Minimum Trade Unit Regulation and Market Quality

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Abstract

Financial market regulators often impose a minimum trade unit (MTU) to facilitate order execution. This paper examines the effect of the unique natural experiment of Borsa Italiana, where in 2002 the MTU was exogenously reduced by the exchange to one unit. After the reduction, we observe a decrease both in the bid-ask spread and in the price impact of orders, as well as an increase in market depth at the best five levels of the book. The results are consistent with a model where liquidity providers operate under asymmetric information; the model shows how market liquidity, informational efficiency and traders' welfare vary under different regimes of transaction size regulation.

KEYWORDS: minimum trade unit, limit order book, market liquidity, informational efficiency

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1. Introduction

Financial market regulators often enforce a minimum trade unit (MTU) to facilitate order execution. Examples of markets where a MTU is imposed are the NYSE, the Toronto, Tokyo, Hong Kong and Tel Aviv stock exchanges. Conversely, most European markets (for example Euronext, Xetra, and the Scandinavian and Baltic exchanges that use the OMX platform) have reduced the MTU to one unit.

The optimal regulation of the MTU is a far-reaching issue as these constraints do not only affect the trading lots they are intended to standardize, but also have an impact on market quality. Furthermore, the increase of high frequency-trading, which produces orders that are smaller in size, makes the research question particularly topical. On a related note, the SEC (Release 34-61358, 2010) has called for research concerning the role and the regulation of trading odd lots. Yet, no theoretical literature and scant empirical evidence has so far been provided on this subject.

In this paper we examine the effect of the unique natural experiment of Borsa Italiana (BIt from now on), where in 2002 the MTU was exogenously reduced to one unit by the exchange. We examine market quality around the event, concentrating on liquidity and on informational efficiency. The results highlight a marked liquidity improvement, measured by a decrease in the bid-ask spread and in the price impact of orders and by an increase in market depth at five book levels. We also observe a concurrent decrease in adverse selection costs and in the informativeness of trades. Informational efficiency, examined by performing tests on the predictability of returns and in the context of the standard Hasbrouck (1993) model, is not substantially affected by the MTU reduction. Furthermore, we find that the MTU change is not associated with price changes.

We interpret these results within the framework of a model with liquidity providers operating under asymmetric information. The model compares different regimes of transaction size regulation and it offers empirical predictions for the effects of a reduction of the MTU. This theoretical benchmark allows us to compare a regime without constraints with a regime where liquidity providers are required by market regulators to quote prices for a minimum number of shares and where this constraint is also imposed on traders' order size. When the MTU is removed, those small liquidity traders that under the MTU regime could not hedge their endowment perfectly, can enter the market; because liquidity providers benefit from the increased uninformed trading and now perceive less adverse selection costs, they reduce the bid-ask spread.

Three previous papers are closely related to our analysis. Amihud, Mendelson and Uno (1999) find that the reduction in the MTU at the Tokyo Stock Exchange is associated with an increase in trading volume and in liquidity, measured, using daily data, by Amihud's liquidity ratio. Ahn, Cai, Hamao and Melvin (2005) also consider voluntary MTU reductions at the Tokyo Stock Exchange, and using an intra-day dataset they obtain results analogous to Amihud, Mendelson and Uno. At the Tokyo Stock Exchange, however, any MTU change is endogenously deliberated by the listed firms that can hence use it as a signalling device. The MTU reduction we study is instead imposed by the exchange and therefore it is exogenously determined. Hauser and Lauterbach (2003) look at an exogenous MTU reduction at the Tel Aviv Stock Exchange, but concentrate on the effects on market valuation using daily data. Hence our contribution adds to previous evidence in at least two ways: we consider a clean natural experiment where, contrary to the analyses on the Japanese market, the reduction in the MTU was exogenously decided by the exchange; moreover, we exploit an intra-day dataset and we are thus able to provide a full-blown description of the different aspects of liquidity around the MTU change, in terms of the bid ask spread, the price impact of orders and market depth (notably, at five book levels).

The plan of the paper is as follows: section 2 presents a theoretical benchmark to assess the effect of transaction size regulation on market quality; section 3 examines the effect of the reduction of the MTU in BIt and section 4 concludes.

2. Theoretical benchmark

To our knowledge there is no theory offering predictions on the minimum trade size regulation. For this reason, we derive some empirical implications from a model along the lines of Glosten and Milgrom (1985) and Easley and O´Hara (1987). In this setting there are three types of agents: risk-neutral dealers quoting bid and ask prices; strategic insiders who know the liquidation value of the asset in advance; and competitive, uninformed liquidity traders. As represented in Diagram 1, nature chooses the final value of the asset ($\tilde{v}$), which is either $\overline{V}$ = 1 or $\underline{V}$ = 0 with equal probability. Dealers face an informed agent with probability α and an uninformed agent with probability $(1-\alpha)$. The insider is risk-neutral and trades in order to exploit private information, whereas liquidity traders trade in order to share risk. Assume that the liquidity traders have a mean variance objective equal to:

