The Impact of Large Orders in Electronic Markets

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1. Introduction

Large orders are security transactions that exceed standard trade lots executed in organized exchanges or over-the-counter markets. The execution of large orders affects prices and liquidity in markets with either limited participation or imperfect information. Such an 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 information, as explained by Scholes (1972). Obizhaeva and Wang (2013) show that liquidity similarly depends on investors' incentives to trade at 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 investors in the Italian stock exchange (Borsa Italiana, BI). We use a unique dataset that represents all displayed and non-displayed orders placed by the whole population of investors participating in continuous trading sessions. Extant literature relies on either trade-level data or proprietary datasets as data availability is limited. This dataset gives us the opportunity to reconstruct the evolution of an order book and track how quotes and market 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 upstairs market, because they are unusually large[1]. The architecture of BI has allowed a parallel over-the-counter market—a de facto consortium-based dark pool—to coexist with the CLOB since 1992. The Italian exchange was, therefore, a fragmented market, with no crossing rule, well before market liberalisation was introduced by the Markets in financial instrument European directive (MIFID).

[1] In the sample period, the New York Stock Exchange defined *block trades* as 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 larger of either one-fortieth of its average daily turnover or 7.5 times the average depth of its inside quotes.

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We draw clear distinctions 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 in an upstairs market. We show that the price impact of potential block orders executed in the BI is lower than in all other exchanges considered in the extant literature. We explain that with the peculiar market structure of block trading in the BI (absence of a crossing rule, delayed communication of upstairs trades and full anonymity of counterparties) induces investors to disseminate the most important pieces of information upstairs.

Reactions to potential block orders at BI are very different depending both on the type of stock—mid-cap or large-cap—and the status of the actual upstairs market. The CLOB of any mid-cap stock is indirectly affected by upstairs trading, even before information on the latter becomes public, 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 have found evidence that the execution of an actual block is followed by highly informative potential block orders before the trade is disclosed.

Besides 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 that of prevailing quotes, we introduce a novel measure of illiquidity that encompasses all orders seen by investors at a given time. Our analysis shows that large orders attract liquidity.

Understanding how large orders affect 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.

Since Black's (1971) ground-breaking paper, electronic order-driven exchanges have been suggested to be the ideal setting for lowering transaction costs and eliminating unnecessary brokers and intermediaries. Glosten (1994) formalised the ideal conditions for an efficient electronic order-driven market. Domowitz (2002) showed that electronic order-driven markets generally lower transaction costs compared to quote-driven markets. Nonetheless, the extant literature on block trading advocates that quote-driven markets are the best venues for ensuring the smooth clearance of large trades. Kraus and Stoll (1972) discussed the role that specialists play when their inventories are used to lower temporary price impacts; Grossman (1992) argued that upstairs brokers have access to a pool of unexpressed liquidity that facilitates the clearance of large orders; Seppi (1990) pointed out that upstairs blocks will be cheaper than downstairs ones in terms of implicit costs, because they are certified as liquidity-driven by brokers who prefer dealing with non-informational orders.

We do not dispute Seppi's (1990) theory per se, but we point out that its validity is specific to a given market's design and may be suboptimal for uninformed traders. The market technology for block trading at BI turns the theory on block order impacts upside-down: dual-capacity block dealers allow the execution of highly informative blocks over-the-counter. Far from constituting a haven for non-informed investors inclined to trade-off some immediacy for low execution costs, the upstairs market may become a netherworld where informed investors can get suspicious orders executed. The costs of such trades are very high and benefit the originator's counterparties. The identity of the latter is hidden and may be 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 a better price as a market order in the CLOB. At any point in time, the whole CLOB can only be seen by brokers, whereas investors placing a block order upstairs see only the first five levels of CLOB and are unable to assess the alternative costs of using its entire market depth. This offers, of course, an arbitrage opportunity to their counterparties.

Potential blocks placed on the CLOB at BI are mostly of large-cap stocks whose ownership dispersion and liquidity allow the trading of large quantities at low implicit costs. Moreover, high total impacts of informed upstairs trades permit the execution of non-informed 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 lower price impacts compared to those reported in the extant literature.

In terms of policy recommendations, 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 a 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 analyse the 778,166 orders valued at over €150,000 posted on BI's electronic CLOB in 2005, when stocks had recovered from the dot-com crash and before the lead-up to the global financial crisis. Such orders accounted for 55% of the exchange's annual turnover and originated 4.5% of annual trades.

The fact that we use the order-level data of all investors makes our analysis ideal, as underlined by Bessembinder and Venkataraman (2004). In fact, in contrast to previous studies, our dataset includes large orders posted by all brokers and dealers taking part in both the downstairs and upstairs markets on a broad range of firm capitalisation.[2] Observing orders allows us to bypass the issue of trade direction, as well as the overestimation of block orders that can occur when they are split into many trades. Moreover, we avoid a problem that has not been addressed in the previous literature and may have affected existing results: many orders of block size are posted to cross genuine blocks. In such cases, 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. This aspect distinguishes our paper from many past studies that were unable to observe the true dynamics of order placement and trading outcomes.

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

[2] Bessembinder and Venkataraman (2004) looked at a dataset of trades. Keim and Madhavan (1996) drew their conclusions from a proprietary database of small firms, which was potentially biased by broker-specific trading strategies and firm characteristics. Chan and Lakonishok (1995) looked at packages of trades executed by a limited number of investment banks. Conrad et al. (2003) also relied on proprietary data, while Madhavan and Cheng (1997) focused on DJIA stocks, which are very large cap stocks.

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

impact. The first potential block that is bought is, on average, the most informative order of the day.

Our explanation follows the ideas of Holthausen et al. (1990) and Allen and Gorton (1992): whereas large buy orders are likely based on the receipt of some information, investors consider sell orders based on liquidity needs. However, we observe that the information content of the resulting potential sell blocks is comparable to that of buy orders. In the days when stocks were not traded upstairs, potential sell blocks exhibited price reversal and had a lower permanent impact than buy blocks. In fact, the opposite happens on days when stock is traded over-the-counter. Secondly, price impacts at BI are consistently lower than in all other international 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. The price impacts of potential blocks in the BI exchange 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 an efficiency gap led to a substantial demise of the upstairs market.

