Order-to-trade ratios and market liquidity*

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Abstract

We study the impact on market liquidity of the introduction of a penalty for high order-to-trade ratios (OTRs), implemented by the Italian stock exchange to curtail high-frequency quote submission. We find that the fee is associated with a collapse in the quoted depth of the stocks that make up the bulk of trading in Italian equities and an increase in price impacts of trading across the treated stocks. Spreads do not change, however. Stocks from a pan-European control sample show no such liquidity changes. Thus, the Italian OTR fee had the effect of making Italian stocks markets more shallow and less resilient. Large stocks are more severely affected than midcaps. We also find evidence of a limited decrease in turnover. Consolidated liquidity, constructed by aggregating across all electronic trading venues for these stocks, decreases just like that on the main exchange. Thus, liquidity was not simply diverted form the main exchange, it was reduced in aggregate.

Keywords: Order-to-trade ratios; High-Frequency Trading; Computerized trading; Italian Stock Exchange; Limit order trading.

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Enforcing order-to-trade ratios (OTRs) on a trading venue involves financially penalising individual member firms if the orders to buy or sell they enter do not lead to a "sufficient" number of trades. As OTRs attack High-Frequency Trading (HFT) at its root – targeting the high number of "messages" that high speed participants rely upon – regulators currently consider them as one of the policy tools of choice to reduce the incidence of HFT. For example Mary Schapiro, then Head of the US Securities and Exchange Commission, indicated that the SEC was considering implementation of an OTR penalty scheme.[1] The EU Parliament and Commission have gone further: the current draft of the piece of legislation that will regulate trading across all EU exchanges from 2016, the "Markets in Financial Instruments Directive" (MiFID), includes across-the-board implementation of OTRs.[2]

In fact, the national regulators of some of the largest EU countries have decided not to wait and have either already implemented OTRs or intend to do so. This includes the Italian stock exchange, which is the focus of our study. On April 2^{nd}, 2012, the Milan Borsa, the historical stock exchange of Italy and part of the London Stock Exchange Group, implemented an order to trade ratio applying to all its member firms. This event presents us with a direct way of estimating the link between messaging activity and liquidity.

There is little doubt that a measure causing high-frequency quoting to contract has the potential to alter pricing, trading and liquidity processes in a significant way. By all accounts, high-frequency flow has become very significant in today's markets. The Tabb Group, a consultancy, estimated the incidence of High-Frequency trading at 39% for Europe in 2012 (reported in "*Understanding High Frequency Trading*", World Federation of Exchanges report, 29 May 2013). Consistent estimates are available for

[1] *Financial Times*, 28 February and 10 April 2012.

[2] Its Article 51(3) states that "Member States shall require a regulated market to have in place effective systems, procedures and arrangements to ensure that algorithmic trading systems cannot create or contribute to disorderly trading conditions on the market including systems to limit the ratio of unexecuted orders to transactions that may be entered into the system by a member or participant (...)." Proposal for a Directive of the European Parliament and of the Council on markets in financial instruments repealing Directive 2004/39/EC of the European Parliament and of the Council, COM(2011) 656 final, 20.10.2011.

a few markets where research-based evidence is available: In Nasdaq data, Brogaard, Hendershott, and Riordan (2013) find that HFT makes up about 42% of traded volume in large stocks over their sample period, a figure that they indicate does not include all HFT flow. In Nasdaq-OMX data, Hagströmer and Nordén (2013) report an interval estimate of 26-30% for pure HF firms, and a total amount of HF trading that could be as high as 52%. (The first figures do not include firms using a mix of low and high frequency strategies.) The effect of a reduction of high frequency quoting is not clear however. If those using large numbers of messages are making markets, then liquidity might decline with the imposition of an OTR. If instead, firms with high messaging rates impose adverse selection costs on other participants, then constraining this behaviour might attract other traders back to market and thus increase liquidity.

We find that the introduction of the OTR penalty scheme is associated with a marked deterioration in quoted depth for Italian stocks. Depth declines particularly steeply in large stocks that make up the bulk of turnover in Italian equities. Price impacts from trading are significantly increased following the introduction of the OTR penalty for all Italian stocks. Measures of quoting and trading activity also fall. Perhaps more surprisingly, we also find that the deterioration of liquidity on the historical exchange extends to measures of consolidated liquidity (where consolidated liquidity is measured from aggregated orders across the historical exchange and alternative trading venues). Thus, activity did not simply move away from Borsa Italiana and towards venues such as Chi-X, but liquidity was reduced in aggregate. This suggests that the historical exchange may dominate price and liquidity discovery. Another interpretation is that only a limited number of liquidity suppliers make markets across all venues, resulting in the maintenance of liquidity at less than competitive levels (see Biais, Bisière, and Spatt (2010) for evidence along these lines from US markets).

In the next Section we discuss the motivation for the Italian OTR scheme. In Section 2, we review relevant theory and evidence and formulate some testable hypotheses. In Section 3 we give details on the data we use and the market from which it is drawn.

Section 4 explains our modelling approach and Section 5 presents estimation results.

1 Policy debates and stated goals of the Italian OTR scheme

There is widespread interest in OTRs on the part of politicians, regulators and exchanges. Policy-makers seem driven by the intuition that there must be something untoward in the submission of a large number of orders that do not lead to executions. With such low probability of execution, high-frequency orders must either have lifetimes so short that they can't be traded against or be too far from current prices to be "bona fide" (O'Hara, 2010). At best, such orders are dismissed as not constituting genuine liquidity, while at worst, extremely short-lived quotes raise suspicions of abusive behaviour, the most obvious example being "quote-stuffing" (attempts to flood the systems of other firms with order entries and cancellations to hide manipulative behaviour.) Other manipulative strategies such as "layering" the order book or "spoofing" also rely on the submission of multiple orders which are subsequently cancelled.[3]

These views are exactly what inspired the Italian OTR scheme – widely reported in the financial press to have been implemented at the request of the national regulators CONSOB (see *Financial Times*, February 20, 2012, and *The Trade*, February 27, 2012.) To a Finance commission of the Italian Senate, the Head of CONSOB gave more details on the rationale behind the fee, stating that "the ability of high frequency traders to suddenly cancel orders placed before they are executed, displacing other investors, can generate a misleading representation of the actual depth of the order book, creating favorable conditions for market manipulation." He went on to say that

[3]The European regulator ESMA defines layering and spoofing as "submitting multiple orders often away from the inside on one side of the order book with the intention of executing a trade on the other side of the order book. Once that trade has taken place, the manipulative orders will be removed." In ESMA, "Guidelines – Systems and controls in an automated trading environment for trading platforms, investment firms and competent authorities", 24 Feb 2012.