$$\max_{q} \; E[(q+I)\tilde{v} - qp] - \frac{\gamma}{2}(q+I)^2 VAR(\tilde{v})$$

where *I* is the endowment of the liquidity trader and γ is the coefficient of risk aversion. When liquidity traders can choose their order size, the first order condition yields:

$$q = \frac{E(\tilde{v}) - p}{\gamma VAR(\tilde{v})} - I$$

Assuming that liquidity traders are infinitely risk-averse, i.e. $\gamma \to \infty$, their trade is just the opposite of their inventory shock, q=-I. This is because they desire to fully share risk, whatever the price. Liquidity traders can have negative or positive inventory shocks with equal probability, and their inventory shock is large with probability β and small with the complementary probability. We interpret uninformed traders with small shocks as retail and those with large shocks as institutional. We assume that competition brings dealers´ quotes to zero-profit level.

In this framework we analyze three market regimes (Diagram 1). First, we consider the regime without quote or trade size constraint (NC). In this case, market makers post quotes equal to the expected value of the asset conditional on the size and the direction of the order. Second, we consider a minimum quote (MQS) of two shares. In this case, market makers are constrained to post prices for all orders of up to two shares. Consequently prices cannot differ conditionally on the size of the order and only depend on its sign. This is the reason why insiders only trade large quantities. Third, we consider a minimum quote and transaction size (MQTS) of two shares, which is indeed the regime prevailing before the MTU was eliminated in the Italian exchange:[1] in the empirical analysis we compare this regime to the no constraint setting. As in the previous case, market makers must quote the same price for small and large orders. Further,

[1] In the case considered in the empirical analysis the minimum trade unit (MTU) is also the minimum quote unit, thus corresponding to the MQTS regime of the model. For consistency with previous empirical works on this issue, we use the notation MTU in the empirical part.

liquidity traders cannot place small orders, so those with a small inventory shock choose to leave the market.

2.1. Equilibrium

NO CONSTRAINTS

When there is neither MQS nor MQTS, the model resembles Easley and O´Hara (1987). A priori, informed agents would like to submit large orders in order to exploit their information, but these large orders might themselves affect the price, as market makers post prices for large trades by anticipating the insiders' choice between large and small orders. Hence in equilibrium insiders will trade large only if in the market there is a relative large proportion of large uninformed traders that produces camouflage to their large orders.

If the proportion of informed agents is not too high relative to liquidity traders placing large orders, i.e. $\beta \geq \frac{\alpha}{1-\alpha}$, insiders will follow an aggressive strategy and always make large orders; this way a semi-separating equilibrium prevails. Here, insiders will choose to trade only large quantities because they anticipate that due to the relatively small proportion of insiders in the market, the price associated with large orders will not embed excessive adverse selection costs. In this context the ask prices for one or two shares are:

$$A_1 = \frac{1}{2} \tag{1}$$

$$A_2 = \frac{\frac{1}{2}(1-\alpha)\beta + \alpha}{(1-\alpha)\beta + \alpha} \tag{2}$$

respectively. Since insiders do not trade small quantities, A_1 incorporates no adverse selection costs and thus equals the unconditional expected value of the asset. Conversely, A_2 includes all the adverse selection costs. On the other hand, if the proportion of informed agents is high, i.e. if $\beta < \frac{\alpha}{1-\alpha}$, they trade small and large orders with probability μ and $(1-\mu)$ respectively. In this context of pooling equilibrium, the ask prices for one or two shares are:

$$A_1 = \frac{1}{2}[(1-\beta) + \alpha(1+\beta)] \tag{3}$$

$$A_2 = \frac{1}{4}[(3-\beta) + \alpha(1+\beta)] \tag{4}$$

respectively (see Appendix).

Clearly, the higher the proportion of insiders in the market, the higher the adverse selection costs that liquidity suppliers will add to prices for large trades[2] and hence the higher the spread associated to these trades.

MINIMUM QUOTE SIZE

Now let´s take the MQS regime. Here, it is not attractive for insiders to follow a mixed strategy, as the price is the same for one or two units. Thus insiders always place large orders. As is shown in the Appendix, the ask price, A_Q, in this market regime is:

$$A_Q = \frac{1}{2}\frac{\beta(\alpha-1) - 3\alpha - 1}{\beta(\alpha-1) - \alpha - 1} \tag{5}$$

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[2] Notice that this paper is different from Easley and O´Hara (1987) in that it endogenizes μ to make the informed agents indifferent as to whether they trade one share at A_1 (Equation 3) or two shares at a worse price, A_2 (Equation 4).

Regardless whether or not the informed agents follow a mixed strategy under NC, it can be easily demonstrated that the ask price under MQS is greater than the ask price for one share under NC, but smaller than the ask price for two shares under the same regime:

$A_1 < A_Q < A_2$

In fact even though insiders play mixed strategies, the price for small orders under the NC regime does not embed as much adverse selection costs as the price under MQS, A_Q, at which all insiders' orders are executed. Conversely, A_2 is greater that A_Q as at this price the adverse selection costs associated with all insiders' large orders are diluted also over retail uninformed orders.