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

Finally, we examine the important issue of the potential effects of market microstructure on stock liquidity and pricing efficiency. First, we introduce a measure of liquidity disruption in the CLOB and track how it reacts to potential block orders. We acknowledge the fact that book liquidity is not characterised by the bid-ask spread. The number of shares offered or demanded at the best quotes does not give the whole picture, particularly in the case of large orders that often "walk the book". Thus, we propose measuring the average multi-level availability of liquidity in both the ask and bid sides of the limit orders book in a novel way. We confirm that illiquidity attracts liquidity. In fact, on average, the book is replenished just 15 minutes after the execution of a potential block. Next, we run tests to verify the level of weak-form and semi-strong forms of market efficiency associated with upstairs block trading. At the weak-form level, we find no evidence that stock prices are serially correlated, and thus more predictable, both before and after a large upstairs trade. As a semi-strong test of market efficiency, we design a standard event study that considers control acquisition announcements by analysing downstairs prices and parallel upstairs trading. Consistent with the mergers and acquisitions (M&A) literature, we observe an average target firm run-up that is statistically significant before public announcements, but no significant price movement around announcement days or in subsequent days. For target firms, upstairs block trading is almost not existent around control acquisition events. When we look at buyers involved in control acquisitions, we find that their downstairs abnormal stock returns are consistent with a vast number of international empirical papers, particularly for cases where acquirers take over private firms. Upstairs trading for the buyer stock market is more active during the run-up, announcement and post-announcement periods, although we detect no negative effects on downstairs price efficiency. Overall, the peculiar BI downstairs-upstairs market design provides supportive evidence of trade efficiency, higher levels of liquidity, and unharmed market efficiency.

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 that give an overview of large trades at BI. Section 3 is a brief review of the different strands of finance literature related to our research. Section 4 provides results on the price impacts of potential blocks in the limit order book. We compare our results to those of previous literature and analyse the impact of market structure. Section 5 presents evidence of the effects of market microstructure on stock liquidity and price efficiency. Finally, Section 6 presents our conclusions.

2. Institutional Details and Sample Characteristics

2.1. Equity Trading in the Italian Stock Market

Italian-listed stocks are traded in an electronic market managed and supervised by BI.[4] We focus on the 161 large- and medium-capitalisation 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 trillion in 2005.

[PLACE TABLE 1 APPROXIMATELY HERE]

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

The daily trading session is organised 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 the market design of BI and block trading rules applicable during our sample period are reported in Appendix A.

Upstairs block trades are arranged in an intermediate way (direct phone-negotiated), and can be executed only when the order size is equal to 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 €150,000 and 1.5 million.

In contrast to 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 the Network Information System (NIS) after a further 45 minutes.

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[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. In 2007, BI merged with the London Stock Exchange and became part of LSE Group.

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

2.2. Sample characteristics

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

We constructed our sample by first selecting all orders of relevant size, i.e. all orders greater than the minimum block trade threshold of €150,000, which may allow trading in the upstairs market. This resulted in 778,166 orders, of which 207,688 are sell orders and 570,478 are buy orders.

We created two subsamples, the first containing all potential blocks that had the opportunity to be placed upstairs, as per regulations. The second comprising what we define as *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 the summary statistics of orders placed on the CLOB. Our focus is on potential blocks, of which only 1.7% are market orders. The 9.5% of potential blocks expressed as limit orders were iceberg orders. Although by definition iceberg orders display only a fraction of their true size in the order book and disclose another fraction of their size only when the previous order is executed, we obtained information on their total size from the time they were placed. We found more iceberg orders among potential block orders to sell than orders to buy.

The average sizes 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 a few larger ones, when compared to buy orders. Such asymmetry reflects

[6] BI was ranked in 2005 as having the 7th-highest trading volume of the world's exchanges.

the number of trades per order which are, on average, 18.5 in the case of buy orders and only 12 in the case of sell orders.

Panel B contains detailed information on the trades comprising our dataset. These were about 5 million blocks downstairs, whereas only 3,760 blocks were traded upstairs. The upstairs block trading dataset was 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 compared to what is placed in the CLOB downstairs. On average, the size of upstairs blocks is about five times that of potential downstairs blocks.[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 accounts, whereas broker-dealers originated only one-fifth of potential blocks. Moreover, in the case of potential block orders to sell, the median size of trades on principal accounts is three time that of clients.

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

3. Related Literature

Easley and O'Hara (1987) showed that trade size may be a proxy for the amount of information. As a consequence, counterparts in a large trade 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, i.e. hybrid exchanges, crossing networks and electronic limit order markets.[8]

[7] Bessembinder and Venkataraman (2004) found 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.

In an attempt to lower explicit and implicit trading costs, exchange regulators in many economies allow for the existence of fragmented markets where the same stock can be traded at the lowest implicit cost. Upstairs markets have been studied and compared with centralised markets to find out whether the latter are in fact needed in a parallel market. The results are diverse in size, but the extant financial literature unanimously claims de facto 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) suggested that brokerage houses may act as principals in the upstairs market. They screen information investors and build an implicit commitment rule with clients 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) claimed 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 orders to be channelled downstairs for liquidity reasons. Thus, no large orders would be executed downstairs unless we believe that the noise investors who populate theoretical models take part in actual transactions.

