs trading on the same security and those posted in days when at least one block with the same trade direction is facilitated upstairs. We examine downstairs potential blocks posted after disclosure of an upstairs block separately from all the others. In such subsample, we further divide potential blocks posted before the upstairs block is cleared from those posted between clearance and disclosure.

[PLACE TABLE 6 APPROXIMATELY HERE]

Table 6 shows that potential blocks posted on the CLOB following an actual block are highly informative. This proves that some blocks in the upstairs market, particularly sales of mid-cap stocks, are not liquidity driven. A potential block to sell has no informational content in days with no upstairs trading. After the execution of an actual block to sell, potential blocks in the same direction are highly informative even before the upstairs trade is disclosed. Informed investors go upstairs, and that lowers the average impact of potential blocks overall. We believe a similar story fits to the case of large-caps. However, informative events are seldom in the case of highly monitored stocks and the dilution effect is stronger.

4.6. Multivariate Analysis of Price Impacts

To understand what explains price impacts in an electronic market such as the CLOB of BI, we regress permanent trading costs on measures of order size, market conditions, stock characteristics and trade difficulty. Since our focus is on the CLOB, the sample of orders we use to regress price impacts is that of orders that investors decided to route downstairs. These may differ in some unmeasured ways from those that are sent upstairs. For instance, orders on stocks that have more hidden info may be more likely to go upstairs and are therefore deducted from our sample in a standard OLS regression.

To address the issue of sample selection, we apply the well known Heckman (1979) technique and regress the probability that an investor routes the block downstairs on a set of variables that are not relate to the actual price impact. The basic idea is that we observe the downstairs price impact of an order only if some criterion is met that induce an investor to prefer the CLOB to upstairs trading.

In the first stage of the model, the dichotomous variable Down determines whether or not the price impact is observed. In the second stage, we model the expected value of the price impact conditional on it being observed.

We estimate the selection equation via Probit, trying to capture the determinants of an investor's choice on whether to route the block order downstairs or upstairs. Given the anonimity and delayed disclosure of orders executed in the upstairs market at BI, a main driver of the selection between upstairs and downstairs is the amount of private information the order may convey. We measure (the inverse of) private information at firm level by using the percentage of free float, which proxy both ownership dispersion and information dissemination.

The specification of our first stage regression is as follows:

$$\text{Down} = \gamma_0 + \gamma_1 \text{Thresh} + \gamma_2 D_{\text{Float}} + \gamma_3 D_{\text{Dealer}} + \gamma_4 D_{\text{Spread\_1h}}, \qquad (4)$$

where Down is the probability that an order is routed downstairs. Thresh is the threshold for upstairs trading that is set by the regulator for all orders on a given stock. It does not affect price impacts in the second stage of the estimation, as required by the Heckman (1979) procedure. Float is the percentage of freefloating shares on that stock. The variable D_{Dealer} tells whether the order is on principal account. Spread1h is the bid-ask spread measured on the CLOB 1 hour before order execution. We use a lagged measure of liquidity to capture the fact that the decision on where to post the order is taken in advance.

We compute the Inverse Mill Ratios and we plug it into the following standard OLS regression equation to explain permanent price impacts of potential blocks:

$$\begin{aligned}\text{Permanent impact} = {} & \beta_0 + \beta_1 \text{RegSize} + \beta_2 D_{\text{First}} + \beta_3 D_{\text{Post}} + \\ & + \beta_4 D_{\text{NoUp}} + \beta_5 \text{Bull}, \end{aligned} \tag{5}$$

where *RegSize* is the potential block order size divided by the upstairs theshold; D_{First} indicates whether the potential block order is the first of block size on a given stock in a day; D_{Post} is a dummy variable which tells whether the immission of the potential block order happens after an actual block order is executed upstairs; ; D_{NoUp} tells whether there is no upstairs trading on the stock on that day; D_{Bull} is a further dummy variable equal to 1 when the stock market index value at close is greater than at opening.

Table 7 shows OLS estimates of the regression model. Order size matters for buy and not for sell orders. That confirms that investors are ready to consider a sell order as a liquidity trade regardless of its size. The coefficient of D_{First} shows that the stock market reaction gives originators of sell orders the benefit of the doubt, but such credit is limited. As one would expect, although one sell order of block size is accepted as a liquidity-driven orders, ensuing sell orders are taken as a signal that some bad news is driving block trading on a particular stock. Buy orders elicit from the market the opposite response: the first buy order of abnormal size is taken as particularly informative, whereas order that follow it are likely to be driven by the same piece of information the market reacted to and have a lower impact on the equilibrium price of the stock. Potential block orders that follow the execution of an actual block order in the same direction are more informative and that is shown by the coefficient of D_{Post}. We cannot exclude that such a high permanent impact captures the price movement caused by the actual block that was executed upstairs. However, the coefficient of D_{NoUp} suggests that the upstairs market plays little part in disseminating information to investors. In fact, potential block orders to sell have the same permanent impact independently of whether there is block trading upstairs. In the case of potential block orders to buy, the permanent impact is more pronounced when there is no upstairs trading. Market conditions have a significative effect on permanent impacts, particularly in the case of sell orders. In fact, a sell order is more likely to be driven by profit taking if the market is bullish, whereas an abnormal buy order with rising prices is considered as more informative than it is on average.

The estimated correlation ρ between the residuals of the two stages is significantly different from zero, thus the Heckman (1979) procedure is correct.