MINIMUM QUOTE AND TRANSACTION SIZE

Finally, let´s consider MQTS. Here, there are only large trades because liquidity traders with small endowments exit the market, while insiders mimic the trades of the liquidity traders with large endowments. As is shown in the Appendix, in this regime the ask price, A_{QT}, is equal to:

$$A_{QT} = \frac{\frac{1}{2}(1-\alpha)\beta + \alpha}{(1-\alpha)\beta + \alpha} \tag{6}$$

Comparing A_{QT} with the ask prices obtained above, we get:

$$B_{QT} \leq B_2 < B_Q < B_1 \leq A_1 < A_Q < A_2 \leq A_{QT} \tag{7}$$

where equality remains in the equilibrium when insiders play pure strategies. Figures 1 and 2 show the respective ask prices for the equilibria with pooling and separation of agent types. The ask price with MQTS is equal to the ask price for large trades under semi-separating equilibrium since in both regimes insiders only trade large and the adverse selection costs are at their highest.

2.2. Market quality

Building on the above analysis, we obtain results on market quality for each regime. This allows us to rank the different regimes of quote and transaction size regulation in terms of liquidity, informational efficiency and traders´ welfare

LIQUIDITY

Proposition 1

- *Bid-ask spread - The bid-ask spread of small trades is smallest with NC and largest with MQTS. The bid-ask spread for large trades is smallest under MQS and largest under MQTS.*
- *Volumes and number of shares - Trading volume and number of shares are highest under MQS and lowest under MQTS. When moving from MQTS to NC, if the separating equilibrium prevails, then volume increases. If instead the new NC equilibrium is pooling, then when the probability of insider trading is higher than 2/3, volume and number of shares are greater under MQTS.*

Proof: see the Appendix.

The impact on liquidity is simply explained by inequality (7), which shows that the inside spread associated with trades of size 2 is the narrowest under MQS and the widest under MQTS:

$A_1 - B_1 < A_Q - B_Q < A_2 - B_2 \leq A_{QT} - B_{QT}$

Under MQS all liquidity traders trade at A_Q or B_Q; for this reason, the adverse selection costs associated with large trades are spread over both institutional and retail traders. Under NC, on the other hand, adverse selection costs are borne only by institutional liquidity traders and therefore the large trade price, A_2, is higher. Large trade prices (and therefore the corresponding bid-ask spread) are highest when insiders trade only large, i.e. with semi-separating equilibrium or with MQTS.

Table 2 summarizes computations for the number of shares:[3] intuitively, when moving from the MQTS to the NC separating regime, volume increases as, coeteris paribus, small traders start trading. Moving instead from MQTS to the NC pooling regime, volume increases only if the proportion of insiders is not extreme. In the latter case in fact, the contribution of the new small orders to volume is overwhelmed by the insiders' trades. In conclusion we expect that the removal of the MQTS will increase volume and number of shares.

WELFARE AND INFORMATIONAL EFFICIENCY

Proposition 2 – *Welfare and Informational efficiency*

- *Welfare - Insiders and large investors are best off under the MQS regime and worst off under both MQTS and NC separating. Small traders are best off under NC and worst off under MQTS.*

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[3] It is interesting to note that, given the symmetry of the equilibrium bid and ask prices around the unconditional expected value of the asset, $E(\frac{A_i + B_i}{2}) = E(\tilde{v}) = \frac{1}{2}$, all the results obtained for the expected trading volumes are equal to those for the expected number of shares multiplied by $E(\tilde{v})$. It follows that these results are qualitatively the same.

- *Informational efficiency - The effect of transaction size regulation on informational efficiency (IE) hinges on the relative proportion of large informed trades. IE is maximized under the regimes with constrains and separating, whereas it is lower with pooling.*

Proof: see the Appendix.

Large institutional investors and insiders trade large quantities and are best off under the regime with the lowest ask (highest bid) price associated with large trades. Hence under pooling equilibrium their welfare is greater than under MQTS (or under a separating equilibrium) where adverse selection costs are highest due to retail traders leaving the market; with pooling, welfare is instead lower than under MQS where adverse selection costs are diluted by small orders.

Retail traders are best off under NC where they can perfectly hedge their endowment and minimize trading costs; under MQS, they can still hedge their endowment, but at a higher price. With MQTS and NC separating they are worst off, as perfect risk-sharing is impeded.

Hence according to the model's prediction the removal of the MTU should make retail and institutional traders better off.

