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The Impact of Large Orders in Electronic Markets

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Abstract

This paper uses order-level data of all traders of the Italian stock exchange *Borsa Italiana* (BI) to resolve three issues that remained unsettled in the extant microstructure literature: the interaction between the exchange and a parallel market for large blocks; the asymmetry between the price impacts of buy and sell orders; and the behaviour of liquidity in the limit order book around large orders. Price impacts and liquidity effects of block trades at BI are surprisingly different from existing empirical literature. Our findings reveal that price effects are much lower in the electronic downstairs market than in the upstairs market. Such result is the opposite of what can be found in previous studies. Moreover, trading costs in the central limit order book at BI are lower than in any other exchange analysed in the past. We explain that in terms of exchange trading architecture. In fact, rules on block trading at BI allowed a parallel dark pool to coexist with the consolidated limit order book well before market liberalization was introduced by the MIFID directive. This left the downstairs market with a selection of liquidity-driven orders and unprecedented low price impacts.

Keywords: Large Orders, Electronic exchange, Upstairs market, Block trading,

Price Impact, Liquidity, Dark Pool.

JEL: G14, G15, G23.

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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 traders' 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 block orders in the Italian stock exchange (BI - *Borsa Italiana*). Block is the jargon for the largest orders, which most exchanges allow to be executed "upstairs" – i.e. in a parallel over the counter market – in force of their specialness.¹ We define *potential blocks* 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 architecture of block trading at BI allowed a parallel dark pool to coexist with the main exchange since 1992, well before market liberalization was introduced by the MIFID directive.

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

¹The New York Stock Exchange defines as block trades those involving 10,000 shares or more. Block trades in the London Stock Exchange are 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 defines 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.

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 traders 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.

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 in general, but we point out that its validity is specific to a given market design and that the latter may be suboptimal. 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 traders inclined to give up some immediacy to get low execution costs, the upstairs market is a netherworld where informed traders may get suspicious orders executed. The cost of such trades is very high and benefits the originator's counterparty. 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 CLOB at any point in time can only be seen by brokers, whereas traders placing a block order upstairs are unable to assess the alternative cost of using the CLOB. 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 liquidity and governance allow trading large quantities at a low implicit cost. Moreover, high total impacts of informed trades upstairs allow the broad sample of noninformed potential block orders to be routed downstairs without the stigma of being uncertified by an upstairs dealer. This allows 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 block orders execution. 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 \in 150k posted on the BI electronic CLOB in 2005. 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

²Bessembinder 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.

we track orders in real time, spurious blocks do not affect our analysis.

Consistent with previous studies, we observe that both seller- and buyerinitiated 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 when there is no block trading in the parallel upstairs market.³ 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. However, 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 upstaris 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. As a consequence, the book is replenished almost completely 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

 $^{^{3}}$ See Holthausen et al. (1987), Gemmill (1996), and Keim and Madhavan (1996) for empirical results on price impacts asymmetries and Saar (2001) for a theoretical explanation.

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.

[PLACE TABLE 1 APPROXIMATELY HERE]

Panel A of table 1 shows summary statistics for such firms, whose annual turnover approached $1 \in \text{tn}$ in 2005.

The architecture of the electronic market is that of a Consolidated Limit Order Book (CLOB). Limit and market orders are inserted into the CLOB only by authorized exchange members, which operate in dual capacity (broker-dealer) but have no market making obligations. Authorized exchange members are either trading arms of commercial banks or independent security houses (SIM – *Societá di Intermediazione mobiliare*).⁵ Trades are settled with both price and time priority.

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). 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 phonenegotiated) between exchange member firms, and can be executed only when

⁴BI 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.

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

the order size is equal or greater than a minimum threshold. Further, the block market does not have any interaction rule and upstairs trades do not have to be crossed downstairs. 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. Exchange members that complete a block trade upstairs must report all trade details to BI within 15 minutes. Subsequently, BI discloses to the market through Network Information System (NIS) a summary of the block trade contract after at least 45 minutes.

2.2. Sample characteristics

Our sample is made of 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 $\in 150,000$ that may allow trading in the upstairs market. This results in 778,166 orders, of which 207,688 are to 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 $\in 150,000$ 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. Among limit orders, a mere 9.5% were hidden as iceberg orders. Moreover, we find more hidden orders among sell potential blocks than among buy ones.