"the increase in the number of orders placed in the trading systems and in the order-to-trade ratio may endanger the regular course of the negotiations and the integrity of markets, given the limits on capacity and the reliability of the infrastructure."[4] This confirms that the OTR scheme was explicitly directed at HF traders and motivated by concern that their rates of order entry may disrupt markets and foster manipulation.

2 Priors and testable hypotheses: HF trading and liquidity

Whether an OTR will enhance or reduce liquidity depends on the net contribution to liquidity of those HF agents targeted by the OTR as using the highest speed (equivalently, the lowest latency). We review both sides of the argument.

An OTR may reduce the likelihood of outright manipulation. If the highest speed targeted by the OTR is chiefly used for manipulative purposes (e.g. through quote stuffing or layering of order books), then the OTR may improve liquidity by reducing the costs that fast traders impose on slower participants. We have no estimate of how much HF flow might be abusive in nature because such behaviour is very difficult to detect unambiguously, particularly in its high-frequency flavour.[5] Few cases are prosecuted successfully and fewer cases still are found to involve HF traders.[6] However, some academic work does raise the possibility that some HFTs engage in behaviour that is consistent with manipulation. Gai, Yao, and Ye (2012) and Egginton, Van Ness, and Van Ness (2013) find patterns consistent with quote-stuffing in their data. Clark-Joseph (2013) finds that HF traders forecast the order flow of slower traders.

[4] "Audizione del Presidente della CONSOB Giuseppe Vegas, Senato Della Repubblica VI Commissione (Finanze)", 26 June 2012, 54 p., Appendix 5, "High-Frequency Trading", pp 39-40. (Our translation.)

[5] There is a suspicion that regulators are overwhelmed by the amounts of data that today's markets generate and that they are lagging behind brokers and exchanges in respect of the skills required to analyse the data. This view is expressed for example in "U.S. Securities and Exchange Commission, Organizational Study and Reform", Boston Consulting Group report, March 10, 2011.

[6] At the time of writing, we are aware of only three cases of successful prosecution of firms considered HF traders: fines were imposed on Trillium Brokerage Services and Panther Energy Trading in the U.S. and on Swift Trade in the U.K.

When they know that liquidity is low and that a big non-HFT order is being worked, then they trade in front of that order and increase the trading costs of slower traders. Using Nasdaq data, Hirschey (2013) finds that HFTs trade in front of other traders and forecast returns associated with price pressure of other traders. All of these examples of behavior (quote stuffing, anticipatory trading) will likely have the effect of increasing the execution costs of slow traders, i.e. reducing realized liquidity.

One might also argue that, if HF traders are better informed than other market participants, then if the OTR was to discourage them from participating in markets, adverse selection risk would drop and liquidity increase. Both Hendershott and Moulton (2011) and Menkveld and Zoican (2014) report evidence of greater adverse selection after systems upgrades that increase the incidence of HF trading by reducing latency on the NYSE and NASDAQ-OMX respectively.

A counter-argument to this last point relies on the idea that an OTR may damage liquidity due to the fact that HF traders may be acting as de facto market makers and the OTR constrains those activities. Decomposing the costs of market making into order processing costs, inventory risk and asymmetric information risk, one can argue that an OTR would increase all of them. Order processing costs may mechanically rise due to the OTR fee itself. Then, as the OTR limits a HF market-maker's latency advantage, it increases both the risk associated with carrying unwanted inventory and the risk of being picked off by fast aggressive traders.[7] Overall, limiting the ability of HF market-makers to revise their quotes may reduce their participation in liquidity supply or cause them to quote poorer prices and smaller sizes.

Finally, a separate argument is that the combination of automation and speed may be a remedy to the issues of "limited attention" in human market-makers that are the focus of a recent behavioural literature (Corwin and Coughenour, 2008; Boulatov, Hatch, Johnson, and Lei, 2009). This work finds that human market-makers are unable to give equal attention to all the stocks they deal in. As a result, their

[7]See Hendershott and Menkveld (2014) for a measurement of the economic significance of inventory costs.

liquidity provision is allocated unevenly, especially at times of increased activity: Corwin and Coughenour (2008) find that market-makers submit fewer quote updates than would be optimal in some of their assigned stocks, grant less price improvement, and market efficiency is adversely affected. Again, the combination of automation and speed provides potential remedies to this issue.

Consistent with these latter lines of reasoning, Hendershott, Jones, and Menkveld (2011) Menkveld (2013) and Hasbrouck and Saar (2013) are examples of studies reporting evidence consistent with greater speed allowing HF traders to narrow the spread and improve liquidity.

2.1 Empirical evidence on the composition of HF activity and on liquidity effects of trading regulations

How significant is liquidity supply as a proportion of HF activity and to what extent would it be affected by an OTR? Using Nasdaq-OMX data where participants can be identified, Hagströmer and Nordén (2013) report that market-making makes up 63 or 72% of HF business depending on the sample period, and in all cases over 80% of all HF order submission. They also point out that "any regulatory policy directed at HFTs as a group would primarily affect market-makers" as a result.

Intuition suggests that enforcement of an OTR seems likely to constrain HF market-making more than other computerised trading activities such as statistical arbitrage or execution of agency flow. Agency execution algorithms are designed to generate executions (trades), and do not rely as heavily on speed as strategies considered "core" HFT territory like stat arb and market-making do. The former can generate significant quote "messaging" but executions are necessary for stat arb strategies to profit from the mis-pricings that they identify. HF liquidity suppliers, on the other hand, must revise their quotes to reflect the continuous arrival of macro and asset-specific news, and to keep inventory risk to a minimum. Consistent with this, Hagströmer and Nordén (2013) report that "market-making HFTs have higher order-to-trade ratios" than directional or other strategies. This suggests that market-making systems may be the first to be revised under an OTR constraint, which is likely to reduce voluntary HF liquidity supply more than other types of HF flow.

We are aware of one recent study that is closely related to ours, by Jorgensen, Skjeltorp, and Odegaard (2014), who evaluate the implementation of a "message to trade" ratio on the Oslo stock exchange. Intriguingly, they find no evidence of impact on variables of liquidity and activity. Their results, considered with ours, may illustrate how different calibrations of a constraint on order submission may have different effects. Other evidence that we have seen is indirect, in that it did not involve implementation of an actual OTR. Gai, Yao, and Ye (2012) find that a reduction in the trading latency permitted by an upgrade in Nasdaq's IT infrastructure has led to an increase in empirical order-to-execution ratios, which in turn had no effect on quoted liquidity. Colliard and Hoffmann (2013) and Meyer and Wagener (2013) study the implementation of a transaction tax in France in August 2012. Although the potential ability of such a tax to reduce the incidence of HFT is sometimes discussed, it is not its main goal and it is a very different type of event to ours, as it targets trades and not HF order submissions.[8]