5. Liquidity effects

Liquidity is an infamously vague concept that can hardly be summarized in one measure.[12] Obizhaeva and Wang (2013) point out that snapshots of the CLOB, such as spread and depth, do not suffice to explain the dynamic properties of buy and sell orders. Parlour (1998) shows that both sides of the CLOB should be considered when measuring liquidity as they are driven by different dynamics, although strictly related. After a market sell (buy) order both the bid and ask prices decrease (increase), with the bid decreasing more than the ask. As a result, the spread itself widens.

[12]For a comprehensive review, see Amihud et al. (2012). Hasbrouck (2009) tests different liquidity proxies on US data.

Biais et al. (1995) show that limit orders are placed more likely when the CLOB is illiquid. This suggests that there is a good deal of hidden liquidity held by investors who observe the book and are ready to step in with a limit order when liquidity is most valuable. The authors explain this phenomenon by asymmetric information. Roşu (2009) shows that the decrease in the ask price following a sell order does not need to come from information. It may simply be the result of sellers adjusting their limit orders in response to a change in the new expected execution time. He also shows that the shape of the CLOB – i.e. the distance between prices in the queue of both sides of the book – matters to strategic investors.

A large order does not affect only the best bid and ask prices. It increases the difference between bid and ask prices at lower levels of the CLOB, determining the hump shape empirically found by Biais et al. (1995), whereas depth decreases. Degryse et al. (2005) investigate resiliency, i.e. how fast best prices, depths and duration recover to their initial, pre-shock level after the market has been hit by an aggressive order.

We acknowledge the fact that CLOB liquidity is not characterized by the bid-ask spread. The number of shares offered or demanded at the best quotes do not give the whole picture, particularly in the case of large orders that often walk the book. We introduce a novel illiquidity measure K_i (i =Ask,Bid) to resolve the daunting task of tracking liquidity around the execution of a block in the CLOB. K_i is meant to measure the average multi-level availability of liquidity in both the Ask and the Bid side of the limit orders book.

Our dataset allows us to see the evolution of the limit order book using at any time all 5 levels of orders that brokers can see. Thus, differently from Biais et al. (1995), our information set downstairs is the same as that of the standard investors. This is of primary importance to link large orders, liquidity, and trading strategies.

The value of K_A (respectively, K_B) is the average of the differences in absolute value between ask (bid) price and mid-point at each level of the CLOB, scaled by order size. Labeling as $\{A_1;\ q_{A1}\}$, $\{A_2;\ q_{A2}\}$, ..., $\{A_n;\ q_{An}\}$ all offer prices and quantities, and as $\{B_1;\ q_{B1}\}$, $\{B_2;\ q_{B2}\}$, ..., $\{B_m;\ q_{Bm}\}$ all pairs of bid price and quantities, we compute K_A and K_B as:

$$K_A = \sum_{j=1}^{5} \frac{A_j - \frac{(A_1 \times q_{A1}) + (B_1 \times q_{B1})}{q_{A1} + q_{B1}}}{q_{Aj}} \tag{6}$$

$$K_B = \sum_{j=1}^{5} \frac{\frac{(A_1 \times q_{A1}) + (B_1 \times q_{B1})}{q_{A1} + q_{B1}} - B_j}{q_{Bj}} \tag{7}$$

The larger the K_i the larger is stock illiquidity.

We are interested in capturing the transitoriness of depth decrease following a block trade. As ask (bid) quotes increase (decrease) the book attracts in fact new sell (buy) order and the pre-trade book liquidity is restored. In particular, we study the resilience of the CLOB as the temporary impact of a potential block is absorbed by new orders bringing fresh liquidity.

To measure the limit order book reaction to a large trade, we track how K_i changes in response to it. We are interested in tracking how liquidity evolves over 15 minutes intervals before a large order is posted and after it gets executed. For this reason, we label as $K_{i,n}$ the illiquidity measured n 15-minute intervals after the potential block, where $n = [-5, 1]$ are quarter-hours around the time $n = 0$ of the potential block execution.

Illiquidity variation due to the large order is then measured as

$$\Delta K_{i,n} = K_{i,n} - K_{i,n-1} \tag{8}$$

[PLACE TABLE 8 APPROXIMATELY HERE]

Resilience is hidden liquidity. In an exchange with few market and hidden orders such as BI one would expect little resilience, whereas both low temporary impacts and our analysis of ΔK suggest there is a good deal of liquidity waiting to replenish the CLOB after a potential block. Table 8 reports our estimates of $\Delta K_{i,n}$. It shows that there is a statistically and economically significant afflux of liquidity to the CLOB right after the passage of a potential block.

5.1. *Multivariate Analysis of Liquidity in the CLOB*

In order to analyze the determinants of liquidity resilience and recovery after the execution of large orders, we regress ΔK_i, where $i = A, B$ on variables that characterize the order, the market, and the CLOB.

$$\begin{aligned}\Delta K_i =& \beta_0 + \beta_1 \text{RelSize} + \beta_2 \text{Bull} + \\ &+ \beta_3 \text{MidCap} + \beta_4 \text{BlockUp} + \beta_5 \Delta K_{i,-1} + \beta_6 \Delta K_{-i,-1},\end{aligned} \tag{9}$$

The baseline regression model captures order size through *RelSize*, that is its ratio with the stock annual turnover. The dummy variable *Bull* accounts for market conditions. We control for market capitalizations using *MidCap*, and look at the connection between upstairs and downstairs markets via *BlockUp*. Liquidity in the CLOB prior to execution of a block order is considered both on the side of the book that is directly affected, through a lagged value $\Delta K_{i,-1}$, and on the opposite side $\Delta K_{-i,-1}$.