The average size of potential block orders to buy and sell have similar magnitudes of $\leq 1,297,920$ and $\leq 1,561,127$, respectively. Median values are much different among order directions: a value of $\leq 1,606,500$ for buy orders contrasts with a value of $\leq 551,100$ in the case of potential blocks to sell, that are then denoted by many relatively small orders and fewer large ones. Such asymmetry

 $^{^6\}mathrm{BI}$ was ranked in 2005 as the 7th exchange in the world by trading volume.

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. Since trade size is considered a proxy for informational content, the fact that block trade details are disclosed to all market participants only 60 minutes after execution introduces a strong asymmetry among investors.

Blocks are evenly split between principal and agency account, whereas brokerdealers 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 trader. 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.⁷

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, but the extant financial literature claims de facto unanimously that upstairs markets improve

 $^{^7\}mathrm{See}$ Madhavan and Cheng (1997), Fong et al. (2004), and Bessembinder and Venkataraman (2004), respectively.

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 traders 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 traders 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.⁸

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 timeliness 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 traders 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 traders to distinguish themselves from the pool of informed traders 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.

 $^{^{8}}$ 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.

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 trader 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 asymmetrics 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.⁹ 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 \in 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). 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. We can then compare implicit trading costs at BI and the LSE focusing only on differences in their market architecture.

⁹Both exchanges adopted a modified version of the old CATS (Computerized Assisted Trading System), first implemented at Toronto Stock Exchange.

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.

Buy (sell) orders of relevant size enter the market with the stigma of positive (negative) new information on the traded asset. 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 the larger the order size, when the latter is compared to the amount of shares investors consider normal to trade. Traders spotting a potentially informational large order revise their assessment of the stock intrinsic value and increase (decrease) the price they are willing to sell (buy) the stock at. A large buy (sell) order has therefore a permanent impact on the stock price that leads to its appreciation (depreciation) until a new relevant event enters traders' information set.

Beside any informational content, a stock price is expected to react to large orders if it is difficult to readily find counterparties. Kraus and Stoll (1972) suggest that large buy (sell) orders are settled at prices above (below) stock intrinsic values, in order to remunerate liquidity providers for the risk they borne by placing limit orders that stand ready for any potentially informed trader to use. Since a large order clears limit orders of opposite direction and walk through the CLOB, its effect on price is more pronounced the larger its size. This temporary impact further prevents the full exploitation of any informational advantage commanding a price reversal as liquidity is restored in the CLOB.

We label respectively as P_b , P_{b-1} , P_{b+1} and $r_{m^{(t,t+1)}}$ the average execution price of a large order, the stock price before its placement, that after its settlement, and the market return between two points in time t and t + 1. 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

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

Therefore, the total effect of a large order is found as the difference between

permanent and temporary effect:

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

Block orders to buy (sell) are expected to display positive (negative) permanent impacts when they are informative. In case of short-run order imbalances, the price reversal shall result in negative (positive) temporary impacts for buy (sell) orders.

4.1. Price Impact of Potential Blocks (CLOB)

Since the downstairs market at BI is fully electronic and fairly liquid, we select intervals of five minutes pre- and post-block execution as the most appropriate measure of price impact.¹⁰

[PLACE TABLE 3 APPROXIMATELY HERE]

Panel A of Table 3 shows estimates of price impacts at BI, that are statistically significant but economically negligible. Our analysis on the whole sample confirms the asymmetries first reported by Holthausen et al. (1987) and Gemmill (1996): buy orders exhibit a continuation of the price impact and show no reversal, whereas the total cost to the originator is lower in the case of sell orders because of their lower permanent impact. We split the sample into mid-cap and large-cap stocks to check whether the asymmetry persists. Figures reported in Panel A show that potential blocks of mid- and large-cap stocks display different patterns. The standard asymmetries hold in the case of large caps, whereas potential blocks on mid-caps exhibit higher permanent impacts in case of sell than in that of buy orders.

The low level of price impacts at BI is a striking result. 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 the cost of block trading downstairs.