To measure informational efficiency, we use the following indicator:

$$IE = \left(E[VAR(\tilde{v} \mid q_{i)}]\right)^{-1} = \frac{1}{\sum_{i=1}^{2}[VAR(\tilde{v} \mid q_i^A)\Pr(q_i^A) + VAR(\tilde{v} \mid q_i^B)\Pr(q_i^B)]}$$

with i=1 for small and i=2 for large trades. Under NC and MQS/MQTS, we get:

$$IE_{NC} = \frac{1}{E[VAR(\tilde{v} \mid q_{i)}]} = \frac{1}{\frac{1}{8}[(1-\alpha)\beta(1-\beta) - 2(1+\alpha)](\alpha - 1)} \qquad (8)$$

$$IE_j = \frac{1}{E[VAR(\tilde{v} \mid q_{i)}]} = \frac{4[\beta(\alpha_j - 1) - \alpha_j]}{[(\alpha_j - 1)(\beta + \alpha_j)]} \tag{9}$$

with j=Q,QT.

Equations 8 and 9 show that the degree of informational efficiency depends on the equilibrium proportions of both insiders (α) and large liquidity traders (β). This result derives from the assumption that only insiders possess private information and that the presence of uniformed traders can add noise to the market. Equation 9 also shows that for given values of α and β, informational efficiency is the same under the two mandatory size regimes. In fact, in both MQS and MQTS the ask price for small and large trades is the same and insiders play pure strategies. Moreover, when switching from the regime with constraint to the NC regime, the effect on informational efficiency depends on the type of equilibrium that will prevail, be it separating or pooling. Under the former informational efficiency does not change, whereas under the latter it can decrease as insiders now trade fewer large orders.

Consequently, the model's prediction for *IE* would be that moving from MQTS to NC, informational efficiency does not improve. However, this quote driven model fails to capture some features of limit order books that can influence *IE*. In real limit order books all market participants can supply liquidity: hence when the constraint is removed and retail traders start trading, they could submit not only market orders (as the model predicts), but also limit orders; depending on their degree of impatience, if they end up submitting more limit than market orders, market depth could increase at all levels of the book. This in turn would reduce the price impact and hence, by reducing the noise, it can increase the ability of traders to learn the fundamental value of the asset from transaction prices.[4]

SUMMARY OF MARKET QUALITY

Table 1 summarizes market quality under NC, MQS and MQTS. NC is best for small retail investors: the inside spread is narrowest and retail traders´ welfare highest. For large institutional investors MQS is most advantageous: both the liquidity of large trades and investors´ welfare are higher. Insiders prefer MQS due to the low ask price associated with large quantities, and this is why MQS is the most information-efficient.

The analysis shows that imposing MQTS reduces liquidity. In addition it reduces the risk-sharing possibilities of small liquidity traders. MQTS is therefore Pareto dominated by the other two regimes.

The empirical analysis that we introduce in the next section examines the effect of a unique natural experiment where the MQTS (from now on MTU) was removed for all the stocks traded in BIt. This is equivalent to switching from the MQTS regime to the NC regime.

3. Empirical analysis

The empirical analysis is concerned with a reduction of the MTU in the limit order book of BIt. On January 14, 2002 the MTU was exogenously reduced to one unit by the exchange. The intention of the regulator was to standardize trading lots of different size. The previous policy of

[4] Models of limit order books are limited and do not generally embed asymmetric information. Rosu (2009) is an exception but do not include effects on market depth as traders can only submit orders of unit size. Parlour, Goettler and Rajan (2009) instead do not provide a closed form solution to derive predictions on informational efficiency.

BIt was instead to revise the MTU periodically to make exchange operation and order execution easier.[5] We consider the stocks belonging to the MIB30 and MIDEX indexes. At the time examined the MIB30 index included the 30 most capitalized and liquid stocks in the exchange. The MIDEX index included the following 25. Table 3 describes the stocks considered.

We compare different measures of market quality in the 20-trading-day period before the reduction of the MTU (denoted by *PRE*) and in the 20-trading-day period after (denoted by *POST*). The choice of the *PRE* period, that starts on December 10, 2001, was determined to avoid confounding effects due to the introduction of a closing call auction on December 3. At the time examined trading takes place in the following phases: an opening call auction (from 8:00 to 9:30am), a continuous trading phase (from 9:30am to 5:25pm), and a closing call auction (pre closing from 5:25 to 5:35pm, and validation from 5:35 to 5:40pm). We consider data in the time period devoted to the continuous trading phase (from 9:30am to 5:00pm); we do not consider the last 25 minutes of trading because they might be affected by the recent introduction of the closing auction.[6]

During the continuous trading phase the market is organized as a pure limit order book. If the price variation exceeds a given threshold, a stock can be suspended from the continuous auction and can be traded in an intra-day call auction; we removed observations for which intra-day call auctions were used. We use an intra-day dataset which includes the quote revisions on the first five levels of the order book and the contracts executed. The analysis covers 5,093,542

[5] The MTU has always been expressed in number of shares.

[6] See Kandel, Rindi, and Bosetti (2009).

records for quotes and 4,598,780 records for transactions. We also adjusted prices for corporate actions that took place in the sample period.

We test the effect of the reduction of the MTU on market quality, concentrating on liquidity and on informational efficiency. We present a number of measures of liquidity, based on the bid-ask spread, market depth and the price impact of orders; we use the dataset including the first five levels of the book to examine transaction costs for large trades that walk up the book. We measure informational efficiency by performing random walk tests and by estimating the standard Hasbrouck (1993) model. To investigate the drivers of the variation in liquidity and informational efficiency we examine adverse selection costs and the informativeness of trades.