Results for ΔK_A, in the case of buy orders, and for ΔK_B, in the case of sell order, are showed in table 9.

[PLACE TABLE 9 APPROXIMATELY HERE]

We see that size does not matter in case of potential blocks, and the fact that an order was large enough to be executed upstairs is what matters. Since the relative size of an order is a proxy for its information content, we conclude that by posting an eligible block downstairs its initiator is sending a signal to all other investors independently of the precise traded amount.[13]

The book is less easily replenished after a potential block to buy when the stock is a mid-cap and there is upstairs trading in the same direction. The latter result suggests that the upstairs market and the CLOB compete for hidden liquidity.

We find that potential block orders have a smaller impact on the amount of liquidity available in the CLOB when the opposite side of the book was already under pressure in the previous 15 minutes. This is true for both buy and sell orders, and the size of estimated coefficients suggests that this is the main driver of illiquidity around the execution a potential block. Such result goes in favour of the hypothesis that liquidity goes where it lacks. An illiquid ask (bid) side of the book attracts sell (buy) orders and allows a large buy (sell) order to be executed against the arriving orders, without worsening the CLOB illiquidity.

6. Concluding remarks

We exploit the peculiar architecture of the Italian exchange BI to study price impact and liquidity effects of large orders executed in the electronic CLOB in a fragmented market.

Our unique dataset contains orders posted by all investors on a broad selection of stocks that account for 95% of turnover at BI. That allows us to overcome the limitations of previous studies of market microstructure, which used trades as basic measure of observation or relied on biased databases of asset management firms.

Findings on trading costs at BI highlight the economic consequences of different market designs. The most striking result

[13]We try a different model specification where the regression is run on all large orders and add an indicator to eligible blocks. We find that such variable is highly significant.

is that price impacts at BI are lower than in any other exchange studied so far.

We define as potential blocks the large orders that investors decide to route downstairs, through the CLOB, although upstairs execution as actual blocks is allowed. We explain the favourable treatment of potential blocks at BI with differences in its structure, in comparison with other markets. The absence of a crossing rule, the full anonymity of trades, and the delayed communication of actual blocks attract informed orders upstairs. Upstairs brokers have no incentive to act as certifiers and benefit from dealing with informed traders because of the mark up they can extract. As a consequence, uninformed investors at BI are induced to route their orders downstairs and concentrate liquidity trades on the CLOB.

We introduce a measure of liquidity disruption in the CLOB and track how the latter reacts to large orders. Since large orders often walk the book, liquidity is not characterized by quantities and prices of the best quotes. We measure the average multi-level availability of liquidity in both the Ask and the Bid side of the CLOB that can be seen by investors at any point in time.

The impact of potential blocks on liquidity does not depend on order size. Pre-trade bid-ask spread does not explain potential blocks impact on liquidity, whereas past realization of our measure of liquidity on each side of the CLOB account for much of the average block impact. This shows that liquidity is resilient on each side of the book. Consistently with the aforementioned result on price impacts, market direction affects also the way liquidity on the CLOB reacts to large orders.

A major policy implication of our study is that an upstairs market lowers price impacts. Differently from what asserted by the extant literature on block trading, such improvement is higher in an exchange such as BI, where non-informational orders are concentrated on the CLOB rather than being taken away, certified, and executed upstairs against a pool of hidden liquidity. The market design of BI, where upstairs brokers face no crossing rule, leaves liquidity-driven orders in the CLOB and attracts informative blocks on illiquid stocks in the upstairs market. This allows concentrating liquidity downstairs and reduces trading costs, so to bound price impacts to a level much lower than those displayed in all other exchanges considered in the market microstructure literature on trade efficiency.

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Bosetti can be reached at Luisella.Bosetti@borsaitaliana.it, Gottardo at pgottardo@eco.unipv.it, Murgia (corresponding author) at maurizio.murgia@unibz.it, Pinna at andrea.pinna@unibz.it.

Appendix A: Block trading at BI

The opening auction last about one hour (8:00-9:05am) and is followed by about eight hours of continuous trading (9:05am-5:25pm). A closing auction, of about ten minutes, concludes the daily trading session. But, for most liquid stocks is also often observed after trading session (6:00-8:30pm).

The security Italian exchange commission CONSOB sets the thresholds that define whether an order can be executed upstairs, out of the electronic CLOB. The objective of size tresholds for upstairs trading is to allow only unusually large orders to be executed outside the CLOB. Therefore, their values depend on a stock normal turnover:

– €150,000 , if the stock average daily turnover in Italian regulated markets was lower than €m1.5 over the last six months.

– €250,000 , if the stock average daily turnover in Italian regulated markets was between €m1.5 and €m3 over the last six months.

– €500,000 , if the stock average daily turnover in Italian regulated markets was between €m3 and €m10 over the last six months.

– €m1.5 , if the stock average daily turnover in Italian regulated markets was greater than €m10 over the last six months.

Appendix B: Dataset

To construct the dataset on downstairs trading we start by selecting all orders with value equal or above e150,000 placed in the CLOB at BI in 2005. Tracking orders and executed trades is allowed in the provided dataset by a unique identification number, and we avoid sampling orders that are not just reaction to original large orders or potential blocks. This yields the 778,166 orders analysed in the present paper.