¹⁰We adopted 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.

4.2. Price Impacts of Actual Blocks (Upstairs)

The upstairs market at BI worked similarly to modern dark pools since its introduction in 1992. Investors can contact dual-capacity brokers to trade any block of shares above the thresholds aforementioned in section 2. The most important features of the upstairs market to the purpose of our study are the delayed communication of trades execution and the absence of a crossing rule.

Since trades 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, since traders are not informed of the trade executed in the upstairs market, such piece of information is not directly incorporated into trades and resulting prices in the CLOB. On the other hand, the fact that an actual block is being worked upstairs may affect liquidity in the CLOB well before its execution. Therefore, we use the stock price one-hour before as pre-trade price. The stock price one-hour after *disclosure* is considered its new equilibrium value.

Panel B of Table 3 shows our estimates of implicit trading costs in the upstairs market. We find in the case of large-cap stocks the usual asymmetry of permanent impacts, whereas temporary price effects are perfectly specular between buy and sell orders. In the case of mid-cap stocks, orders to sell are more informative but the standard asymmetry of temporary impacts is confirmed.

The level of temporary impacts in blocks of mid-caps traded upstairs is huge. This is true relatively to what we find in the CLOB of the same exchange, but it will become more evident in the next section where we compare the costs of upstairs trading at BI with that of exchanges whose downstairs block trading is by contrast more expensive.

It is worth specifying that temporary price impacts in the upstairs market at BI do not necessarily correspond to a "market reaction" in terms of liquidity. Differently from all other exchanges, the upstairs broker at BI is free to set the trading price to any level accepted by the client, indipendently of the type of stock and amount of liquidity available on the CLOB. Thus, part of the temporary impact is a mark-up the broker receives for dealing with the originator of a (possibly information-driven) block order. Although the figures in Panel B suggest there is little information in actual block orders, we show in what follows that such result arises because the largest liquidity-driven orders on mid-caps are forced to go upstairs for lack of liquidity in the CLOB. That dilutes the informative effect of actual blocks, but the abnormal informative content of some among them arises through subsequent potential blocks routed to the CLOB.

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 traders to chose such venue. This is the 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.

4.3. Comparison of Price Impacts at BI and in Other Exchanges

We find that price impacts of block orders in the CLOB at BI are statistically significant, but they are economically negligible. We replicate our analysis using all different metrics adopted in the extant literature, in order to both allow a direct comparison of BI with other exchanges and to make sure our surprisingly low results do not come from the deliberate decision of using short time intervals.

[PLACE TABLE 4 APPROXIMATELY HERE]

Table 4 shows the price impacts reported in some prominent papers on block trading and those we find at BI, by using exactly the same metrics to allow a direct comparison. Total price impacts of block orders placed downstairs at BI are lower than those recorded in all other exchanges, and such result is driven by permanent impacts.

Potential blocks at BI produce price impacts that are less than two-third 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 is the cheapest CLOB.

Such a result is not due to the fact that our data are more recent than those analysed in most studies we had available for comparison. In fact, Gregoriou (2008) reports significatively higher price impact estimates in the more liquid London Stock Exchange, over a time window that encompasses that of our dataset. To explain our surprisingly low price impacts we focus on the architecture of the block market at BI. In fact, if one believes in the Seppi (1990) theory on upstairs certification, potential blocks are the most suspicious orders the CLOB can display and shall result in high permanent and total impacts. We see that the opposite happens at BI: potential blocks display permanent impacts far below those of block orders executed upstairs.

4.4. Interaction Between CLOB and the Upstairs Market

Before showing the informative impact of actual blocks upstairs on potential block trding in the CLOB, we provide evidence that the Seppi (1990) hypothesis of certification does not fit to BI. Since brokers do not need to price stocks inside the prevailing quotes in the CLOB, they can charge uncertified informed traders any mark-up. Whenever the trading price is higher than the weighted average execution prices available in the CLOB, the broker is facing an arbitrage opportunity. Thus, upstairs brokers at BI have no incentive to avoid dealing with informed traders.