However, Burdett and O'Hara (1987) and Keim and Madhavan (1996) stressed the additional temporary costs that 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 use when setting up the operation of upstairs markets.[9]

Kyle (1985) suggested that to hide their information, informed investors make many small trades rather than single large ones. However, this comes with costs in terms of timeliness and execution costs. Barclay and Warner (1993) found that the relationship between size and price impact is not linear. Because of the possibility of informed trading, they predicted that medium-size transactions have higher price impacts. Seppi (1990)

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

showed 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 measurement of the implicit costs of large transactions in the downstairs market at BI, we contribute to the literature on block trading. Madhavan and Cheng (1997) studied block trading in Dow Jones Industrial Average stocks. They found that most block trades are executed downstairs and did not find any significant difference between the execution costs of block trades handled downstairs 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 (which are among the most liquid that one may conceive of) and proprietary trading (the sample was restricted to a 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 characteristic that is common to many past studies on block trading. Some investment strategies affect price impacts because of investors' different time horizons and because of different price elasticities of demand. On the latter point, Mikkelson and Partch (1985) suggested 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 sizes are comparable to that of BI.

Keim and Madhavan (1996) measured price impacts in the NYSE across different investment strategies. The fact that they found sizable differences among trading styles confirms that any dataset that does not contain the whole range of market participants may lead to inaccurate results. We adopted their measure of trading costs to allow comparison and found 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) found 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) gave a plausible explanation in terms of asymmetry between liquidity purchases and liquidity sales: it is difficult for the market to believe that an investor needs to buy a security immediately for liquidity reasons, whereas it makes sense that they want to sell because of liquidity needs. We found asymmetric results for buyer- and seller-initiated blocks, but the direction of such asymmetry depended on the type of order being considered.

Fong et al. (2004) studied blocks executed on Australian stocks to compare price impacts in three different trading venues. The authors used a dataset of orders that, although spanning six years (1993–1998), contained only around 70,000 trades. The small sample size was due to the Australian Stock Exchange (ASX) only allowing huge orders, independently of stock capitalisation, to be traded upstairs. Results of the ASX limit order book are similar to those of Madhavan and Cheng (1997) but are in strong contrast to the findings of Bessembinder and Venkataraman (2004)—that upstairs trades have little informational content.

Bessembinder and Venkataraman's (2004) study is the one most 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, centralised, limit order book.[10] Large orders are allowed to be executed upstairs depending on their size, whereas the downstairs market is only informed of such trades after some delay. Bessembinder and Venkataraman (2004) looked at blocks above roughly €90,000, finding that both temporary and permanent effects are higher downstairs than upstairs. This does not come as a surprise, given that around two-thirds of the overall volume of eligible blocks is cleared upstairs in the French exchange. The difference between the two exchanges in terms of downstairs price impacts is particularly striking because of the aforementioned similarities. We suggest that differences in crossing rules may be the explanation.

Smith et al. (2001) is an example of research that focuses on large orders executed on the downstairs order-driven Toronto Stock Exchange (TSE) that also has a parallel

[10] Both exchanges adopted a modified version of the old CATS (Computerized Assisted Trading System) before it was first implemented at the 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). Meanwhile, Steil (1996) presents an in-depth international analysis of the evolution of European securities markets after a decade of market reforms and trading systems innovation.

upstairs market to clear large trades. This paper found that the upstairs market complements the downstairs market, provides liquidity, and allows transactions to be executed with price impacts that would be about 20 times larger downstairs. Booth et al. (2002) analyse price impacts in the Helsinki Stock Exchange (HSE), a further example of order-driven market with a parallel upstairs market to execute most large trades. Again, also in this exchange environment price impacts were almost ten times larger than in the BI exchange.

Gregoriou (2008) studied the asymmetry of price impacts in the London Stock Exchange (LSE) and found the impacts to be considerably higher than those we observed in the BI. His estimates are of particular importance to the present paper since the time windows of the two studies overlap. In fact, this allows us to neglect the possibility that BI lower price impacts are driven by technological improvement. 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 make a distinction between the temporary and permanent components of the price change associated with 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 they are on the buying or selling side.Investors spotting a potentially informational large order revise their assessment of the stock's intrinsic value and update their bid or ask price. Easley and O'Hara (1987) and Holthausen et al. (1987) provide a theoretical basis and empirical evidence for the idea that such an informative effect is more pronounced for larger orders, in terms of the number of shares that investors consider is normal to trade. Therefore, a large order has a greater impact on the stock price. Such an impact is permanent since it lasts until a new relevant event changes investors' information set.

Beside 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) suggested 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, which adds to the permanent price change and is of the same direction. Such a liquidity effect depends on size since limit orders standing at lower levels of the book must be used to fulfil 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 define the variables P_b, P_{b-1}, P_{b+1} and $r_{m(t,t^j)}$ as the average execution price of a large order, the stock price before its placement, the stock price after its execution, and the market return between time points t and t^j, respectively. 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 the difference between the permanent and temporary effects:

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

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 results 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 to trading costs, we provide a direct comparison between price impacts in the CLOB and upstairs market of BI, and published data.

[PLACE TABLE 3 APPROXIMATELY HERE**]**

Table 3 shows the price impacts reported in some prominent papers on block trading and those we found at BI when using the same definition of price impact. Only the use of such a diverse set of metrics allows direct comparison among different exchanges. Moreover, the direct comparison approach shows that low trading costs are robust to the choice of metric and they are not dependent on the selected time window.

In Table 3, Panel A shows that the total price impacts of potential block orders placed in the BI CLOB are lower than those recorded in all other exchanges. Such a result is driven by permanent impacts. Our dataset displays price impacts that are two-thirds of 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 HSE, Paris Bourse and LSE, BI has the cheapest CLOB. This result is not driven by the use of a dataset that is more recent than those of other studies available for comparison. In fact, Gregoriou (2008) reports significantly higher estimates for the fairly liquid LSE 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 BI upstairs market 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 focused on market architecture to explain the surprisingly lower price impact of orders in the CLOB. Our results show that Seppi's (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 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 internalisation, their own capital. We show that such theory does not fit the BI exchange.

Since brokers do not need to price stocks inside the prevailing quotes of 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 faces an arbitrage opportunity. In the context of delayed communication regime, broker 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 services.

[PLACE TABLE 4 APPROXIMATELY HERE]

Table 4 shows that, in terms of net 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 in the CLOB, almost 38% of buy and more than 36% of sell actual blocks would find better execution downstairs.