Each order (pdn: *proposta di negoziazione*) comes with a number that is uniquely associated with all trades, together with the following characteristics: the time it was placed, last modified, and executed on the CLOB of a given stock; trade direction; price and quantity; whether it is on principal or agency account; limit order, market order, or iceberg order; number of resulting trades; weighted average execution price; price of the last trade, best bid and best ask before the order was placed and those immediately after its full execution; the price of the last trade, best bid and best ask at least 60 minutes before the order was placed and those 60 minutes after its full execution.

We have full details of the traded stock, in terms of listing and annual statistics; opening and closing prices; average daily bid-ask spread; opening and trading volume of the stock over the five previous days and relative closing prices.

Potential blocks are isolated from large trades by using the rules set by the Italian security exchange commission (CONSOB).

References

Allen, F., Gorton, G., 1992. Stock price manipulation, market microstructure and asymmetric information. European Economic Review 36 (2-3), 624–630.

Amihud, Y., Mendelson, H., Murgia, M., 1990. Stock market microstructure and return volatility: Evidence from Italy. Journal of Banking and Finance 14 (2–3), 423 – 440.

Amihud, Y., Mendelson, H., Pedersen, L. H., 2012. Market Liquidity: Asset Pricing, Risk, and Crises. Cambridge University Press.

Barclay, M. J., Warner, J. B., 1993. Stealth trading and volatility: Which trades move prices? Journal of Financial Economics 34 (3), 281–305.

Bessembinder, H., Venkataraman, K., 2004. Does an electronic stock exchange need an upstairs market? Journal of Financial Economics 73 (1), 3–36.

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

Black, F., 1971. Toward a fully automated stock exchange, part I. Financial Analysts Journal 27 (4), 28–35.

Booth, G. G., Lin, J.-C., Martikainen, T., Tse, Y., 2002. Trading and pricing in upstairs and downstairs stock markets. Review of Financial Studies 15 (4), 1111–1135.

Burdett, K., O'Hara, M., 1987. Building blocks: An introduction to block trading. Journal of Banking & Finance 11 (2), 193–212.

Chan, L. K., Lakonishok, J., 1995. The behavior of stock prices around institutional trades. The Journal of Finance 50 (4), 1147–1174.

Chiyachantana, C. N., Jain, P. K., Jiang, C., Wood, R. A., 2004. International evidence on institutional trading behavior and price impact. The Journal of Finance 59 (2), 869–898.

Conrad, J., Johnson, K. M., Wahal, S., 2003. Institutional trading and alternative trading systems. Journal of Financial Economics 70 (1), 99–134.

Degryse, H., De Jong, F., Van Ravenswaaij, M., Wuyts, G., 2005. Aggressive orders and the resiliency of a limit order market. Review of Finance 9 (2), 201–242.

Domowitz, I., 2002. Liquidity, transaction costs, and reintermediation in electronic markets. Journal of Financial Services Research 22 (1-2), 141–157.

Easley, D., O'Hara, M., 1987. Price, trade size, and information in securities markets. Journal of Financial economics 19 (1), 69–90.

Fong, K., Madhavan, A., Swan, P. L., April 2004. Upstairs, downstairs: Does the upstairs market hurt the downstairs? University of New South Wales, Working Papers.

Glosten, L. R., 1994. Is the electronic open limit order book inevitable? The Journal of Finance 49 (4), 1127–1161.

Gregoriou, A., 2008. The asymmetry of the price impact of block trades and the bid-ask spread: Evidence from the London Stock Exchange. Journal of Economic Studies 35 (2), 191.

Grossman, S. J., 1992. The informational role of upstairs and downstairs trading. Journal of Business, 509–528.

Hasbrouck, J., 2009. Trading Costs and Returns for U.S. Equities: Estimating Effective Costs from Daily Data. The Journal of Finance 64 (3), 1445–1477.

Heckman, J. J., 1979. Sample selection bias as a specification error. Econometrica 47 (1), 153–161.

Holthausen, R. W., Leftwich, R. W., Mayers, D., 1987. The effect of large block transactions on security prices: A cross-sectional analysis. Journal of Financial Economics 19 (2), 237 – 267.

Holthausen, R. W., Leftwich, R. W., Mayers, D., 1990. Large-block transactions, the speed of response, and temporary and permanent stock-price effects. Journal of Financial Economics 26 (1), 71 – 95.

Keim, D. B., Madhavan, A., 1996. The upstairs market for large-block transactions: Analysis and measurement of price effects. Review of Financial Studies 9 (1), 1–36.

Kraus, A., Stoll, H. R., 1972. Price impacts of block trading on the New York Stock Exchange. The Journal of Finance 27 (3), 569–588.

Kyle, A. S., 1985. Continuous auctions and insider trading. Econometrica, 1315–1335.

Lee, C., Ready, M. J., 1991. Inferring trade direction from intraday data. The Journal of Finance 46 (2), 733–746.

Madhavan, A., Cheng, M., 1997. In search of liquidity: Block trades in the upstairs and downstairs markets. Review of Financial Studies 10 (1), 175–203.

Mikkelson, W. H., Partch, M. M., 1985. Stock price effects and costs of secondary distributions. Journal of Financial Economics 14 (2), 165–194.

Obizhaeva, A. A., Wang, J., 2013. Optimal trading strategy and supply/demand dynamics. Journal of Financial Markets 16 (1), 1–32.

Parlour, C., 1998. Price dynamics in limit order markets. Review of Financial Studies 11 (4), 789–816.

Roşu, I., 2009. A dynamic model of the limit order book. Review of Financial Studies 22 (11), 4601–4641.

Saar, G., 2001. Price impact asymmetry of block trades: An institutional trading explanation. Review of Financial Studies 14 (4), 1153–1181.