2.2 Testable hypotheses

Quoted liquidity at the inside and beyond Existing estimates suggest that market-making represents the bulk of HF activity, which itself makes up a large proportion of total activity. The effect of the OTR will depend on whether the constraint it places on genuine market making strategies dominates the improvement in liquidity that might result from the reduction in HFT-generated adverse selection. The bulk of extant empirical work suggests that the negative effect could dominate here, causing liquidity to fall. In particular, the OTR may cause order submitters to

[8] In fact, Italy introduced a specific tax on high speed trading in the year after the OTR we study was enforced. The French Government also introduced a specific tax on HF trading at the same time as its general tax on transactions.

curtail liquidity supply with low execution probabilities. This could reduce order book depth away from the inside spread. A similar reasoning applies to price impact of trades: it may increase (market resilience decrease) if the OTR hampers the ability of fast liquidity suppliers to refresh their quotes when liquidity is depleted. Price impacts might also rise if fast informed liquidity suppliers become fast, informed liquidity demanders under the OTR. If the OTR reduces the ability of HF traders to trade in front of other traders, price impacts might instead fall.

Activity The average trade size could be affected in opposite ways by an OTR. Two effects may cause it to increase: First, high-frequency trading seems characterised by small trade sizes (see, for example, Chordia, Roll, and Subrahmanyam, 2011). Hence under an OTR that reduces HF participation, trade sizes might increase. Additionally, an OTR may encourage more impatient trading and liquidity consumption rather than supply and one might expect HF traders to conduct the same activity using fewer, larger trades. On the other hand, a decrease in depth (increase in price impact) may force traders controlling their execution costs to trade in smaller lots.

In terms of total trading activity, the effect of the OTR will depend on whether it causes HFTs to withdraw from trading and whether slower traders might participate more in less HFT-dominated venues. In fragmented markets, activity may simply move to other venues which do not impose an OTR, leaving total turnover unchanged.

Cross-sectional effects The effect of the OTR in the cross-section of stocks remains to be identified empirically. Anecdotal evidence from the financial press suggests that HFT interest is focussed on the largest names in terms of sheer quoting frequencies, but this neither indicates that their OTRs in those stocks are higher nor that HF market-making leads to smaller improvements in the liquidity of smaller stocks. A small amount of HF activity in midcaps may significantly reduce spreads, for example, while in large caps, as spreads are already very tight due to high natural trading interests, adding HF market makers to the mix may not improve liquidity much. Alternatively, if HF market making was very limited in midcaps already, then imposing an OTR could have little real effect on them but a detrimental effect on large caps (through the constraints placed on market-making). Also, if order submission becomes more expensive, liquidity suppliers may lose incentives to quote aggressively in stocks where execution probabilities are smallest and focus on larger issues only. This might lead to substitution of HF activity towards larger issues to the detriment of mid-caps.

Fragmentation, competition between order books and consolidated market quality The impact of an OTR on consolidated measures of liquidity and activity will depend on two effects. First, does independent price and liquidity discovery occur on the rival electronic order books? If venues are substitutable in terms of their ability to contribute to price discovery, then the result of an OTR on one venue should be a wholesale migration of HF quoting to an alternative market and little effect on consolidated, market-level liquidity. Second, how keen is competition in liquidity supply across venues? If only a limited number of liquidity suppliers operate on both, they may be able to adopt rent-seeking (collusive) behaviour to maintain liquidity at uncompetitively low levels on the smaller venues. A finding with exactly this flavour was reported by Biais, Bisière, and Spatt (2010) for Nasdaq and Island in the US. Further, if those demanding liquidity are constrained by technology, by history or by mandate to seek execution on the historical main exchange then the ability for liquidity supply to migrate to alternative venues is limited.

3 Market structure and data

The Italian stock exchange (Borsa Italiana), located in Milan and part of the London Stock Exchange Group, operates a standard electronic order-driven system. The trading day begins with a pre-opening auction phase that runs from 8 to 9 a.m., followed by the main continuous auction phase between 9 a.m. and 5.25 p.m. During the continuous periods, order execution is determined by the usual price and time priorities. The market is closed by a batch auction at 5.30 p.m.

Over the sample period, the market share of electronic trading in Italian stocks held by the Milan exchange stood at over 80% by value. The next largest competitor was the newly merged BATS/Chi-X Europe with market share of roughly 15%, followed by Turquoise (about 2%). Other markets are too small to mention. As such, at the time, the Milan exchange had retained a much larger market share of total order flow in its domestic equities than the historical exchanges of the UK, Germany or France but a smaller share than the Spanish exchange.[9]

3.1 Features of the OTR scheme and preliminary evidence

The order-to-trade ratio is computed for each exchange member firm over all orders they enter and the trades that result. The numerator includes all order entries, irrespective of order type or price placement, of the proprietary or agency nature of the order or of the phase of trading (opening and closing batch auctions or continuous auction). For each firm, the ratio is calculated across its orders and trades in the stocks belonging to the Milan exchange's main segment called MTA. These 250 or so stocks represent very close to 100% of total exchange market capitalization and turnover by value.

From the ratio, the Italian exchange determines fees on a daily basis, thus reducing the flexibility for a firm to engage in bursts of quoting activity on some days and make up for those bursts on quieter days. There are three threshold ratios of 100:1, 500:1 and 1000:1 corresponding to a schedule of increasing fees (€0.01, €0.02 and €0.025 per order respectively). That is, a firm having an OTR between 100:1 and 500:1 on a given day will pay 1 Euro cent (1.4 U.S. ¢) extra for each order entered over 100:1. The fee increases to 2 cents per order for realised OTRs between 500:1

[9]Source: Thomson Reuters monthly market share reports, February to May 2012.

and 1000:1, and then to 2.5 cents per order entry above 1000:1. An added condition is that fees are capped at €1,000 per firm-day.

Whilst an OTR of 100 to 1 by firm-day may may represent a strict constraint for some firms, a maximum fee of €1,000 does not, on the face of it, look large.[10] In spite of this, evidence generated by the Italian regulators (CONSOB) themselves, shows that the OTR fee caused a sharp decline in realised OTRs (Caivano et al., 2012). In the study, the authors compute order-to-trade ratios for all exchange member firms over four months of data before imposition of the OTR fee. They find that seven exchange members firms had average daily ratios that exceed the 100:1 threshold. Out of perhaps 90 firms, four of them are clear outliers, the largest having an average OTR of 1947 during the sample period. The authors then focus on 10 "pure-play" HF firms that operate on the Milan exchange and report that four of them clearly dominate activity, representing 90% of the trades conducted by the HF firms in their sample. It is likely that the four firms that dominate trades are the same that are outliers in OTR terms. Taken together, this suggests that the OTR fee applied to a very small number of HF firms, to the exclusion of other agents.