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

Since we are looking 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 BI upstairs market would be executed at better prices downstairs—is a fact and not a puzzle; block brokers are free to execute trades at the price they wish, so long as their clients agree. Since investors cannot monitor all quotes in the CLOB, the high mark-up they pay to brokers is not surprising.

The 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's 1992 turnover 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 unless an order is too large to be executed downstairs.

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, quite different to that of other exchanges. Unexpectedly low price impacts at BI are explained by the interaction between the two parallel markets of the CLOB and upstairs. We found additional evidence of the peculiarities of informational content in these two parallel markets when we focused specifically on price impacts.

4.3. Price Impact of Potential Blocks (CLOB)

We selected time points of five minutes pre- and post-block execution as the most appropriate moments at which to measure price impacts in the fully electronic and fairly liquid CLOB of BI.[11]

[PLACE TABLE 5 APPROXIMATELY HERE]

Table 5 shows estimates of price impacts in the CLOB, measured in basis points (bps) and broken down by stock capitalisation. Trading costs are statistically significant, but they are economically negligible. The highest total impact is just 46 bps for buy orders on mid-caps. Results for the whole sample confirm the conventional idea, as first explained by Holthausen et al. (1987), that buy orders have a higher permanent effect

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[11] We tried different time intervals, ranging from one minute to one trading day. We selected the five-minute interval as a trade-off between the fact that no orders are posted on illiquid stocks over very short intervals, and the possibility that many blocks and pieces of information mingle within a single time window. The speed of information flow makes the measurement of price impacts over different trading days irrelevant in modern markets.

whereas sell orders have a higher temporary effect. The total impacts of potential buy and sell blocks are of the same magnitude.

When we estimate costs separately for stock capitalisation, 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 the NYSE, London, Paris, Toronto or Helsinki exchanges, exist 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 their effect on block trading downstairs.

4.4. Price Impacts of Actual Blocks (Upstairs)

Since its introduction in 1992, the upstairs market at BI has worked similarly to modern consortium-based dark pools. Investors can contact dual-capacity brokers to trade any block of shares above a given threshold (see Appendix A for institutional details).

Since trade execution is disclosed with a one-hour delay, we cannot use the same five-minute intervals we adopted in the analysis of impacts in the CLOB for actual blocks. On the one hand, such a 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 attested to by comparing it 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 the pre-trade price to capture the effect of delayed disclosure. The stock price just after disclosure is taken as the 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 information-driven buy ones comes as no surprise.

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

Although the figures in Panel B (Table 3) suggest that there is little information in actual blocks, such a result arises because the largest liquidity-driven orders on mid-caps are forced to go upstairs due to 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 the 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 examined downstairs potential blocks posted after disclosure of an upstairs block separately from all the others. In this subsample, we further divided 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, which lowers the average impact of potential blocks overall. We believe a similar story fits the case of large-caps. However, informative events are rare 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 regressed 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 used to regress price impacts was 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 information may be more likely to go upstairs and were therefore deducted from the sample used for standard OLS regression.

To address the issue of sample selection, we applied the well-known Heckman (1979) technique and regressed the probability of an investor routing a block downstairs on a set of variables unrelated to actual price impacts. The basic idea is that we observe the downstairs price impact of a large order only if some criteria are met that induce an investor to prefer the CLOB to upstairs block 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 estimated the selection equation via a probit model, trying to capture the determinants of an investor's choice to route a block order downstairs or upstairs. Given the anonymity and delayed disclosure of orders executed in the upstairs market at BI, a main driver of the choice between upstairs and downstairs routing 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 ($Float$) as a proxy for both ownership dispersion and information dissemination.

The specification of our first-stage regression is as follows:

$$\text{Down} = \gamma_0 + \gamma_1 Thresh + \gamma_2 Float + \gamma_3 D_{Dealer} + \gamma_4 Spread_{1h} \tag{4}$$

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 modelling, as required by the Heckman (1979) procedure. $Float$ is the percentage of free-floating shares in that stock. The dummy variable D_{Dealer} denotes whether the order is on principal account. $Spread_{1h}$ is the bid-ask spread measured on the CLOB one hour before order execution. We use a lagged measure of liquidity to capture the fact that the decision on where to enter the order is made in advance.

We compute the inverse Mill ratio and use it in the following standard OLS regression equation to explain the permanent price impacts of potential blocks:

$$\text{Permanent Impact} = \beta_0 + \beta_1 RegSize + \beta_2 D_{First} + \beta_3 D_{Post} + \beta_4 D_{NoUp} + \beta_5 D_{Bull} \tag{5}$$

where $RegSize$ is the potential block order size divided by the upstairs threshold; D_{First} is a dummy equals to 1 when the potential block order is the first block of a given stock in a day; D_{Post} is a dummy variable denoting whether the insertion of the potential block order occurs after an actual block order is executed upstairs; D_{NoUp} is a dummy variable denoting whether there is no upstairs trading on the stock on that day; and D_{Bull} is another dummy variable, which equals 1 when the stock market index value at close is greater than at opening.

Table 7 shows the results for both model selection and OLS regression. Order size matters for buy orders but not sell orders. This confirms that investors will be inclined to consider sell orders as liquidity trades regardless of their size. The coefficient of $DFirst$ 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 order, ensuing sell orders are taken as a signal that some bad news is driving block trading on a particular stock. Buy orders elicit the opposite response from the market: the first buy order of abnormal size is taken as particularly informative, whereas orders 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 this is shown by the coefficient of $DPost$. We cannot deny the fact that such a high permanent impact captures the price movement caused by the actual block that was executed upstairs. However, the coefficient of $DNoUp$ 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 significant 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 more informative than average.

The estimated correlation ρ between the residuals of the two stages is significantly different from zero, thus the Heckman (1979) procedure is not rejected.