Scholes, M. S., 1972. The market for securities: Substitution versus price pressure and the effects of information on share prices. The Journal of Business 45 (2), pp. 179–211.

Seppi, D. J., 1990. Equilibrium block trading and asymmetric information. The Journal of Finance 45 (1), 73–94.

Smith, B. F., Turnbull, D. A. S., White, R. W., 2001. Upstairs market for principal and agency trades: Analysis of adverse information and price effects. The Journal of Finance 56 (5), 1723–1746.

Steil, B., 1996. Equity Trading I: The evolution of European Trading Systems. In Benn Steil, The European equity markets: The state of the union and an agenda for the millennium. Ch. 1, pp. 1-58. The Royal Institute of International Affairs and European Capital Markets Institute, London, UK.

Table 1: **Sample Summary Statistics and Stock Characteristics**
This table contains sample summary statistics for year 2005. Panel A provides overall statistics for Borsa Italiana (BI). Panel B shows sample stock characteristics.

Panel A: Borsa Italiana (BI) Summary Statistics in 2005	
Listed firms	282
Market capitalization (€bn)	676
Annual turnover (€bn)	954.7
Blue Chip and Star annual turnover (€bn)	935
% over exchange	98%
Annual upstairs trading (€bn)	72.1
% over exchange	7.5%
Trading days	256
Bull days (%)	57%
Bear days (%)	36%
Panel B: Sample Stock Characteristics	
Firm common stock in sample	161
Sample capitalization over exchange (%)	90%
Average capitalization mid-cap (€bn)	4.916
Average capitalization large-cap (€bn)	35.824
Annual turnover over exchange (%)	95%

Table 2: **Large Orders and Blocks in the Electronic CLOB - Consolidated Limit Order Book (downstairs) - and Upstairs Markets of BI.**

This table presents descriptive statistics and distribution of large orders and trades in the electronic CLOB and the upstairs market of BI in year 2005. Downstairs orders are taken directly from the electronic limit order book, whereas upstairs block trades are signed according to the Lee and Ready (1991) algorithm. Panel A shows summary statistics of large orders and potential blocks in the electronic CLOB. Potential blocks are defined as individual orders posted into the electronic CLOB with size equal or greater than minimum threshold required by Security regulation to allow execution in the upstairs market. Panel B presents descriptive statistics of Trades executed in the electronic CLOB and the upstairs market. Panel C contains statistics on the distribution of large orders and trades in the electronic CLOB. Panel D contains statistics on the distribution of potential block orders and trades in the electronic CLOB. Panel E contains statistics on the distribution of block trades in the upstairs market.

Panel A: Descriptive statistics of Large and Block Orders in Electronic Market.

	Large Orders	Potential Blocks
All Orders		
Total number	756,998	21,168
Limit orders	734,935	20,804
Market orders	22,063	364
Iceberg orders	25,072	1,987
Buy Orders		
Total number	556,270	14,208
Limit orders	539,991	13,965
- over buy orders	97%	98%
Market orders	16,279	243
Iceberg orders	15,593	1,080
- over buy limit orders	3%	8%
Principal account	148,027	3,166
- over buy orders	27%	22%
Agency account	408,243	11,042
Order size in Euro: Mean	326,592	1,561,127
Order size in Euro: Median	243,216	1,606,500
Order immediacy vs. best ask: Mean	-1.2	5.58
Order immediacy vs. midq: Mean	2.68	4.68
Sell Orders		
Total number	200,728	6,960
Limit orders	194,944	6,839
- over sell orders	97%	98%
Market orders	5,784	121
Iceberg orders	9,479	907
- over sell limit orders	5%	13%
Principal account	52,796	1,228
- over sell orders	26%	18%
Agency account	147,932	5,732
Order size in Euro: Mean	298,698	1,297,920
Order size in Euro: Median	227,800	551,100
Order immediacy vs. best bid: Mean	-3.3	1.44
Order immediacy vs. midq: Mean	2.69	5.21

Panel B: Descriptive statistics of Trades in Electronic (Downstairs) and Upstairs Markets.

	Electronic Market		Upstairs
	Large Trades	Potential Blocks	Upstairs Blocks
All Trades			
Total Number	4,801,126	375,217	3,760
Buy Trades			
Total number	3,397,273	265,213	1,532
Mean size in €	58,418	96,532	32,238,179
Mean trades number per order	6.11	18.50	1
Median trades number per order	4	12	1
Mean execution time in minutes	7.77	11.91	N.A.
Median execution time in minutes	0.18	0.12	N.A.
Principal (%)	27%	22%	51%
Agency (%)	73%	78%	49%
Sell Trades			
Total number	1,403,853	110,004	2,228
Mean size in €	46,849	113,763	12,617,877
Mean trades number per order	6.99	15.81	1
Median trades number per order	5	10	1
Mean execution time in minutes	17.60	21.16	N.A.
Median execution time in minutes	0.72	0.42	N.A.
Principal (%)	26%	18%	49%
Agency (%)	74%	82%	51%

Panel C: Distribution of Large orders in the Electronic (Downstairs) market.