The authors of the CONSOB study then show that the mean realised OTR on the electronic system collapsed after introduction of the fee. The daily average OTR shifted down from pre-OTR levels ranging between 30 and 200:1 to a level of 10:1 or less under the fee. Caivano et al. (2012) also compare the notional fees that would have been charged under the OTR scheme before its imposition, showing that only 3 firms would have contributed most of the fees and, further, that after the OTR is introduced, fee revenue drops to more or less zero. Therefore the constraint had much sharper teeth than financial considerations alone would suggest.

As noted above, the OTR was decided upon by CONSOB. The threat that they would have asked for the penalties to be stepped up if they were not seen to make a difference to the behaviour of member firms might have been very real. The exchange

[10]We are unable to proxy the actual fees levied by the exchange as a result of the ratio as it would require data identifying the member firm behind all order submissions and trades.

is perfectly able to communicate this to the few members concerned via unofficial channels. We can only surmise that those few HF firms exceeding the OTR threshold before the fee have thought it wise not to provoke the regulator into further action. (They were not completely successful in that respect, though, as Italy introduced a specific tax on low latency trading in October 2013. We suspect that at the time of the OTR, the regulators had already sent clear signals to HF participants that they meant business.)

3.2 Data and sample construction

We build our treated and control samples from the components of the Stoxx Europe 600 index, which comprises large, medium and smaller firms from across the Eurozone. We select all Italian companies that were constituents of this index as of the beginning of 2012 and with market caps above Euro 1bn at the beginning of 2012 as our treated sample. After deleting a small number of stocks that experienced major corporate actions or have data limitations during our sample period we are left with 51 treated stocks. Our sample stocks include 38 of the 40 components of the blue chip FTSE MIB index and taken together, they represent 93.6% of Euro turnover in all 296 listed Italian companies in 2012.[11] Hence we can be confident that any economically significant changes brought about by the OTR will be captured in our sample.

Our control sample serves to separate any effects occurring in Italian stocks from changes that might impact Eurozone stocks. We select our control stocks from all French, German, Spanish, Dutch and Belgian constituents of the Stoxx 600 Europe. Following Davies and Kim (2009), for each treated stock we identify a match that minimises distance based on mean market cap and turnover in the pre-event period. We use the Mahalanobis distance metric to match one-for-one and without replacement. Hence our control sample comprises as many stocks as the treated one, i.e. 51. Our samples are very diversified across industries. Panel (a) in Table 1 presents descriptive statistics for the stocks in the treated and control samples respectively.

[11] Source: computed from 2012 annual turnover report, Borsa Ialiana.

Besides the 38 MIB40 components alluded to above, 12 more of our sample stocks are members of the FTSE Italia Midcap index, and 1 is not in any index. None of them are small enough to qualify for the FTSE Italia Small Cap, let alone for the FTSE Italia Micro Cap. Due to the size and composition of the Stoxx Europe 600 index, treated and control stocks are very closely matched, not only on the variables of market capitalization and turnover that were used for that purpose, but also on number of trades and, to a slightly smaller extent, on spreads.

The OTR fee was introduced on April 2^{nd} 2012. The event window we focus on covers two calendar months before and after the event, thus comprising over 8,500 stock-days in total (with roughly half of the data points either side of the event). We do not use an exclusion period based on the results in the CONSOB study that market Order-to-Trade ratios declined abruptly at the time of the event.[12]

Over our event window the FTSE MIB index, which includes most of our treated sample stocks, and the Stoxx Europe 600 index, to which all of our sample securities belong, showed a moderate downward movement and, more importantly for us, they were very highly correlated (their daily return correlation was 0.918).

4 Empirical specification

We estimate a difference-in-differences specification, a widely used methodology in the economic analysis of market reforms and regulatory events. Diff-in-diff estimation combines a control group with the treated sample to "difference out" confounding factors and isolate the effect of an event.

We first construct a set of market quality and activity metrics to be used as dependent variables. For each stock, we use high frequency data to construct daily figures, based on equally-weighted averages or cumulative sums.[13] We build three liquidity and three

[12]Trading behaviour may have adapted ahead of the event, but removing two weeks of data before it makes no difference to our results below.

[13]Examples of recent work that uses similar daily panel modelling of events include Boehmer, Saar, and Yu (2005) and Hendershott, Jones, and Menkveld (2011).

activity measures: the best bid-ask spread (in basis points); the daily average depth available at the best bid and offer prices, in thousands of Euros; the daily average cumulative depth up to the 5^{th} price level of the limit order book, again in Euros; the number of trades (in thousands); the number of quote updates, defined as a change in either price or size at any of the best five bid or ask levels, again in thousands; the turnover in millions of Euros. All measures expressed in cash (both depth and the turnover variables) are scaled by a pre-OTR average turnover figure so as to roughly equalise the scale of these variables across stocks.[14]

We regress these dependent variables on a set of treatment indicators that includes a dummy variable picking out the treated group of Italian stocks ($D^{treated}$), a dummy picking out the period after the OTR fee introduction (D^{OTR}) and the interaction of those two dummies. If there is any difference in the behaviour of the variable for main and control sample stocks in the OTR penalty period, it will appear as a significant coefficient on the ($treated \times OTR$) interaction variable. Thus, denoting the dependent variable of interest with $y_{i,t}$, the coefficient (γ_3) in the equation below is the focus of our attention.

$$
\begin{aligned}
y_{i,t} &= \alpha + \beta_1 RVol_{i,t} + \beta_2 Trades_{i,t} + \beta_3 MktCap_{i,t} + \beta_4 RelTick_{i,t} \\
&\quad + \gamma_1 D_i^{treated} + \gamma_2 D_t^{OTR} + \gamma_3 D_{i,t}^{treated \times OTR} + \epsilon_{i,t} \qquad (1)
\end{aligned}
$$

We also include a set of control variables. For the liquidity measures, these are stock-day level return volatility (the sum of intra-day absolute returns expressed in basis points), trading activity by value and market capitalisation both in millions of currency units, as well as the relative tick size, equal to the ratio of the tick size on to the stock's volume-weighted average price. This latter variable is intended to capture the constraints that the tick size exerts on liquidity. A large literature shows that the ratio of the tick size to the stock price affects the spread and quoted depth in

[14] This is just for ease of interpretation. Our results hold whether depth is rescaled by turnover or simply expressed in Euros.

opposite directions. When we use an activity measure as dependent variable in (1) the control variables are volatility and market cap only. Note that, for panel econometric purposes, all of our control variables vary across both stocks and time. Both volatility and turnover are rescaled by their pre-event stock-specific means. Market value and tick size are re-computed on a monthly frequency.

We estimate all panel models using robust covariance matrix estimators that allow for clustering within stock and within time period (Cameron, Gelbach, and Miller, 2011; Petersen, 2009; Thompson, 2011). We see no a priori reason to allow for clustering along other dimensions. The potential cost of using clustered estimation is a loss of efficiency that will generate excessively low t-statistics when clustering is not needed.