[PLACE TABLE 6 APPROXIMATELY HERE]

Table 6 shows that, net of brokerage fees, about 22% of sell orders and 31% of buy orders executed in the upstairs market would get better weighted-average prices if they were placed as market orders in the CLOB.

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 more than one fourth 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 quotes on the CLOB, the high mark-up they pay to brokers is not surprising.

We demonstrate that upstairs brokers improve average block execution in the CLOB by taking informed traders 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 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 5 APPROXIMATELY HERE]

Table 5 shows that potential blocks posted on the CLOB following an upstairs block are highly informative. This proves that some actual blocks, particularly sells of mid-cap stocks, are not liquidity driven. Such result is not evident in our estimates on the impact of upstairs trading, because relatively few informative blocks are diluted among many liquidity-driven ones. What matters to our analysis is that highly informative blocks were taken upstairs whereas their execution in the CLOB would have increased average impacts downstairs. 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.

4.5. 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. We estimate the following regression for permanent price impacts:

Price impact =
$$\beta_0 + \beta_1 \text{RelSize} + \beta_2 D_{\text{Dealer}} + \beta_3 D_{\text{Bull}} + \beta_4 D_{\text{MIDCAP}} + \beta_5 \text{BlockUp} + \beta_6 \text{RNetDay} + \beta_7 \text{Spread},$$
(4)

where RelSize is the potential block order size divided by stock annual turnover; D_{Dealer} indicates whether the potential block originator is a dual-capacity dealer; D_{Bull} is a dummy variable that accounts for market conditions; D_{MIDCAP} is another dummy variable, taking the value 1 when the stock is part the of mid-cap and 0 of the large-cap segment; BlockUp indicates whether the stock is traded upstairs in the same day; RNetDay is the stock return since market opening, net of market return; and Spread is the bid-ask spread one hour before the order entered the CLOB. Table 7 shows OLS estimates of the regression model. Order size matters, and its effect is more pronounced in the case of buy orders. Principal trades are cheaper than agency ones, whereas we do not find any significative impact of market conditions on trading costs.

The informative content of potential blocks on mid-caps is higher than on large-caps in the case of sell orders, whereas the opposite happens whe the block order is to sell. The fact that stock-specific performance since market opening affects permanent price impacts strongly but in opposite directions points to momentum as primary explanation. Thus, it is not the market condition but rather the sentiment on a specific stock that drives permanent impacts of potential blocks.

The fact that an order in the same direction is executed upstairs increases greatly the impact of potential blocks to sell. This is in line with the finding that, among stocks with low market capitalization and higher probability of information-driven trading, sell blocks upstairs are more informed than buy ones.

The amount of liquidity available in the CLOB has no significant effect on permanent impacts. This confirms that our choice of an unusually short time window is correct: what we are capturing is truly a permanent price impact, rather than a shor-run overshooting of the stock price.

5. Liquidity effects

Liquidity is an infamously vague concept that can hardly be summarized in one measure.¹¹ 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.

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 traders who observe the book and are ready to step in with a limit order when

 $^{^{11}{\}rm For}$ a comprehensive review, see Amihud et al. (2012). Has brouck (2009) tests different liquidity proxies on US data.

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 traders.

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 traders. 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, scaled by each 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:

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

$$K_B = \sum_{j=1}^{5} \frac{\frac{(A_1 \times q_{A1}) + (B_1 \times q_{B1})}{q_{A1} + q_{B1}} - B_j}{q_{Bj}}$$
(6)

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 settlement.

Illiquidity variation due to the large order is then measured as

$$\Delta K_{i,n} = K_{i,n} - K_{i,n-1} \tag{7}$$

[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.

$$\Delta K_{i} = \beta_{0} + \beta_{1} \text{RelSize} + \beta_{2} \text{Bull} + \beta_{3} \text{MidCap} + \beta_{4} \text{BlockUp} + \beta_{5} \Delta K_{i,-1} + \beta_{6} \Delta K_{-i,-1},$$
(8)

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 traders independently of the precise traded amount.¹²

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

Using a new order-level dataset of all traders in the Italian Stock Exchange, this paper studies the price impact and liquidity effects of large orders executed downstairs in the electronic CLOB. Both the technology and microstructure characteristics of block trading at BI are different from other exchanges, allowing our

¹²We 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.

study to highlight new results on the economic consequences of different market designs. We define potential blocks as block orders that investors decide to route downstairs, through the CLOB, although upstairs execution is allowed. We estimate both the temporary and permanent price effects of potential blocks downstairs and actual blocks upstairs, pointing out the interaction among the two markets.