	Orders Number	Order Size in €		Trades per Order		Execution (minutes)	
		Mean	Med	Mean	Med	Mean	Med
Buy Orders							
Capitalization							
Mid-cap	9,290	229,886	195,500	10.41	8	14.08	0.13
Large-cap	546980	328,234	244,500	6.04	4	7.66	0.18
Account							
Principal	148,027	347,786	250,000	5.97	4	6.78	0.20
Agency	408,243	318,907	241,000	6.16	4	8.13	0.18
Order type							
Market	16,279	300,588	228,414	6.14	5	1.03	0.00
Limit	539,991	327,376	219,945	6.11	4	7.97	0.20
- Iceberg	15,593	349,227	254,100	12.40	10	7.87	0.30
Sell Orders							
Capitalization							
Mid-cap	7,833	223,746	190,000	9.86	8	18.87	0.35
Large-cap	192,895	301,741	229,400	6.88	5	17.55	0.73
Account							
Principal	52,796	313,261	233,700	6.81	5	14.98	0.65
Agency	147,932	293,500	225,244	7.06	5	18.53	0.73
Order type							
Market	5,784	261,350	211,500	8.00	6	3.04	0.00
Limit	194,944	299,806	228,298	6.96	5	18.03	0.78
- Iceberg	9,479	314,009	231,177	13.32	11	12.23	0.60

Panel D: Distribution of Potential Block orders in the Electronic (Downstairs) market.

	Orders Number	Order Size in €		Trades per Order		Execution (minutes)	
		Mean	Med	Mean	Med	Mean	Med
Buy Orders							
Capitalization							
Mid-cap	5,542	363,131	240,121	11.38	8	13.20	0.05
Large-cap	8,666	2,327,260	1,899,000	23.05	15	11.09	0.18
Account							
Principal	3,166	2,063,728	1,846,016	20.35	14	11.17	0.13
Agency	11,042	1,417,021	1,519,000	17.96	11	12.13	0.12
Order type							
Market	243	1,160,345	403,130	15.16	10	4.73	0.00
Limit	13,965	1,568,102	1,6414,030	18,55	12	12.04	0.12
- Iceberg	1,080	1,149,663	470,875	26.41	20	14.44	0.50
Sell Orders							
Capitalization							
Mid-cap	4,023	389,292	248,500	12.53	9	19.52	0.28
Large-cap	2,937	2,542,526	1,900,800	20.29	12	23.41	0.65
Account							
Principal	1,228	1,728,794	1,570,000	19.09	12	23.17	0.78
Agency	5,732	1,205,611	512,500	15.11	9	20.73	0.37
Order type							
Market	121	639,295	244,200	16.19	12	14.87	0.00
Limit	6,839	1,309,573	562,266	15.80	10	21.27	0.42
- Iceberg	907	892,049	290,700	23.94	20	22.97	1.17

Panel E: Distribution of Block trades in the Upstairs market.

	Orders Number	Order Size in €	
		Mean	Med
All Trades			
Capitalization			
Mid-cap	838	11,204,953	850,000
Large-cap	2,872	13,224,873	3,435,000
Account			
Principal	1,860	12,429,570	2,180,000
Agency	1,873	12,064,341	2,590,000
Buy Trades			
Capitalization			
Mid-cap	271	10,252,140	1,200,000
Large-cap	1,500	11,602,727	3,270,000
Account			
Principal	877	11,781,984	2,900,000
Agency	879	8,765,609	3,150,000
Sell Trades			
Capitalization			
Mid-cap	567	11,920,564	750,000
Large-cap	1,372	14,538,987	3,680,000
Account			
Principal	955	12,489,403	3,190,000
Agency	972	15,060,412	2,200,000

Table 3: **A direct comparison of Block trades price Impact between BI and the Block Trading literature.**
This table presents a direct comparison between our results (BGMP) on block trading price impacts at BI and the empirical findings of published papers in the block trading literature. Block trading price impacts at BI are computed by using the same metric adopted in the published paper, in order to allow a direct comparison. Metrics formulas are listed in the table footer and BI results are in bold. All figures are expressed in basis points. Panel A contains comparison results for blocks executed in the downstairs markets (whether electronic or not) and Panel B shows comparison results for blocks executed in the upstairs markets.

Time window	Market	Data provider	Research paper	Metric	Sell			Buy		
					Permanent Impact	Temporary Impact	Total Impact	Permanent Impact	Temporary Impact	Total Impact
Panel A: Downstairs Markets (CLOB)										
1998-2005	LSE	Exchange	Gregoriou (2008)	a	-27	-2	-23	32	4	33
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-11***	***-3***	***-14***	***19***	***-2***	***17***
1997-2001	39 countries	Plexus	Chiyachantana et al. (2004)	b	-	-	-42	-	-	33
2005	***Borsa Italiana***	***Exchange***	***BGMP***		-	-	***-14.83***	-	-	***21.77***
1997-1998	Paris Bourse	Exchange	Bessembinder and Venkataraman (2004)	c	-35	-17	-52	128	-38	90
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***10.06***	***-30.63***	***-20.57***	***36.23***	***52.6***	***88.83***
1993-1995	Helsinki	Exchange	Booth et al. (2002)	d	-63.5	-4.8	-68.3	61.3	7.2	68.5
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-2.59***	***-0.98***	***-3.57***	***5.32***	***-0.6***	***4.72***
1993-1994	DJIA NYSE	Exchange	Madhavan and Cheng (1997)	e	-10.68	-5.28	-15.96	15.27	3.27	18.54
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-3.1***	***-1.98***	***-5.08***	***8.2***	***-1.59***	***6.61***
1982	NYSE	Fitch	Holthausen et al. (1987)	f	-113	-133	-246	150	6	156
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***1.42***	***-5.54***	***-4.12***	***-10.78***	***14.67***	***3.89***
1968-1969	NYSE	Vickers	Kraus and Stoll (1972)	g	-42.5	-71.3	-113.8	65.73	9.05	74.78
2005	***Borsa Italiana***	***Exchange***	***BGMP***		**3.64**	***-7.71***	***-3.79***	**-9.15**	***13.09***	***4.11***