5 Results

5.1 Liquidity (main market)

Estimation results for the three dependent variables measuring liquidity appear in Table 2. For ease of interpretation, we have demeaned the control variables prior to inclusion in the regression. Thus the intercept coefficient combined with the appropriate dummy variable coefficients show any shifts that may have occurred in average values of the dependent variable for the main sample pre and post event and also for the control sample. The units are common to the sample securities so economic interpretation of the magnitudes is straightforward.[15]

Starting with inside spreads as a measure of liquidity, the dummy coefficients show no statistical difference between treated and control stock spreads prior to the introduction of the OTR. After the OTR event, both control and treated stock spreads rise, but there is no significant increase in treated stock spread *relative to* control stock spreads – the estimated coefficient on the key interaction variable is positive

[15]As using stock-level fixed effects seemed to make very little difference to our estimates, we present the simplest results obtained from fitting a common constant.

but close to zero. The coefficients on the control variables are all of the expected sign, where significant. Greater turnover is associated with smaller spreads and stocks with greater market cap have smaller spreads.

Conversely, analysis of depth shows economically and statistically large effects of the OTR on treated stock liquidity: the coefficients on the interaction dummies for both total and inside depth are negative, large and significant. To understand the size of these coefficients, recall that depth is expressed relative to pre-OTR turnover. Thus, after the introduction of the OTR penalty, depth at the best drops by around 10% of average turnover while depth across the first five levels of the order book drops by approximately a whole day's turnover. These reductions equate to 20% and 30% of mean pre-OTR depth respectively.

Thus, as expected, depth outside the best quotes is more strongly affected than depth at the best, consistent with liquidity suppliers reducing their submission of orders with low execution probabilities more than they reduce submission of orders at the front of the book. For both depth regressions, most of the control variables have the expected sign and are statistically significant. The negative coefficient on market cap in these regressions is due to the fact that for larger stocks, depth on display in the order book tends to be smaller as a proportion of turnover than for smaller stocks. If we run these regressions with raw cash depth as dependent variable, the market cap coefficients are, as expected, positive (and significant). Finally, unlike spreads, depth does not change in the control sample in the OTR fee period.

This strong effect on depth is perhaps surprising given that HF liquidity suppliers are often suspected of not supplying liquidity in size compared to more traditional liquidity suppliers – partly because their business model involves taking small inventory positions that can be quickly turned around. Our findings, economically the strongest in our study, suggest instead that HF liquidity suppliers do contribute significant displayed depth. The counter-argument could be that much of this depth may be fickle or even a result of manipulative strategies conducted away from the inside e.g. "layering" the order book or "spoofing". This view is hard to support because we find that depth declines significantly at the best quotes too, if not by as much as depth away from them.

5.2 Order book activity (main market)

The estimates from the regressions that use measures of quoting and trading activity on the left-hand side also tend to be consistent with our priors. Results appear in Table 3, where the units are: thousands of quote events, raw number of trades, thousands of Euros for trade size and millions of Euros for turnover. Turnover is rescaled by its stock-level pre-event mean.

Common to the four sets of estimates is the result that prior to the OTR there is no significant difference between treated and control sample stocks in any of the dependent variables. After the introduction of the OTR, however, activity patterns diverge for treated and control stocks. Our treated stocks show significantly smaller quoting activity, smaller trade size, fewer trades and, thus, lower turnover. The reductions in trading activity and turnover are both statistically and economically significant, at around 10% of pre-OTR levels, while those for trade size and quoting activity are more muted (either economically or statistically). It is likely that these drops in activity are related to the decreased depth that Italian stock markets display after the introduction of the OTR fee.

5.3 Liquidity in the cross-section

Is there evidence that the OTR constraint affected our sample stocks differently in the cross-section? To test this, we split both treated and control samples into two equally-sized groups, with the separation based on market capitalization. Panel (b) of Table 1 shows descriptive statistics for these subsamples, for market values and turnover (the variables used to match the treated and control securities). The match is very close again.

The results for depth at the best quotes for these subsamples, presented in Table 4, show very large effects for the subsample comprising larger stocks.[16] For these stocks, depth at the inside drops by around 40%. There is no significant change in inside depth for the smaller stock subsample. The same table presents results for the depth measures across the first five levels of the order book. Here the reduction in depth is significant for both subsamples, including a fall of around 20% for smaller stocks.

Hence, from Table 4, we knew that the negative effect of the OTR fee operated on depth and from Table 2 we find that it has a cross-sectional flavour with large caps more severely affected. This is consistent with the view that HF traders focus on large, liquid stocks, where frequent information releases allow them to exploit their latency advantage and active trading renders quick inventory management easier. In liquid securities, restrictions on order placement activity do not prevent spreads from reaching competitive levels, but the constraints discourage order placement at and behind the best quotes, due to those orders' increased cost and lower execution probability.

5.4 Price impacts

As Bessembinder and Venkataraman (2010) note, some authors have argued that the price impacts of trades are the best estimators of realised trading costs. Price impacts are particularly relevant to institutional traders who have to work large orders gradually on electronic systems. A persistent controversy concerns whether HF traders conduct "predatory" or "order anticipation" strategies that increased the execution costs of worked orders. If the OTR fee limits the ability of fast traders to re-price or withdraw liquidity as it is demanded, then it may result in less predation/anticipation, a more stable order book (its avowed goal) and lower price impact. If, on the other hand, genuine liquidity is only refreshed more slowly under the fee, then impacts will increase.

[16] We also tried the subsample analysis for bid-ask spreads but, just as in the full sample, there was no significant effect from the OTR.

We estimate the 10-trade price impacts and then construct their stock-day averages. Impact is measured simply as the basis point change in price from one trade before the current observation to ten trades after. The sign of the impact of sell trades is reversed so that we would expect mean impact across all trades to be positive.

Table 5 presents diff-in-diff estimation results similar to those previously conducted, controlling for volatility, turnover and stock size. These impact results provide further evidence that the OTR penalty reduced liquidity. Price impacts rise significantly for the aggregate sample and each of the two size-based subsamples. For the aggregate sample, the rise is around 45%. It is interesting to note here that the change in price impact post-OTR is greater for smaller stocks. Thus while the effect on depth for these stocks is more muted, they become much less resilient.

These impact results confirm and complement our earlier results on quoted depth. First, the large increase in price post-OTR indicates that the depth that was supplied before the fee was genuine and not purely transient. Second, they show that the cross-sectional effect of the OTR may depend on the measure of liquidity used. Using impacts, it's the smaller stocks in our sample that were most affected by the fee.