We show that the electronic CLOB reaction to potential block orders at BI is cheaper than in all other exchanges analysed in past studies on block trading. 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. A a consequence, uninformed traders at BI are induced to route their orders downstairs and concentrate liquidity trades on the CLOB. Our study shows asymmetric results for buyer and seller initiated block orders.

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 traders 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 noniformational 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 to concentrate 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 block trading literature.

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 (*an unofficial?*) 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:

 $- \in 150,000$, if the stock average daily turnover in Italian regulated markets was lower than $\in m1.5$ 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.

 $- \in 500,000$, if the stock average daily turnover in Italian regulated markets was between $\in m3$ and $\in m10$ 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.

Rules of transparency and disclosure...

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).

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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 (\in bn)	676
Annual turnover (€bn)	954.7
Blue Chip and Star annual turnover (\in 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 (\in bn)	4.916
Average capitalization large-cap (\in 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.

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

	Electroni	Upstairs	
	Large	Potential	Upstairs
	Trades	Blocks	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 \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 \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 (%)	49%	82%	51%

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

	Orders Number	Order S	ize in €	Trades per Order		Execu (minu	ution utes)
		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 C: Distribution of Large orders in the Electronic (Downstairs) market.

	Orders Number	Order S	Size in \in	$f \in \frac{\text{Trades}}{\text{per Order}}$		Execu (minu	ution utes)
		Mean Med		Mean	Med	Mean Me	
Buy Orde	ers						
Capitalizat	ion						
Mid-cap	$5,\!542$	363, 131	240,121	11.38	8	13.20	0.05
Large-cap Account	8,666	2,327,260	1,899,000	23.05	15	11.09	0.18
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 Order	rs						
Capitalizat	ion						
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 D: Distribution of Potential Block orders in the Electronic (Downstairs) market.

	Orders Number	Order S	ize 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	84,629,630	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	$15,\!060,\!412$	$2,\!200,\!000$

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

Table 3: Price Impact of Block Trades

This table contains 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 largecap 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 pretrade price is sampled 1 hour before execution and the post-trade 1-hour 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: Potenti	Panel A: Potential Blocks (CLOB)										
Whole sample buy	2***	19***	17^{***}								
Whole sample sell	3***	-11***	-14***								
Mid-cap buy	0	11***	11***								
Large-cap buy	3***	23***	20***								
Mid-cap sell	4***	-17***	-21***								
Large-cap sell	2***	-5***	-7***								
Panel B: Actual	Blocks (Upsta	uirs)									
Whole sample buy	-62***	15***	63***								
Whole sample sell	192***	-14***	-104***								
Mid-cap buy	-192***	10	170***								
Large-cap buy	-35***	16^{***}	44***								
Mid-cap sell	510***	-31***	-325***								
Large-cap sell	35***	-10***	-41***								