a: perm=$ln(P_{d+5m}/P_{d-5m}) - r_M$; temp=$ln(P_b/P_{d+5m}) - r_M$ b: tot=$[P_b/P_{d-1}] - r(M)$.
c: perm=$ln(P_{d+1}/P_{d-1}) - r_M$; temp=$ln(P_b/P_{d+1}) - r_M$.
d: perm=$ln(P_{b+3}/P_{b-5})$; temp=$ln(P_b/P_{b+3})$.
e: perm=$ln(P_{b+20}/P_{b-20})$; temp=$ln(P_b/P_{b+3})$.
f: perm=$ln(P_d/P_{b-1})$; temp=$ln(P_b/P_d)$.
g: tot=$(P_b - P_{b-1})/P_{b-1}$; temp=$-(P_d - P_b)/P_d$.

Table 3 continued...

Time window	Market	Data provider	Research paper	Metric	Sell			Buy		
					Permanent Impact	Temporary Impact	Total Impact	Permanent Impact	Temporary Impact	Total Impact
Panel B: Upstairs Markets										
1997-1998	Paris Bourse	Exchange	Bessembinder and Venkataraman (2004)	c	6	-48	-42	54	2	56
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-7***	***-192.87***	***-199.87***	***-24.93***	***64.83***	***39.9***
1993-1995	Helsinki	Exchange	Booth et al. (2002)	d	-10.9	-26.5	-37.4	15.2	20.1	35.3
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-0.53***	***-178.99***	***-179.52***	***-0.39***	***75.55***	***75.16***
1993-1994	DJIA NYSE	Exchange	Madhavan and Cheng (1997)	e	-7.59	-5.81	-13.4	7.02	5.15	12.17
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***0.24***	***-161***	***-160.76***	***1.38***	***65.3***	***66.68***
1985-1992	NYSE, AMEX, NASDAQ	DFA	Keim and Madhavan (1996)	c	-150	-284	-434	160	-15	145
2005	***Borsa Italiana***	***Exchange***	***BGMP***		***-7***	***-192.87***	***-199.87***	***-24.93***	***64.83***	***39.9***

c: perm=$ln(P_{d+1}/P_{d-1}) - r_M$; temp=$ln(P_b/P_{d+1}) - r_M$.
d: perm=$ln(P_{b+3}/P_{b-5})$; temp=$ln(P_b/P_{b+3})$.
e: perm=$ln(P_{b+20}/P_{b-20})$.

Table 4: **Upstairs Blocks that could be executed downstairs by inserting Potential Block market orders in the Electronic CLOB**

This table presents average percentages of upstairs block trades that could be executed downstairs as market orders, given the liquidity available in the CLOB at the time of their execution. The second column shows average figures for the proportion of block trades that could not be executed downstairs because of insufficient depth of the electronic CLOB. The third column shows average figures for the proportion of block trades that could be executed downstairs at higher cost than upstairs. The fourth column shows average figures for the proportion of block trades that could be executed downstairs at equal cost than upstairs. The fifth column shows average figures for the proportion of block trades that could be executed downstairs at lower cost than upstairs. Average percentages are presented for the whole sample of upstairs blocks and for the two subsamples of upstairs blocks executed for mid- and large-cap stocks.

	Insufficient depth	Cost Up< Cost Down	Same cost	Cost Up> Cost Down
Whole sample				
Buy	17.84	49.12	1.86	31.17
Sell	38.47	37.39	1.75	22.38
Large-cap				
Buy	11.47	52.00	2.07	34.47
Sell	25.73	46.50	2.33	25.44
Mid-cap				
Buy	53.14	33.21	0.74	12.92
Sell	69.31	15.34	0.35	14.99

Table 5: **Price Impact of Block Trades**

This table shows average price impact of block trades in the BI for year 2005. Average price impact results are presented for temporary, permanent and total effects and between the whole sample and the two subsamples of mid- and large-cap stocks, net of market return. Temporary effect is defined as change in price from the block price to the post-trade price. Permanent effect is defined as change from the pre-trade price to the post-trade price. Total effect is defined as difference between block price and pre-trade price. The pre-trade and post-trade price for blocks executed downstairs are the prevailing price five minutes before and after block execution, respectively. In the case of upstairs blocks, the pre-trade price is sampled 1 hour before execution and the post-trade just after disclosure. Panel A shows average results for potential blocks in the electronic CLOB. Potential blocks are defined as individual orders posted into the electronic CLOB with size equal or greater than minimum threshold required by Security regulation to allow execution in the upstairs market. Panel B presents average results for blocks executed in the upstairs market. All figures are expressed in basis points.