5.5 Consolidated order book liquidity and activity

The OTR constraint was enforced on Borsa Italiana only and not on rival electronic venues, chief of which is Bats/Chi-X. That seems to supply a simple way around the constraint to high-frequency firms, who could just redirect order flow (both liquidity supply and consumption) towards rival order books devoid of an OTR penalty. This prompts us to ask whether *consolidated* market liquidity and activity may have deteriorated. In Table 6, we present the results of estimation of some of the same models as in Section 5.1, but with dependent variables constructed from different data. Now the dependent variables (inside spreads and depth, the number of events at the inside quotes and total turnover) are constructed from data aggregated across multiple electronic order books. Thus, for example, the spread is the distance in basis points between the lowest offer price on any venue and the highest bid and turnover takes in trading activity across all venues. The number of quote events now looks at changes in liquidity supply at the best quotes, where the best is defined from all trading venues. (Thus, these data are in the spirit of those that would be seen by a smart order-router as in Foucault and Menkveld (2008).)

The first regression shows that spreads for Italian stocks exhibit no significant increase after the implementation of the OTR, similar to the result observed in Table 2 for the main market only. However, consolidated depth in Italian stocks is significantly reduced by the OTR just like its main market counterpart. The coefficient is, in magnitude, only a little smaller than for the main market. This effect is statistically significant and provides evidence that liquidity supply has not just migrated to alternative venues with the introduction of the OTR on the main market. Finally, consolidated turnover also falls significantly post-OTR, by just less than 10%. Thus while there may have been a small migration of turnover to alternative venues, this in no way makes up for the decline on the historical exchange.

Table 7 shows that the cross-sectional depth results observed in Table 4 also hold in the consolidated data. The OTR fee significantly reduces the depth available for trade for the large subsample of Italian stocks. That consolidated depth in large caps should be reduced to almost the same degree as it was on the main exchange is striking, given that the market share of the Milan Borsa was smallest in those stocks (with an unconditional average of 77%) and we might expect liquidity supply and consumption to move more freely between venues than in smaller caps.

Thus, in sum, there is clear evidence that the OTR has damaged *overall* liquidity supply, rather than just supply on the main market. Two interpretations for this result are possible and they are not mutually exclusive. First, the historical exchange may entirely dominate price and liquidity discovery and other venues simply cannot fulfil these roles. Also, there may be institutional impediments to some brokers executing away from the main exchange that help cement its dominant role.

Second, the decrease in liquidity is consistent with less than competitive liquidity supply across venues. Our findings are reminiscent of Biais, Bisière, and Spatt (2010), who study liquidity in US stocks traded on both the Nasdaq and the Island order book. They find evidence consistent with rent-seeking by a limited number of liquidity suppliers who effectively make markets on Island as an oligopoly. While they couch their results in terms of spreads because the event they study is a change in tick sizes, the same intuition extends to our event and setup which seems to affect depth throughout the order book. Overall, our findings might be interpreted as suggesting that impediments to full competition between venues exist, even if we are unable to say more about their nature.

5.6 Market share of the historical exchange

XXX This section shifted after the previous one.

We finally examine whether imposition of the OTR constraint on the main exchange has caused some redirection of order flow to the alternative order books by measuring the market share (in total traded volumes) of the historical exchange in total order flow by value before and after the event. The deterioration of liquidity observed in consolidated quotes suggests that the incentives to redirect order flow to alternative order books may be limited. The pre-event and post event mean market shares, equally-weighted across stocks for the treated stocks stand at 81.7% and 78.7% respectively. The hypothesis that no change occurred in the Milan pre and post mean market share is rejected but not strongly, with t-stat of 1.73 (51 observations pre and post). The same test for our control sample stocks (comparing their respective main markets with electronic competitors pre and post the introduction of the Italian OTR) shows no economically and statistically detectable change in the average market share across the European exchanges involved. The pre-event and post event means are virtually identical at 66.25 and 66.17% respectively with t=0.039.

The figures suggest that the OTR has caused some redirection of order flow away from the main market – for a market share decrease of 3% to occur in a matter of weeks is far from trivial, even if it is limited in statistical significance. A caveat is that for many of the midcaps in our sample, the Milan market retained a near-monopoly on the trading of Italian shares, with a market share of total turnover by value of 90-100%. The equity market may not have been mature enough in that respect for more sizeable shifts in order flow to occur. (For comparison, during the same period, the London Stock Exchange retained marginally more than a 50% share in U.K. equity turnover).

5.7 Possible effects of an OTR not considered here

Our focus is on measurable, but relatively immediate effects of the OTR on liquidity and activity. It may be that longer-term effects also materialise, including some related to liquidity. The argument has been made that under a slower-moving order book, the "market ecology" may change in a positive way. O'Hara (2010) or Brogaard (2011) emphasise that some investors are disturbed by quotes with durations so short that they are very hard to trade upon. A more stable order book may encourage more participation on the part of those who are currently deterred by quote "flickering". Similarly, it might convince slower liquidity suppliers previously evicted by high frequency players to come back to market and perhaps contribute more depth than HF agents. Brogaard (2010) finds that HF traders contribute less depth than do slower liquidity suppliers, consistently with one leg of this argument. Their participation in liquidity supply may also be more stable than that of HF agents, who are sometimes accused of "fair-weather" market-making.

Regulators may also have other social benefits in mind when adopting an OTR. One of them could be the "arms race" argument, analysed for example in the model of Biais, Foucault, and Moinas (2014), where HF traders increase adverse selection for slower participants because they process public information faster. By making it more costly for fast traders to exploit their speed advantages, regulators might be trying to dissuade firms from investing excessive amounts in trading technology.

Either because they are not to do with liquidity or because they seem by their nature likely to remain very hard to identify empirically, these long-term hypotheses are outside the scope of our analysis. Note, though, that doubling the duration of our post-event window to cover four months of the OTR regime makes no difference to our results.

6 Conclusion

We assess the effect that a measure designed to constrain the order submission frequency of low latency traders has had on liquidity. We find a clear picture of reduced liquidity supply, with quoted depth affected across the board and dramatically so for large stocks, whether at the best quotes or beyond. HF firms may be more significant contributors to depth than previously thought.

We also report that the same changes observed for liquidity and activity on the Milan exchange extend, albeit with slightly less strength, to a consolidated order book that includes quotes from rival electronic venues. Depth does not simply migrate to other order books where the OTR does not apply. We speculate that this negative externality could have two, not mutually exclusive, explanations – first, the historical exchange may have retained a completely dominant role in price formation and other venues feed off prices set on it. Second, there may be rent-seeking on the part of a limited number of liquidity suppliers who operate across rival electronic systems. Those market-makers may be able to keep liquidity supply below competitive levels, as Biais, Bisière, and Spatt (2010) have found in the context of much more liquid US stocks.