3.1. A first glance at trading activity

Table 4 summarizes measures of market activity.[7] Firstly, notice that the reduction of the MTU has an important effect on trading activity. We find that, on average across the stocks, 16.89% of contracts are executed at a size lower than the MTU in the *POST* period (1.78% of contracts are instead executed at the new MTU i.e. one unit). Therefore, the MTU was indeed a binding constraint for traders willing to submit small orders.[8]

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[7] Univariate tests in this table and in the rest of the analysis are based on signed rank Wilcoxon tests for the null hypothesis that the median variation (from the *PRE* to the *POST* period) in individual stock period-averages (*PRE* or *POST*) is equal to zero.

[8] At the time examined, retail traders played a fundamental role in the Italian equity market. BIt estimates that at the end of 1999 retail investors held more than 26% of total market capitalization (BIt Notes n.°2, and n.°3, 2001). BIt investigated the amount and the composition of retail trading executed through the on-line channel (BIt Notes n° 11, 2004, BIt Notes n° 16, 2006). The results of BIt surveys indicate that approximately 25% of trades in the equity market are executed by retail on-line traders.

The interpretation of these results as a greater participation of small traders to the market is supported by the significant increase in the number of contracts (by 15.95%) and trading volume (by 14.56%) after the event, and by the fact that the increase in trading volume is driven by an increase in the number of shares traded rather than by a change in prices.

We also find a significant increase in the autocorrelation of the series of buy/sell contracts (by 4.13%). This can be due to the greater participation of small traders, who place orders following the direction of the market trend. The increase in autocorrelation could alternatively be due to large traders taking advantage of the possibility to split their orders. However, this explanation seems unlikely, as the average value of the MTU before the reduction (808 Euro, the greatest value being 2,177 Euro) was already far smaller than the typical value of institutional traders' orders (according to BIt monitoring department, worth at least 10,000 Euro); thus, the MTU was probably not a binding constraint for institutional traders. On the other hand, we cannot exclude the possibility that there has been an increase in order splitting by small traders.

At the same time, we observe a decrease in price volatility, measured by both the price range, which is the difference between the highest and the lowest transaction price in a day, and the realized volatility[9], that we compute following Anderson, Bollerslev and Labys (2003) and that can be interpreted as the standard deviation of the midquote under the hypothesis that prices follow a Brownian motion.

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[9] The realized volatility is computed as: $[1/N \times \sum_{i=1}^{N} \ln^2(p_i / p_{i-1}) / [(t_i - t_{i-1})/T]^{1/2}$; where p_i is the midquote at time t. N is the number of observations in the specific sample period and T is the number of seconds in the time interval considered. Because the time between two subsequent observations is not constant, we weigh each observation by the duration (in seconds) between subsequent quote updates.

Finally, it is important to remark that the reduction in the MTU does not have a significant effect on prices. This result does not come unexpected, as the MTU change was exogenous and could not be perceived as a positive signal by market participants. The price pattern of the MIB30 and MIDEX indexes is presented in Figure 3. We also compute cumulative abnormal returns around the event (Table 5) and find them to be not significantly different from zero.[10]

3.2. Liquidity

The analysis takes daily averages (obtained from intra-day data) of the liquidity measures as input. The measures are obtained from the snapshot of the limit order book; they are all weighted on the time span between each revision of the quotes at any of the five levels, therefore at any limit or market order submitted to the market. We consider three sets of liquidity measures and end up with the following indicators of liquidity relating to these three sets:

(a) Bid-ask spread: the difference between the ask and the bid as a percentage of the midquote. We analyze the bid-ask spread at all 5 levels of the order book. We also consider a measure of the quoted bid-ask spread in level, which is not standardized on the corresponding midquote.

(b) Market depth: the number of shares offered (or the corresponding Euro value) at each of the 5 levels of both the buy and the sell side of the book. In addition, we compute cumulative depth as the sum of shares available at all these 5 book levels.

[10] We also computed abnormal trading volume, measured as the idyosincratic component of turnover (Lo and Wang, 2000). The results, not reported for brevity, are analogous to those found by looking at cumulative abnormal returns.

(c) Price impact of orders: it is computed as the absolute difference between the ask (for buy orders) or the bid price (for sell orders) and the midquote corresponding to the trade. In computing the price impact of an order that walks up the book, the difference is weighted on the quantities corresponding to the different trades executed.[11] We also consider the price impact of orders as a percentage of the prevailing midquote. We compute the price impact of orders considering different sizes: 5,000, 10,000, 20,000 and 30,000 Euro/midquote.

Table 6, 7 and 8 present descriptive statistics for the measures of liquidity used. We compute a Wilcoxon signed rank test for the null hypothesis that the cross-sectional median variation after the reduction of the MTU is equal to zero. Liquidity for small trades can be measured by the bid-ask spread and the depth on the first level of the book. Liquidity for orders that walk up the book can be assessed by looking at the bid-ask spread and depth at further levels of the book. To compare the liquidity change of orders of different size, the price impact has been computed for orders of different value, as a proportion of the midquote. Overall the results of the univariate analysis clearly highlight a liquidity increase for all trade sizes.