5. Liquidity and Pricing Efficiency Effects

In this section, we examine the important question of whether the trade efficiency we observe in the peculiar BI downstairs-upstairs market design affects fluctuations in liquidity and variations in the degree of market efficiency.[12] The microstructure effects we observe at BI may create certain market conditions that reduce liquidity. However, it is an empirical question as to whether illiquidity will be associated with return predictability as

[12] We are grateful to the anonymous referee for suggesting this line of inquiry.

per Fama (1970), or will reduce the amount of private information reflected in prices as per Kyle (1985).[13]

5.1 Liquidity Effects

Liquidity is an infamously vague concept that cannot be summarized in one measure.[14] Obizhaeva and Wang (2013) point out that snapshots of the CLOB, such as its spread and depth, are insufficient for explaining the dynamic properties of buy and sell orders. Parlour (1998) showed 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) showed that limit orders are more likely placed 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 be based on 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 only affect 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) investigated resiliency, i.e. how fast best prices, depths and durations 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 characterised by the bid-ask spread. The number of shares offered or demanded at the best quotes does not give the whole picture, particularly in the case of large orders that often “walk the book”.

[13] Chordia et al. (2008) use intra-day data to provide evidence that a liquid market is more efficient by incorporating more private information.

[14] For a comprehensive review, see Amihud et al. (2012).

Our dataset allows us to see the evolution of the limit order book using, at any time, all five levels of orders that brokers can see. This is of primary importance for linking large orders, liquidity and trading strategies. It is also a detailed dataset that permits direct testing of whether and how liquidity develops around block trading in an electronic market. Because of a lack of data resulting from the typical structures of high-frequency databases, no paper (of which we are aware) has verified it directly. Thus, in our empirical analysis, which is different from, for example, Biais et al. (1995), the downstairs information set is the same as that of the standard investors.

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 bid sides of the limit orders book.

The value of K_A (respectively, K_B) is the average of the differences in absolute value between the ask (bid) price and the mid-point of each level of the CLOB, scaled by order size. Labelling $\{A_1;\ q_{A1}\}, \{A_2;\ q_{A2}\}, \ldots, \{A_n;\ q_{An}\}$ as all offer prices and quantities, and $\{B_1;\ q_{B\,1}\}, \{B_2;\ q_{B\,2}\}, \ldots, \{B_m;\ q_{B\,m}\}$ as all pairs of bid prices 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 value of K_i, the larger is stock illiquidity.

We are interested in capturing the transience of depth decreases following block trades.

As ask (bid) quotes increase (decrease), the book actually attracts new sell (buy) orders and 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's 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-minute intervals before a large order is posted and after it gets executed. For this reason, we label $K_{i,n}$ as the illiquidity measured a number n of 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[15].

5.2 Price Efficiency Effects

We tested for pricing efficiency effects in two ways. In the first, which we describe as a weak-form level of efficiency (Fama, 1970), we follow the approach of Chordia et al. (2005), which examines serial correlations in stock returns. Thus, we design a test similar to the standard Fama-MacBeth (1973) regression model to analyse the change in downstairs daily serial correlations observed before and after upstairs block trades. In the second test, which we describe as a semi-strong level of efficiency, we use a standard

[15] We also estimate a regression model to examine the determinants of liquidity fluctuations using variables that characterise the order, the market and the CLOB. Multivariate analyses show that liquidity goes where it is lacking. 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 CLOB illiquidity. These results are not reported in order to save space. They are, however, available in an earlier version of the paper and are also available on request.

event study approach to analyse both downstairs stock returns and upstairs block trading of companies involved in M&A transactions.

5.2.1 Weak-form efficiency of downstairs stock returns around upstairs block trading

We take the sample of upstairs blocks and collect each company's downstairs daily stock returns (adjusted for splits and cash dividends) from the Thomson Reuters Datastream database within a 61 day-window (-30,..0,..+30) centred on the day (Day 0) when an upstairs block is executed. To overcome a potential bias arising when a company has more than one upstairs block in the selected time window, in a subsequent test we restricted our analysis to the sub-sample of firms that only had one upstairs block at Day 0 and, in the subsequent thirty days, no upstairs trading was detected. Our test employs the Fama-MacBeth regression model approach to test whether downstairs stock serial correlation is affected by the execution of large blocks in the upstairs market. Table 9, Panel A1 shows the results for the whole sample of upstairs blocks, whereas Panel A2 shows the results for the restricted sample of firms that have no block trades after the initial upstairs block in Day 0. As Panels A1 and A2 show, in our sample, we found no cases where a significant change in daily serial correlations was detected after the execution of a large block in the upstairs market. Furthermore, on average, downstairs serial correlations pre- and post-block trading were virtually zero and statistically insignificant. Thus, the empirical findings exclude any relation between upstairs trading and the time-series pattern of downstairs stock daily serial correlations in our sample, confirming the weak form of price efficiency.

[PLACE TABLE 9 APPROXIMATELY HERE]

5.2.2. Downstairs stock returns and upstairs trading around corporate control transactions

The semi-strong form of the efficient markets hypothesis predicts that the open market price of risky stocks reflects all publicly-available information (Fama, 1970). We implement a test of this semi-strong hypothesis by ascertaining how downstairs daily returns and upstairs block trading are affected by the announcement of a corporate control transaction. We collected data from the Thomson Reuters M&A database for merger and acquisition transactions announced in year 2005 where an Italian-listed firm was either the target or the buyer. We filtered identified transactions by retaining deals where only full control transfer (>50%) was disclosed in the public announcement. The final sample contained six public targets and 35 public acquirers. Next, we collected daily returns for identified common stocks (adjusted for splits and cash dividends) and the stock market index from the Thomson Reuters Datastream database within a 21-day window (-10,..0,..+10) centred on the transaction's first announcement day (Day 0). We implemented a standard event study by computing market-adjusted cumulative average abnormal returns (CARs) and followed Schwert's (1996) methodology to obtain pre-bid runup (days -10,..2) CARs, announcement (days -1,0,+1) CARs, and post-bid markup (days +2..+10) CARs. Finally, for sample firms, we identified upstairs blocks in the same 21-day window.