Our study also highlights the extent to which market liquidity may be affected by a very small number of extremely active participants. A study by the Italian regulators shows that only three firms out of the roughly 90 member firms that participate in trading and quoting had OTRs consistently above the fee threshold before it was enforced. It is changes to their order submission behaviour that likely caused the effects on liquidity and activity that we detect in our paper. This is consistent with other evidence such as that in Menkveld (2013), who finds for Dutch stocks that the entry of one single HF market-maker caused detectable changes to liquidity.

OTR experiments are under way on several exchanges. We are aware of at least one market that scrapped its OTR only three months after voluntarily introducing it. On June 1^{st} 2012, the American electronic trading venue DirectEdge put in place a scheme that financially penalised individual firms if they exceeded a monthly average message-to-trade ratio greater than 100 to 1 under the name of "Message Efficiency Incentive Program" (MEIP). At the end of August 2012, DirectEdge justified the removal of its scheme with the SEC in the following terms: "(...) the Exchange believes that, by not adequately isolating purely inefficient message flow, the MEIP may have unintentionally captured, and therefore disincentivized, order behavior that benefits market liquidity. For example, the MEIP potentially discourages market participants from posting multiple levels of liquidity in less actively traded securities. Thus, while the Exchange's intention was to encourage efficiency and consequently attract more liquidity, the MEIP appears to have resulted in the opposite effect."[17] In an interview, DirectEdge COO Bryan Harkins further commented: "When we looked at MEIP over a few months, we decided it wasn't having the effect that we wanted. (...) people want to make liquidity away from the inside and they want to create deeper markets. Well, obviously if you're sending liquidity away from the inside, that's additional message traffic but that would be discounting the value of a deeper order book away from the inside price. Another example is, our market needs to be able to trade illiquid securities, exchange-traded funds, a lot of these stocks that don't trade actively. Oftentimes the market-maker has to update a quote very frequently."[18] These specific references to a reduction in order book depth beyond the inside quotes and to a more negative impact on the liquidity of less active assets appear remarkably consistent with the effects we document.

[17] Proposed Rule Change by EDGX Exchange, Inc., pursuant to Rule 19b-4 under the Securities Exchange Act of 1934, 31 August 2012.

[18] "Mixed Messages: Direct Edge Equivocates on HFT", *WatersTechnology*, 27 September 2012.

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Table 1: Summary statistics for treated and control sample stocks

		Mean	Median	Std Dev	Maximum
(a) Full sample					
Treated stocks					
Market Cap (€ mn)		7085.4	2699.7	11236.3	69058.6
Turnover (€ mn)		30.7	10.2	53.6	253.4
Number of trades		3877.8	2327.6	4041.0	19001.7
Spread (b.p.)		13.21	11.64	8.53	42.68
Control stocks					
Market Cap (€ mn)		6819.1	2639.0	11272.3	70498.8
Turnover (€ mn)		36.0	10.3	69.1	409.9
Number of trades		3958.5	2175.7	5201.7	30383.2
Spread (b.p.)		17.20	15.55	8.11	43.89
(b) By sample halves above and below the median					
Treated stocks					
Market Cap (€ mn)	H1	1685.3	1386.4	587.1	2699.7
	H2	12277.8	7795.9	13963.5	69058.6
Turnover (€ mn)	H1	4.8	4.1	4.3	16.4
	H2	55.9	29.7	66.3	253.4
Control stocks					
Market Cap (€ mn)	H1	1653.9	1352.7	599.7	2809.5
	H2	11785.6	6568.8	14193.4	70498.8
Turnover (€ mn)	H1	8.5	4.8	11.8	46.8
	H2	62.0	26.3	89.5	409.9

Notes: the table reports summary statistics for liquidity and trading variables for our sample stocks. In panel (a), for each stock we compute average market cap in millions of Euros over the pre-event period, average time-weighted daily spreads in basis points, mean daily number of trades and mean daily quantity traded, expressed in Euros. The table reports, for each variable, the equally-weighted mean and median, and the standard deviation and maximum from the cross-stock distribution. Panel (b) presents the same statistics for the variables of market cap and turnover, but where the sample is broken down into two using the median stock size as cutoff (the two equally-sized subsamples are denoted H1 and H2).

Table 2: Difference-in-differences regression analysis of the effect of the OTR constraint on main exchange liquidity

	Spreads	Inside Depth	Level 5 depth
Turnover (value)	-3.247***	0.149***	0.987***
	(5.22)	(6.19)	(5.65)
Volatility	3.158***	-0.156***	-1.324***
	(2.93)	(3.67)	(3.38)
Market cap	-0.0004***	-1.07×10^{5}***	-6.45×10^{5}**
	(3.98)	(2.74)	(2.53)
Relative tick size	0.606	0.0318	0.305
	(1.32)	(1.36)	(1.61)
Treated sample	1.140	0.105	0.968
	(0.42)	(0.87)	(1.06)
OTR period indicator	2.105***	0.0066	0.0310
	(4.50)	(0.53)	(0.26)
Treated $\times$ OTR	-0.720	-0.0895***	-0.996***
	(1.24)	(5.01)	(6.09)
Constant	15.36***	0.454***	3.52***
	(9.30)	(6.21)	(6.39)
R^2	0.27	0.16	0.16
N	8,550	8,382	8,382

Notes: the table reports the results of daily panel difference-in-differences estimation of variables measuring inside bid-offer spreads, depth at the inside spread, and depth at the 5^{th} price level for the main and control sample shares against measures of activity, realised volatility, firm size and relative tick size. Two indicator variables pick out main sample stocks and the OTR period respectively, and a further indicator variable interacts the previous two. All variables are defined in Section 4. The estimator used is robust to clustering effects both within and across panels. One, two or three stars indicates 10, 5 and 1% significance respectively.

Table 3: Difference-in-differences regression analysis of the effect of the OTR constraint on measures of activity

	Quote Events	Number of trades	Average trade size	Turnover (value)
Volatility	14.15***	1,863.5***	-0.214	0.667***
	(3.05)	(5.56)	(1.18)	(7.36)
Market cap	0.0022**	0.218***	2.8×10^{4}***	-2.59×10^{7}
	(2.46)	(3.20)	(8.26)	(0.31)
Treated sample	6.115	144.7	0.475	-0.00007
	(0.67)	(0.19)	(1.16)	(0.01)
OTR period indicator	12.76***	-276.1***	-0.1047	-0.187***
	(3.86)	(2.66)	(1.18)	(4.44)
Treated × OTR	-6.549*	-311.1**	-0.329***	-0.140**
	(1.86)	(2.43)	(3.60)	(2.46)
Constant	46.86***	4,018.3***	5.343***	1.093***
	(6.36)	(8.59)	(16.67)	(58.02)
R^2	0.17	0.25	0.63	0.22
N	8,550	8,550	8,550	8,550

Notes: each column in the Table reports the results of daily panel difference-in-differences estimation of variables measuring the number of events occurring at the first five levels of the order book, the number of trades, the average trade size and total turnover by value for the main and control sample shares respectively. Turnover is rescaled by stock-specific, pre-event Average Daily Turnover. These variables are regressed against measures of realised volatility and firm size. Two indicator variables pick out main sample stocks and the OTR period respectively, and a further indicator variable interacts the previous two. All variables are defined in Section 4. The estimator used is robust to clustering effects both within and across panels. One, two or three stars indicates 10, 5 and 1% significance respectively.