[11] For example, assume that the best bid is equal to 13 Euro, the best ask is equal to 15 Euro (with 100 shares offered) and the ask on the second level of the book is equal to 17 Euro (with 200 shares offered). Suppose that one has to compute the price impact of a buy order of 300 shares. The order hits the best ask and gets partial execution, the rest being then executed against the second level of the book. The price impact is thus given by: [100*(15-14)+200*(17-15)]/300=1.6667Euro.

MULTIVARIATE ANALYSIS

We also examine liquidity in the context of a multivariate setting. Following Böhmer, Saar and Liu (2005), the analysis of the liquidity change after the event is based on two econometric specifications:

a) We firstly regress the variation (from *PRE* to *POST*) in the period-average (*PRE* or *POST*) daily level (obtained from intra-day observations) of the liquidity measures, *L*, of each stock, *i*, on: the variation in the period-average daily trading volume (the sum of trading volume in Euro in a day), *VLM*, the variation in the period-average daily volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, and the variation in the period-average daily transaction prices, *P* (the average transaction price in a day):

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i \qquad (10)$$

We focus on the intercept value and we compute heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance matrix). The regression involves 55 observations (as the number of stocks considered).

The results are presented in Panel A of tables 9 to 11. The coefficient of the intercept is negative for the spread and the price impact of orders and positive for market depth. All the coefficients are significantly different from zero. Thus, there is a strong indication of an increase in liquidity.

b) Because the reduction of the MTU happens for all the stocks at the same time, the error terms in specification (10) might be cross-correlated. This would not affect the consistency of the OLS coefficients but would imply the standard errors to be biased. Therefore, we check the robustness of the results by considering the following model:

$$L_{it} = \alpha + \Sigma_{k=1}^{20}(\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it} \quad (11)$$

We here regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intra-day data) on dummy variables for the days in *POST* (Day^k is equal to one for day *k* after the MTU reduction and zero otherwise), on daily trading volume, on daily price volatility and on daily transaction price. We estimate the model using all the days in the *PRE* and *POST* periods. We focus on the 20 coefficients of the post-event dummies; to assess their statistical significance we test, using a Wilcoxon signed rank test, the hypothesis that the median across the 20 coefficients is equal to zero.[12] The regression involves 2,200 observations (corresponding to 55 stocks over 40 days).

The estimation results of specification (11) are presented in Panel B of tables 9 to 11. The median of the dummy coefficients has the expected sign and it is significantly different from zero for all the liquidity measures, confirming the results of specification (10).

ROBUSTNESS CHECKS

We consider two further robustness analyses:

i) There might be an endogeneity problem in specifications (10) and (11) if trading volume depends on the liquidity measure. Therefore, we estimate a two-equation model where the variation in liquidity is modeled simultaneously with the variation in volume. To identify the model, we include two exogenous variables in specification (10): the

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[12] The approach is similar to Fama and MacBeth (1973) and it allows us to obtain robust standard errors in presence of potentially cross correlated error terms (see, again, Böhmer, Saar and Liu, 2005).

systematic component of volume (Lo and Wang, 2000) and the fixed cost component or the adverse selection component of the bid-ask spread (obtained from the model of Glosten and Harris, 1988). We then estimate the following model with three-stage least squares (as in specification (10), there are 55 observations, corresponding to the number of stocks).:[13]

$$\begin{cases} \Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta Exogenous1_i + \varepsilon_i \\ \Delta VLM_i = \chi_0 + \gamma_1 \Delta L_i + \gamma_2 \Delta VLT_i + \gamma_3 \Delta P_i + \gamma_4 \Delta Exogenous2_i + u_i \end{cases} \tag{12}$$

ii) To further examine the robustness of the results to a problem of cross-correlated error terms, we estimate a specification considering the cross-sectional averages (of daily values, obtained from intra-day observations) of the variables and a dummy for the *POST* period (there are 40 observations, corresponding to the number of days in the analysis):

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t \tag{13}$$

The results concerning robustness checks are presented in tables 12 through 14. They are qualitatively analogous to the previous findings with only slight exceptions. In the model with cross-sectional averages, the price impact of sell orders of different size is not significantly affected by the reduction of the MTU when it is not standardized on the midquote. Similarly, the depth in Euro value on the fourth level of the book (on the bid side of the market) is not significantly influenced by the event.

[13] We also estimated the model with two stage least squares and we obtained analogous results.

To sum up, the results highlight an increase in liquidity both for small and large trades. The bid-ask spread decreases at all five levels of the book, and the quantities offered increase at every book depth; in addition, the price impact of orders of different size decreases.