Table 9, Panel B presents the findings for the event study and the upstairs trading around corporate control transactions. Panel B1 shows the results for target firms. In the pre-bid time window, there was a statistically significant 5.1% CAR—a result that indicates significant insider trading in the electronic market ahead of the first public announcement.[16] However, when we turn our attention to the upstairs market, we find little evidence that large blocks are executed for target firms in the run-up period. As the upstairs market is constrained to negotiate only very large blocks, we hypothesise that insiders could make small or medium-size trades (e.g., Kyle (1985) and Barclay and Warner (1993)) in the more liquid downstairs market. At the announcement and post-bid times, we detected no statistically significant CARs for target firms, and very little upstairs trading. This finding indicates that most price revelation on corporate control transactions occurs on days before the public announcement day and, afterwards, no further price effects are observed. This result is not different from available evidence in other markets, and it shows no trace of price inefficiency in the downstairs market because of the peculiar market architecture. Panel B2 shows the results for acquirer firms. Public firms involved

[16] See Linciano (2003) for evidence of insider trading in the BI stock market for the period 1998–2000 around announcements of corporate events. A more extensive literature review on the behavior of stock prices around takeover announcements is provided in Eckbo (2008).

as buyers in control acquisitions showed positive but insignificant price effects in the downstairs market in the three time windows: before, during and after the public announcement. This result parallels the vast international empirical evidence for buyers involved in M&A deals, and again confirms the expected and normal pattern of downstairs prices. We inspected deal characteristics to find out some factors that may explain the empirical results and found that all transactions were controlled acquisitions of private firms. Thus, the buyer CAR's positive sign is also in line with the M&A literature, which reports that when public buyers acquire control of private firms, the stock market reaction is, on average, positive. This is a well-known empirical regularity that contrasts the mean negative CARs observed when a public buyer takes over a public target. We interpret this result as a further indication that downstairs prices efficiently reflect private information and conform to patterns observed elsewhere around the world. Upstairs trading for buyer stocks was more frequently observed compared to the target firm sample. However, more frequent block trading upstairs does not seem to generate any adverse impact on downstairs prices, presumably because of its higher degree of liquidity.

6. Concluding Remarks

We exploited the peculiar architecture of the Italian stock exchange (BI) to study the price and liquidity impacts of large orders executed in the electronic CLOB in a fragmented market.

Our unique dataset contains orders posted by all investors for a broad selection of stocks accounting for 95% of the turnover in the BI. This has allowed us to overcome the limitations of previous studies of market microstructure, which used trades as the basic measure of observation or relied on the proprietary databases of asset management firms.

The findings regarding trading costs at BI highlight the economic consequences of different market designs. The most striking result is that price impacts at BI are lower than in any other exchange studied so far.

We defined potential blocks as the large orders that investors decide to route downstairs through the CLOB, although their upstairs execution as actual blocks is also allowed. We explained the lower price impact of potential blocks in the BI compared to other international exchanges as arising from market microstructure design. 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 introduced a measure of liquidity disruption in the CLOB and tracked how it reacts to large orders. Since large orders often “walk the book”, liquidity is not characterised by the quantities and prices of the best quotes. We measured the average multi-level availability of liquidity in both the ask and bid sides 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. The pre-trade bid-ask spread does not explain the impact of potential blocks on liquidity, whereas past realisation of our measure of liquidity on each side of the CLOB accounts for much of the average block impact. This shows that liquidity is resilient on each side of the book. Consistent with the aforementioned results on price impacts, the market’s direction also affects the way CLOB liquidity reacts to large orders.

We conducted two tests of market efficiency to verify that the observed trade efficiency is not harming stock pricing efficiency. In the first, we examined how serial correlations of downstairs prices are affected by upstairs block trading. In the second, we analysed how downstairs stock returns and upstairs trading behave around disclosure of important corporate control events. In both tests, we found the behaviour of downstairs pricing to be consistent with the predictions of efficient market theory and with the vast amount of empirical evidence from international markets.

A major policy implication of our study is that an upstairs market lowers price impacts. In contrast to what is asserted in the extant literature on block trading, such improvement is greater 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 the concentration of liquidity downstairs and reduces trading costs so as to limit price impacts to much lower levels than those exhibited in the other exchanges that have been considered in the market microstructure literature on trade efficiency.

Appendix A: Block trading at BI

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

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

– €150,000, if the average daily turnover of stock in the Italian regulated markets was less than €1.5 million over the past six months.

– €250,000, if the average daily turnover of stock in Italian regulated markets was €1.5–3 million over the last six months.

– €500,000, if the average daily turnover of stock in Italian regulated markets was €3–10 million over the last six months.

– €1.5 million, if the average daily turnover of stock in Italian regulated markets was greater than €10 million over the last six months.

Appendix B: Dataset

To construct the dataset on downstairs trading, we began by selecting all orders with values ≥ €150,000 placed in the CLOB at BI in 2005. Tracking of orders and executed trades was allowed for in the dataset by a unique identification number, and we avoided sampling orders that were imply reactions to original large orders or potential blocks. This yielded the 778,166 orders analysed in the present paper.

Each order (*pdn: proposta di negoziazione*) came with a number that was 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 was on a principal or agency account; whether it was a 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 prices before the order was placed and those immediately after its full execution; the price of the last trade, the best bid and best ask prices 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 were isolated from large trades by using the rules set by the Italian security exchange commission (CONSOB).

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Table 1. Borsa Italiana and sample summary statistics

This table presents Borsa Italiana (BI) and stock sample summary statistics. Panel A shows BI descriptive figures in year 2005: total number of listed firms, total market capitalisation (in €bn), total annual turnover (expressed in €bn), turnover (in €bn) of two largest market segments of Blue Chips and Star stocks and percentages over total market turnover, upstairs trading volume expressed in €bn and as percentage of total market trading volume, the number of BI year 2005 trading days, the percentage of trading days that were identified as bull days (when stock market index level at close is higher than at opening) and bear days (when stock market index at close is lower than at opening). Panel B shows stock sample main characteristics in year 2005: number of common stocks, sample market capitalisation over total market capitalisation, average market capitalisation for mid-cap stock in sample and average market capitalisation for large-cap stock in sample, annual turnover of sample stocks as percentage to market turnover.