Table 4: Difference-in-differences regression of depth at the best quotes and at the 5^{th} price level, splitting main and control samples into market cap halves

	Inside Depth		Level 5 Depth	
	H1	H2	H1	H2
Turnover (value)	0.186***	0.110***	1.220***	0.816***
	(5.14)	(3.95)	(4.18)	(5.96)
Volatility	-0.191***	-0.161***	-1.722***	-1.198***
	(2.95)	(4.20)	(3.01)	(3.88)
Market cap	$-2.33\times10^{4**}$	-3.10×10^{6}	$-1.87\times10^{3**}$	-1.79×10^{5}
	(2.38)	(1.48)	(2.35)	(1.21)
Relative tick size	0.0347	0.0430**	0.3151	0.3863**
	(0.75)	(2.31)	(0.80)	(2.41)
Treated sample	-0.0282	0.1578	-0.1557	1.487*
	(0.11)	(1.48)	(0.07)	(1.78)
OTR period indicator	-0.0447	0.0319***	-0.1813	0.0788
	(1.47)	(2.99)	(0.63)	(0.99)
Treated × OTR	-0.0824	-0.1036***	-1.0673**	-1.0594***
	(1.59)	(4.99)	(2.26)	(6.67)
Constant	0.739***	0.241***	5.410***	2.158***
	(4.49)	(4.91)	(4.13)	(5.38)
R^2	0.12	0.28	0.12	0.33
N	4,070	4,318	4,068	4,317

Notes: The Table presents estimations where the dependent variable is quoted depth at the best quotes and at also the 5^{th} price level of the order book. Estimations are conducted on stock-day averages. The panel models are specified as those presented in Table 2 but they are run separately on two subsamples constructed from splitting the main and control samples in two groups around the median capitalisation of sample stocks. The two equally-sized subsamples are denoted H1 and H2. They are described in panel (b) of Table 1.

Table 5: Difference-in-differences price impact regression (10 trades), splitting main and control samples into market cap halves

	Full sample	H1	H2
Turnover (value)	-0.263***	-0.315***	-0.323***
	(4.44)	(3.60)	(6.02)
Volatility	0.487***	0.537***	0.359***
	(4.96)	(3.29)	(3.45)
Market cap	-3.15×10^{5}***	-6.44×10^{5}	-1.84×10^{5}***
	(4.17)	(0.43)	(4.05)
Treated sample	0.036	0.321*	-0.137
	(0.32)	(1.88)	(1.29)
OTR period indicator	-0.102	-0.189	0.0269
	(1.37)	(1.54)	(0.44)
Treated × OTR	0.445***	0.684***	0.195***
	(4.99)	(4.46)	(2.83)
Constant	0.997***	1.223***	0.710***
	(11.54)	(8.15)	(9.36)
R^2	0.10	0.06	0.20
N	8,292	4,020	4,269

Notes: The Table presents panel regressions where the dependent variable is the price impact, measured as the basis point change in price from one trade before the current observation to ten trades after it. The sign of the impact of sell trades is reversed so the expected mean impact across all trades is positive. The impact is then averaged across all trades for each stock-day. The control regressors are turnover, volatility and market capitalisation, as defined in Section 4. The estimations are run on the full sample and also on subsamples constructed from splitting the main and control samples around the median capitalisation of sample stocks. The two equally-sized subsamples are denoted H1 and H2 and are described in panel (b) of Table 1.

Table 6: Liquidity and activity regressions, consolidated order book

	Spreads	Inside Depth	Turnover (value)
Turnover (value)	-0.0285***	0.126***	
	(3.13)	(4.62)	
Volatility	2.308***	-0.120***	0.6068***
	(2.70)	(2.62)	(6.29)
Market cap	-2.18×10^{4}**	-1.10×10^{5}***	-4.58×10^{7}
	(2.34)	(2.86)	(0.61)
Relative tick size	0.364	0.0454*	
	(1.13)	(1.86)	
Treated sample	2.822	0.0852	-0.00017
	(1.32)	(0.69)	(0.02)
OTR period indicator	1.699***	-0.0346	-0.165***
	(3.94)	(1.58)	(3.94)
Treated × OTR	-0.279	-0.0530**	-0.109*
	(0.53)	(2.57)	(1.92)
Constant	13.30***	0.456***	1.087***
	(9.98)	(5.95)	(59.01)
R^2	0.26	0.18	0.53
N	8,461	8,378	8,461

Notes: each column in the Table reports the results of daily panel difference-in-differences estimation of variables measuring inside spreads, the number of events occurring at the inside spread and total turnover by value for the main and control sample shares respectively. Turnover is rescaled by stock-specific, pre-event Average Daily Turnover. These variables are regressed against measures of activity, realised volatility, firm size and relative tick size. All variables are constructed from data for the electronic order book of the main stock exchange but also those of rival venues. Two indicator variables pick out main sample stocks and the OTR period respectively, and a further indicator variable interacts the previous two. All variables are defined in Section 4. The estimator used is robust to clustering effects both within and across panels. One, two or three stars indicates 10, 5 and 1% significance respectively.

Table 7: Inside depth estimation, splitting main and control samples by market cap, consolidated order book

	H1	H2
Turnover (value)	0.174***	0.0817***
	(4.18)	(3.20)
Volatility	-0.215***	-0.0907*
	(2.75)	(1.92)
Market cap	-0.0002**	-3.15×10^{6}
	(2.26)	(1.54)
Relative tick size	0.0666	0.0408**
	(1.41)	(2.23)
Treated sample	-0.0712	0.138
	(0.26)	(1.44)
OTR period indicator	-0.0951**	0.0050
	(2.20)	(0.36)
Treated × OTR	-0.0333	-0.0646***
	(0.58)	(4.00)
Constant	0.76***	0.223***
	(4.54)	(4.83)
R^2	0.16	0.27
N	4,058	4,313

Notes: The Table presents estimations where the dependent variable is quoted depth at the best quotes from consolidated order book data. Estimations are conducted on stock-day averages. The panel models are specified as those presented in Table 2 but they are run separately on two subsamples constructed from splitting the main and control samples in two groups around the median capitalisation of sample stocks. The two equally-sized subsamples are denoted H1 and H2.