ADVERSE SELECTION COSTS

The model predicts an increase in liquidity for small trades as now dealers are allowed to quote prices for a smaller size. It also predicts an increase in liquidity for large trades if the proportion of insiders in the market is sufficiently high for a pooling equilibrium to prevail, in which case liquidity under the NC regime is higher than under the MQTS regime. After the reduction in the MTU more liquidity traders have access to the market and, under a pooling equilibrium, informed traders submit both small and large orders. Therefore, the probability that a large order comes from an informed trader decreases thus reducing adverse selection costs associated with those orders.

To measure adverse selection costs we use the Foster and Viswanathan (1993) model, as presented in Brennan and Subrahmanyam (1996). The model considers the following specification:

$$\Delta p_t = \alpha_p + \psi(D_t - D_{t-1}) + \lambda\tau_t + v_t \tag{14}$$

where p is the price, D is the sign of the trade (it is equal to +1 for buyer-initiated trades and to -1 for seller initiated trades), and τ is the residual from a regression relating trade size to the previous variation in price and to lagged trade size:

$$q_t = \alpha_q + \sum_{i=1}^{5} \beta_j \Delta p_{t-j} + \sum_{i=1}^{5} \gamma_j q_{t-j} + \tau_t \tag{15}$$

To avoid tracking the effect of the bid-ask bounce, we estimate the price as the midquote corresponding to the trade, i.e. the average of the price of the trade and the prevailing ask (bid) for a sell (buy) contract.

To classify trades as buys or sells we use the algorithm proposed by Lee and Ready (1991). A trade is classified as a buy if its execution price is above the previous midquote and it is classified as a sell if its execution price is below; if the execution price is equal to the previous midquote, then it is compared to the price of the previous trade and the trade is classified as a buy (sell) if there has been an upward (downward) price change.[14]

The coefficient of τ is related to the unexpected component of trade size and can be interpreted as a measure of adverse selection costs. The absolute value of the coefficient of the variation in trade sign can be interpreted as a measure of illiquidity due to lack of depth.

The results of the estimation are given in Panel A of Table 15. As expected, the adverse selection component of the spread decreases significantly after the reduction of the MTU. More uninformed traders access the market after the event and this reduces information asymmetries and adverse selection costs.[15]

Furthermore, in line with the findings on depth, the absolute value of ψ significantly decreases, indicating that illiquidity decreases after the MTU reduction. Notice that ψ is negative, which means that in correspondence of an inversion in trade, e.g. from a market buy to a market sell, the midquote increases (analogously a market sell followed by a market buy induces a reduction of the midquote).

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[14] We do not use the 5-second time adjustment, as advised by Bessembinder (2003).

[15] We also estimated the standard Glosten and Harris (1988) model, which relates price variations to the order flow. The results indicate a decrease in the adverse selection component of the bid-ask spread after the MTU reduction. These results are not reported for brevity.

To explain this result, we refer to the example reported in Figure 4. Assume that at time *t*, 3 shares are available both on the best ask and the best bid price of the market. Assume that a buyer now arrives and hits the best ask price via a market order of 1 share: the transaction price associated to this market order will be A_t and the midquote M_t. According to Parlour (1998), we expect that the reduction of the ask depth induces incoming buyers to choose market rather than limit buy orders. This is because the buyer anticipates that the next seller will have an incentive to submit a limit sell rather than a market sell order, thus reducing the execution probability of the current buyer limit order. So this buyer will choose a market order (as predicted in Parlour, 1998) and the associated transaction price will be A_{t+1} (M_{t+1} correspondent midquote). Similarly, still following Parlour, we expect that the next buyer will have an incentive to choose a market buy order with an associated transaction price equal to A_{t+2}. However, since this order will hit the last unit available on the ask side, the ask price will increase to -say- A_{t+3}. At this point the next buyer will probably switch (due to the increase in the ask price) to a limit buy order, that perhaps he posts within the inside spread at -say- B_{t+4}. If this happens, the increase in the bid price will create an incentive for the next seller to submit a market order, that will be recorded with an associated transaction price equal to B_{t+4}.

By looking at the arrows on Figure 4, we notice that when a buy order (executed at the last recorded ask price, A_{t+2}) is followed by a sell order (hitting the new bid price B_{t+4}), the midpoint M increases from M_{t+2} to M_{t+4} (solid arrow), and in our dataset this may explain the negative sign of ψ. Unlike in the Parlour example, real market books are not infinitely liquid and the more illiquid the market, the stronger this effect is.[16]

[16] See Buti, Rindi and Werner (2010) where this effect is described in a theoretical framework.

Conversely, we expect that when the book becomes deeper, as it happens after the reduction of the MTU, the chances to observe the Parlour's effect increase as, going back to the example in Figure 4, the ask price A_{t+3} should increase less frequently and traders should have less incentive to switch from market to limit buy orders. Empirically, we should see an increase in the probability of continuation vs. reversal, which is again what we observe in the dataset (measured by sign autocorrelation). In addition, a higher probability to observe the Parlour's effect also explains the observed reduction in the magnitude of the parameter ψ.