Panel A: Borsa Italiana 2005 summary statistics	
Listed firms	282
Market capitalization (in €bn)	676
Total stock market turnover (in €bn)	954.7
Blue Chip and Star stocks annual turnover (in €bn)	935
% over Exchange	98%
Total Upstairs trading (in €bn)	72.1
% over Exchange	7.5%
Exchange trading days	256
Bull days (%)	57%
Bear days (%)	36%
Panel B: Sample stock summary statistics	
Number of common stock in sample	161
Sample capitalization over market capitalization	90%
Average capitalization mid-cap stocks (in €bn)	4.92
Average capitalization large-cap stocks (in €bn)	35.82
Sample annual turnover over exchange (in %)	95%

Table 2. Large orders and blocks in the electronic CLOB (downstairs) and upstairs markets of BI

This table presents descriptive statistics and distributions of large orders and trades in the electronic CLOB and the upstairs market of BI in 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 sizes equal to or greater than the minimum threshold required by security regulations 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 the 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
Mean order size (Euros)	326,592	1,561,127
Median order size (Euros)	243,216	1,606,500
Mean order immediacy vs. best ask	-1.2	5.58
Mean order immediacy vs. midquote	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
Mean order size (Euros)	298,698	1,297,920
Median order size (Euros)	227,800	551,100
Mean order immediacy vs. best bid	-3.3	1.44
Mean order immediacy vs. midquote	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 per order	6.11	18.50	1
Median trades per order	4	12	1
Mean execution time (minutes)	7.77	11.91	N.A.
Median execution time (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 per order	6.99	15.81	1
Median trades per order	5	10	1
Mean execution time (minutes)	17.60	21.16	N.A.
Median execution time (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 (in minutes)	
		Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
Buy Orders							
Capitalization							
Mid-cap	9,290	229,886	195,500	10.41	8	14.08	0.13
Large-cap	546,980	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 (in minutes)	
		Mean	*Median*	*Mean*	*Median*	*Mean*	*Median*
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	414,030	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	Order size in €	
	Number	Mean	Median
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. Comparison of block trade price impacts in BI (this study) and other exchanges (from the block trading literature)

This table presents a direct comparison between our results (henceforth, MPGB) on block trading price impacts at BI and empirical findings from the block trading literature. Block trading price impacts at BI were computed by using the same metrics adopted in published papers in order to allow direct comparisons. Metric formulas are listed in the table footer and BI results are in bold. All figures are expressed in basis points. Panel A contains comparisons for blocks executed in downstairs markets (whether electronic or not) and Panel B shows comparisons for blocks executed in 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	MPGB		-11	-3	-14	19	-2	17
1997-2001	39 countries	Plexus	Chiyachantana et al. (2004)	b	-	-	-42	-	-	33
2005	Borsa Italiana	Exchange	MPGB		-	-	-14.83	-	-	21.77
1997-1998	Paris Bourse	Exchange	Bessembinder and Venkataraman (2004)	c	-35	-17	-52	128	-38	90
2005	Borsa Italiana	Exchange	MPGB		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	MPGB		-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	MPGB		-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	MPGB		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	MPGB		3.64	-7.71		-3.79		-9.15	13.09		4.11

a: perm$=\ln\left(\frac{P_{d+5m}}{P_{d-5m}}\right) - r_M$; temp$=\ln\left(\frac{P_b}{P_{d+5m}}\right) - r_M$

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$= ln(Pb+20 / Pb-20)$; temp$= ln(P_b / P_{b+3})$.

f: perm$= ln(Pd / Pb-1)$; temp$= ln(P_b / P_d)$.

g: tot$=(P_b - P_{b-1}) / Pb-1$; 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	MPGB		-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	MPGB		-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	MPGB		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	MPGB		-7	-192.87	-199.87	-24.93	64.83	39.9

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

d: $\text{perm} = ln(P_{b+3} / P_{b-5})$; $\text{temp} = ln(P_b / P_{b+3})$.

e: $\text{perm} = ln(P_{b+20} / P_{b-20})$

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 in 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 large- and mid-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 net market returns of the whole sample and the two subsamples of mid- and large-cap stocks. A *temporary effect* is defined as a change in price from the block price to the post-trade price. A *permanent effect* is defined as a change from the pre-trade price to the post-trade price. A *total effect* is defined as the difference between the block and pre-trade prices. The pre-trade and post-trade prices for blocks executed downstairs equal the prevailing prices five minutes before and after block execution, respectively. In the case of upstairs blocks, the pre-trade price was sampled one hour before execution and the post-trade price was sampled just after disclosure. Panel A shows the average results for potential blocks in the electronic CLOB. Potential blocks are defined as individual orders posted into the electronic CLOB with a size equal to or greater than the minimum threshold required by security regulations for execution in the upstairs market. Panel B presents the average results for blocks executed in the upstairs market. All reported figures are in basis points. *** = $p < 0.01$; ** = $p < 0.05$.

Direction	Temporary	Permanent	Total
Panel A: Potential blocks (CLOB)			
Whole sample buy			
Whole sample sell	0	15***	15***
	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***

Table 6: Price impact of block trades in the electronic CLOB under different timings and simultaneous upstairs trading

This table presents the average price impact of block trades in the BI for year 2005. Average price impacts are presented for temporary, permanent and total effects and for the two sub-samples of mid- and large-cap stocks. Average price impact for potential blocks in the electronic CLOB are presented when no upstairs trading was observed in the same trading day or at least one upstairs block was executed in the same trading day. When upstairs trading was observed in the same day, average price impacts are shown separately for a) before the upstairs block was executed (*pre-block*); b) between upstairs block execution and its public disclosure (*pre-com*); and c) after the upstairs block execution was publicly disclosed (*post-com*). Average price impacts for upstairs blocks are shown in the bottom row of each panel. Panel A shows the average price impacts for buy blocks and Panel B shows the average price impacts for sell blocks. All figures are expressed in basis points. ***$p < 0.01$; **$p < 0.05$; *$p < 0.1$.