Direction	Temporary	Permanent	Total
Panel A: Potential Blocks (CLOB)			
Whole sample buy	0	15***	15***
Whole sample sell	5***	-11***	-15***
Mid-cap buy	-1	46***	43***
Mid-cap sell	12***	9	-3
Large-cap buy	0	13***	14***
Large-cap sell	5***	-13***	-17***
Panel B: Actual Blocks (Upstairs)			
Whole sample buy	-47***	15***	53***
Whole sample sell	117***	-11***	-118***
Mid-cap buy	-172***	10*	192***
Mid-cap sell	296***	-14**	-316***
Large-cap buy	-39***	15***	43***
Large-cap sell	78***	-10***	-75***

***=p-value < 0.01, *=p-value < 0.05. Reported figures are in bp.

Table 6: **Price Impact of Block Trades in the electronic CLOB under different timing and simultaneous upstairs trading**
This table presents average price impact of block trades in the BI for year 2005. Average price impact results are presented for temporary, permanent and total effects and for the two subsamples of mid- and large-cap stocks. Average price impact results for potential blocks in the electronic CLOB are presented when no upstairs trading is observed in the same trading day or at least one upstairs block is executed in the same trading day. When upstairs trading is observed in the same day, average price impact results are shown distinctly for: a) before the upstairs block is executed; b) between upstairs block execution and its public disclosure, and c) after the upstairs block execution is publicly disclosed. Average price impact results for upstairs blocks are shown in the bottom line of each panel. Panel A shows average price impact results for buy blocks and Panel B shows average price impact results for sell blocks. All figures are expressed in basis points.

Panel A: Buy Orders

		Temporary		Permanent		Total	
		Mid-cap	Large-cap	Mid-cap	Large-cap	Mid-cap	Large-cap
Potential Blocks (CLOB)	No-Upstairs days	4***	4***	36**	29***	32***	24***
	Upstairs days	-19***	2***	58**	28***	77**	26***
	- Pre-Block	-12***	3***	64	27***	149**	25***
	- Pre-com	-7*	4*	52	23***	170**	20***
	- Post-com	-38***	1	53*	30***	91**	29***
Upstairs Blocks		-192***	-35***	10	16***	208***	44***

Panel B: Sell Orders

		Temporary		Permanent		Total	
		Mid-cap	Large-cap	Mid-cap	Large-cap	Mid-cap	Large-cap
Potential Blocks (CLOB)	No-Upstairs days	6***	2***	0	-4*	-5	-6***
	Upstairs days	6	2*	-175***	-6*	-187***	-9***
	- Pre-Block	0	1	4	-10***	-10	-10***
	- Pre-com	-54***	6***	-303***	-6	-245***	-11
	- Post-com	22*	4***	-192***	-2	-218***	-6
Upstairs Blocks		510***	35***	-31***	-10***	-325***	-41***

***:p-value <0.01; **:p-value <0.05; *:p-value <0.1.

Table 7: **Multivariate analysis of downstairs Potential Block price impacts**

This table presents coefficient estimates from the OLS model:
Permanent impact $= \beta_0 + \beta_1 \text{RegSize} + \beta_2 D_{\text{First}} + \beta_3 D_{\text{Post}} + \beta_4 D_{\text{NoUp}} + \beta_5 \text{Bull}$

	Sell	Buy
Intercept	-35.30***	-26.48***
RegSize	-4.03	4.71**
D_{First}	8.17***	11.54***
D_{Post}	-23.46***	4.02***
D_{NoUp}	-8.14	10.38***
D_{Bull}	13.25***	2.02***

Selection model:

$$\text{Down} = \gamma_0 + \gamma_1 \text{Thresh} + \gamma_2 \text{D}_{Flot} + \gamma_3 \text{D}_{Dealer} + \gamma_4 \text{D}_{Spread1h}$$

Intercept	1.01***	1.39***
Thresh	-0.61***	-0.73***
D_{Float}	0.69***	1.07***
D_{Dealer}	-0.65***	-0.40***
D_{Spread1h}	-3.76***	-1.49***
Rho	0.57***	0.77***

***:p-value <0.01; **:p-value <0.05.

Table 8: **Potential Blocks impact on the liquidity of electronic CLOB**

This table presents coefficient estimates of illiquidity changes surrounding the execution of a potential block in the downstairs electronic CLOB. $\Delta K_{i,n}$ are either lagged $K_{i,n}$ or simultaneous or subsequent changes in the electronic book available liquidity for the top 5 levels which are publicly disclosed. .

	Buy PB	Sell PB
$\Delta K_{A,-4}$	-9.3***	-8.8*
$\Delta K_{A,-3}$	-4.4**	-15.2***
$\Delta K_{A,-2}$	-8.1***	-8.1*
$\Delta K_{A,-1}$	-4.2***	-6.7
$\Delta K_{A,0}$	26.17***	31.72***
$\Delta K_{A,1}$	-24.1***	-35.8***
$\Delta K_{B,-4}$	-1.4	-11.9***
$\Delta K_{B,-3}$	-5.7***	-12.1***
$\Delta K_{B,-2}$	-5.8***	-7.1**
$\Delta K_{B,-1}$	-8.2***	-6.9*
$\Delta K_{B,0}$	2.9*	6.8
$\Delta K_{B,1}$	-3.3**	-17.1***

***:p-value<0.01, **:p-value<0.05, *:p-value<0.10

Table 9: **Multivariate analysis of liquidity effects by downstairs Potential Blocks**

This table presents coefficient estimates from the OLS model of illiquidity changes surrounding the execution of a potential block in the downstairs electronic CLOB. $\Delta K_{i,n}$ are either lagged $K_{i,n}$ or simultaneous or subsequent changes in the electronic book available liquidity for the top 5 levels which are publicly disclosed.

	Buy ΔK_A	Sell ΔK_B
Intercept	0.307***	0.093
RelSize	-0.883	-0.467
D_{Bull}	0.103	-0.128
D_{MidCap}	0.921***	0.220
D_{BlockUp}	0.313***	-0.021
$\Delta K_{A,-1}$	-47.904***	2.127*
$\Delta K_{B,-1}$	0.789	-29.926***

***:p-value <0.01; *:p-value<0.1.

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