***=p-value ≤ 0.01 . Reported figures are in basis points.

Table 4: A direct comparison of Block trades price Impact between BI and the Block Trading literature. This table presents a direct comparison between 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	Monleot	Data	a Research			Sell			Buy	
window	Market	provider	paper	Metric ·	Permanent Impact	Temporary Impact	Total Impact	Permanent Impact	Temporary Impact	Total Impact
Panel A:	Downstairs Mar	rkets								
1998-2005 2005	LSE Borsa Italiana	Exchange Exchange	Gregoriou (2008) BGMP	a	-27 -11	-2 -3	-23 -14	32 19	4 -2	33 17
1997-2001 2005	39 countries Borsa Italiana	Plexus Exchange	Chiyachantana et al. (2004) $BGMP$	b	-	-	-42 -14.83	-	-	33 21.77
1997-1998 2005	Paris Bourse Borsa Italiana	Exchange Exchange	Bessembinder and Venkataraman (2004) $BGMP$	с	-35 10.06	-17 -30.63	-52 -20.57	128 36.23	-38 52.6	90 88.83
1993-1995 2005	Helsinki Borsa Italiana	Exchange Exchange	Booth et al. (2002) BGMP	d	-63.5 -2.59	-4.8 - 0.98	-68.3 -3.57	61.3 5.32	7.2 - 0.6	68.5 4.72
1993-1994 2005	DJIA NYSE Borsa Italiana	Exchange Exchange	Madhavan and Cheng (1997) \pmb{BGMP}	е	-10.68 - 3.1	-5.28 -1.98	-15.96 -5.08	15.27 8.2	3.27 - 1.59	18.54 6.61
1982 2005	NYSE Borsa Italiana	Fitch Exchange	Holthausen et al. (1987) BGMP	f	-113 1.42	-133 -5.54	-246 -4.12	150 - 10.78	6 14.67	156 3.89
1968-1969 2005	NYSE Borsa Italiana	Vickers <i>Exchange</i>	Kraus and Stoll (1972) BGMP	g	-42.5 3.64	-71.3 -7.71	-113.8 -3.79	65.73 -9.15	9.05 13.09	74.78 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 4 continued...

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

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

c: perm= $ln(P_{a+1}/P_{a-1}) = P_M$, cemp= $ln(P_b/P_{b+3})$ 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 5: Price Impact of Block Trades in the electronic CLOB under different timing and simultaneous upstairs trading

This table contains 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:	Sell Orders						
		Tem	porary	Pern	nanent	Total	
	No-Upstairs days	Mid-cap 6***	Large-cap 2***	Mid-cap 0	Large-cap -4*	Mid-cap -5	Large-cap -6***
Potential							
Blocks	Upstairs days	6	2^{*}	-175***	-6*	-187***	-9***
	- Pre-Block	0	1	4	-10***	-10	-10***
(CLOB)	- Pre-com	-54***	6***	-303***	-6	-245***	-11
	- Post-com	22^{*}	4***	-192***	-2	-218***	-6
Ups	tairs Blocks	510***	35***	-31***	-10***	-325***	-41***
Panel A:	Buy Orders						
	-	Tem	porary	Pern	nanent	Т	otal
	No-Upstairs days	Mid-cap 4***	Large-cap 4***	Mid-cap 36**	Large-cap 29***	Mid-cap 32***	Large-cap 24***
Potential	1 5						
Blocks	Upstairs days	-19***	2^{***}	58^{**}	28***	77**	26***
	- Pre-Block	-12***	3***	64	27***	149**	25***
(CLOB)	- Pre-com	-7*	4*	52	23***	170**	20***
, , ,	- Post-com	-38***	1	53*	30***	91**	29***
Ups	tairs Blocks	-192***	-35***	10	16***	208***	44***
	***:p-value -	< 0.01: *	*:p-value	< 0.05: *	;p-value <	< 0.01.	

Table 6: Upstairs Blocks that could be executed downstairs by insertingPotential 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 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 7: Multivariate analysis of downstairs Potential Block price impacts

This table presents coefficient estimates from the OLS model:

Price impact = $\beta_0 + \beta_1 \text{RelSize} + \beta_2 D_{\text{Dealer}} + \beta_3 D_{\text{Bull}} + \beta_4 D_{\text{MIDCAP}} + \beta_5 \text{BlockUp} + \beta_6 \text{RNetDay} + \beta_7 \text{Spread},$

	Sell	Buy		
Intercept	0.854^{***}	1.877^{***}		
RelSize	0.086^{***}	0.158^{***}		
D_{Dealer}	-0.026	-0.098***		
D_{Bull}	0.160^{***}	-0.041		
$D_{\rm MidCap}$	-0.400***	-0.252***		
RNetDay	2.361^{***}	1.728^{***}		
Spread	0.184	-0.286		
BlockUp	-3.820***	-0.075**		
***:p-value <0.01; **:p-value <				

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	Sell	
	ΔK_A	ΔK_B	
Intercept	0.307^{***}	0.093	
RelSize	-0.883	-0.467	
D_{Bull}	0.103	-0.128	
$D_{\rm MidCap}$	0.921^{***}	0.220	
$D_{\rm BlockUp}$	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.			