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
	No-upstairs days	6***	2***	0	-4*	-5	-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
	Upstairs Blocks	510***	35***	-31***	-10***	-325***	-41***

Table 7: Multivariate analysis of downstairs potential block price impact

This table presents regression analyses of the fundamental variables affecting the permanent trading costs of potential blocks executed in the CLOB. Panel A shows estimates of the Heckman (1979) probit model used to address issues of sample selection and endogeneity and compute the inverse Mill ratio. Panel B presents coefficient estimates from the OLS model where the inverse Mill ratio is inserted jointly with measures of order size, market conditions, stock characteristics and trade difficulty to explain the permanent price impacts of potential blocks. In Panel A, probit model variable Down is the probability that an order is routed downstairs, $Thresh$ is the block size threshold for upstairs trading that is set by stock exchange regulator for all orders on a given stock, $Float$ is the percentage of free-floating shares on that stock, D_{Dealer} is a dummy variable equal to one when the order is on principal account, $Spread_{1h}$ is the bid-ask spread measured on the CLOB one hour before order execution. In Panel B, the OLS model's dependent variable *Permanent impact* is the permanent trading cost of potential block executed on CLOB, $RegSize$ is the potential block order size divided by the upstairs threshold; D_{First} is a dummy variable that 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 denotes whether the entry of the potential block order occurs after an actual block order is executed upstairs; D_{NoUp} is a dummy variable equal to one when no upstairs trading on the stock on that day; and D_{Bull} is a dummy variable equal to one when the stock market index value at close is greater than at opening. ***$p < 0.01$; **$p < 0.05$.

Panel A: Probit (Heckman, 1979) selection model

$$\text{Down} = \gamma 0 + \gamma 1\, Thresh + \gamma 2\ Float + \gamma 3 \mathbf{D}\ Dealer + \gamma 4\ Spread\ 1h$$

	SELL	BUY
Intercept	1.01***	1.39***
Thresh	-0.61***	-0.73***
Float	0.69***	1.07***
D_{Dealer}	-0.65***	-0.40***
$Spread_{1h}$	-3.76***	-1.49***
Rho	0.57***	0.77***

Panel B: OLS model:

$$\text{Permanent Impact} = \beta_0 + \beta_1 RegSize + \beta_2 D_{First} + \beta_3 D_{Post} + \beta_4 D_{NoUp} + \beta_5 D_{Bull}$$

	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***

Table 8: Potential block impacts on the liquidity of the electronic CLOB

This table presents coefficient estimates of the 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 five levels which are publicly disclosed. ***p < 0.01; **p < 0.05; *p < 0.1.

	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***

Table 9: Market efficiency in the electronic CLOB around upstairs block trading

This table presents the empirical results of tests of efficient market hypotheses in the CLOB downstairs market around block trading in the upstairs market. Panel A presents results of weak-form efficiency tests. For each company with an upstairs block trade in year 2005, downstairs daily stock returns (adjusted for splits and cash dividends) were extracted from the Thomson Reuters Datastream database within a 61-day window (-30,..0,..+30) centred on the day (0) when the upstairs block was executed. In Panel A1, mean daily serial correlation statistics are presented for the 30 days of pre-block trading (-30,..-1), 30 days' post-block trading (+1,..+30), and mean Fama-MacBeth (1973) *t*-test statistics of serial correlation differences. In Panel A2, empirical results are presented for the sub-sample of companies that had no further block trades in the 30 days following block trading in Day 0. Panel B presents the results of semi-strong form efficiency tests using a standard event study analysis for mergers and acquisitions (M&A) announcements. Panel B1 presents results for six targets and Panel B2 presents results for 35 acquirers. Italian-listed firms in year 2005 that were targets of an announced merger or control acquisition (> 50%), or acquirer of announced merger or control acquisition (> 50%) were identified in the Thomson Reuters M&A database along with deal characteristics and announcement days. Downstairs daily stock returns (adjusted for splits and cash dividends) were extracted from the Thomson Reuters Datastream database within a 21-day window (-10,..0,..+10) centred on the M&A announcement day (0). Market-adjusted cumulative average abnormal returns (CARs) are presented for three time windows following Schwert's (1996) methodology: pre-bid run-up (days -10,.._2), announcement (days -1,0,+1), and post-bid mark-up (days +2..+10). The total numbers and daily averages of upstairs blocks are shown for the three time-window. The *t*-statistics of means are shown in parentheses. $^{**}p < 0.05$.

Panel A – Weak-form efficiency tests

Daily serial correlations	*Pre-block trading (-30,..-1)*	*Post-block trading (+1..+30)*	*Number of serial correlation >0*	*t-test of mean differences*
Panel A1				
Whole sample (nob 2371)	*-0.009*	*-0.018*	*0*	*0.74*
Panel A2				
Restricted sample (nob 411)	*-0.037*	*-0.049*	*0*	*0.78*

Panel B – Semistrong-form efficiency test

	Pre-announcement run-up window (-10,…-2)	*Announcement window (-1,.0,.+1)*	*Post-announcement markup window (+2,..+10)*
Panel B1 – Targets (nob=6)			
Downstairs CARs	*0.051***	*-0.018*	*-0.004*
t-stat	*2.88*	*-0.16*	*-0.20*
Upstairs trading (total number of blocks)	*1*	*0*	*2*
Upstairs trading (daily average blocks)	*0*	*0*	*0*
Panel B2 – Buyers (nob=35)			
Downstairs CARs	*0.011*	*0.001*	*-0.000*
t-stat	*1.11*	*0.20*	*-0.08*
Upstairs trading (total number of blocks)	*32*	*18*	*46*
Upstairs trading (daily average blocks)	*3.56*	*6*	*5.11*