CONTROL FOR A LIQUIDITY TREND

To make sure that the documented improvement in liquidity is not due to a secular trend within the Italian market, we also examined the 20-trading-day period (we denote this period as *PRE1*) before the *PRE* period. We obtained from BIt data on the quotes at the best level of the book in the *PRE1* period.[17] We then compared our measures of spread in the *PRE1* and *PRE* periods. The results are reported in Table 16: the median difference in the spread measures is not significantly different from zero. The findings suggest that the improvement in liquidity after the MTU reduction cannot be attributed to a secular market trend.

We also investigated whether a global liquidity trend within the time sample considered may have influenced our results. We followed the approach proposed by Brockman, Chung and Perignon (2009) in their analysis of global commonality in liquidity. Specifically, we related

[17] We received from BIt data starting from November 1, 2001. If we take all the trading days from November 1 to December 7 (which is the trading day before the start of the *PRE* period) the results are qualitatively analogous as the ones obtained considering the *PRE1* period.

liquidity (measured by the percentage spread on the first level of the book) in the Italian market to liquidity in a set of 29 other countries[18] using the following specification:

$$\Delta S_{BIT,t} = \alpha + \beta_1 \Delta S_{G,t} + \beta_2 \Delta S_{G,t-1} + \beta_3 \Delta S_{G,t+1} \\ + \delta_1 RET_{G,t} + \delta_2 RET_{G,t-1} + \delta_3 RET_{G,t+1} + \delta_4 \Delta VLT_{BIT,t} + \varepsilon_t \qquad (16)$$

where *S* is the percentage spread on the first level of the book; *RET* is the daily return; *VLT* is the previously defined measure of volatility, i.e. the difference between the highest and the lowest transaction price; Δ refers to the percentage variation from day *t*-1 to day *t*; the subscript *BIT* refers to the Italian sample (i.e. S_{BIT} and VLT_{BIT} are the equal-weighted average across the 55 firms in the Italian sample of the spread and of volatility, respectively); the subscript *G* refers to the global sample (i.e. S_G and RET_G are the equal-weighted average across all the firms in the global sample of the spread and of daily return, respectively). The model is estimated using the 41 days (this corresponds to 40 observations regarding spread variations) including the *PRE* period, the event day and the *POST* period.

As Brockman, Chung and Perignon (2009), we focus on the coefficient of the contemporaneous change in global liquidity. The results (reported in table 16, Panel B) show that the coefficient of $\Delta S_{G,t}$ is not significantly different from zero (nor are the coefficients of $\Delta S_{G,t-1}$ and $\Delta S_{G,t+1}$ significant), indicating that in the time sample considered there is no evidence of a global trend in liquidity affecting the liquidity pattern in the Italian market.[19]

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[18] Brockman, Chung and Perignon (2009) use data from 38 countries. We replicated their analysis using daily data; for the same set of countries, we selected all the countries with available data in Datastream and we obtained US data from CRSP. The countries considered, besides Italy, are: Austria, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Norway, Poland, Portugal, Spain, Sweden, Switzerland, UK, Australia, Hong Kong, Japan, New Zealand, Singapore, China, Indonesia, Malaysia, Philippines, Thailand, South Africa, Brazil, Mexico, US.

[19] We also estimated the model including in the global sample only European or non-European countries, separately. The results (untabulated) are qualitatively unchanged.

Finally, we also included the global liquidity measure, S_G, in the cross sectional regression (13):

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \beta_5 S_{G,t} + \varepsilon_t \qquad (17)$$

We estimated the model for all the measures of spread, market depth and price impact. The results (not reported for brevity) are qualitatively analogous to the ones obtained without controlling for the global liquidity level (reported tables 12, 13 and 14, panel B); furthermore, for none of the liquidity measures is the coefficient of S_G significantly different from zero.

3.3. Informational efficiency

RANDOM WALK TESTS

As a first approach to study informational efficiency, we examine the autocorrelation of intra-day returns and intra-day variance ratios (see, for example, Campbell, Lo, MacKinley, 1997, Böhmer, Saar and Liu, 2005, and O´Hara and Ye, 2009). These measures aim at testing whether prices follow a random walk (and therefore the extent of predictability in the time series). We here consider the returns on the midquote to abstract from the bid-ask bounce. We take 5, 10, 15, 20 and 30 minute returns (we choose these lags, as, for example, Chordia, Roll and Subrahmanyam, 2005). Furthermore, we exclude overnight returns. The results of the informational efficiency tests are presented in table 17.

We compute the autocorrelation of intra-day returns at different lags and we focus on its absolute value to check for deviations from the random walk hypothesis. We also compute variance ratios, denoted as *VR(m,n)*, i.e. the ratio of the return variance over *m* minutes to the return variance over *n* minutes, both divided by the length of the period; because a random walk implies that variance ratios are equal to one, we examine the quantity |*VR*-1|. The results indicate that the absolute value of autocorrelation and the absolute value of variance ratio deviations from one do not significantly change after the reduction of the MTU; moreover, the sign of the variation is highly dependent on the choice of the lag.

A STRUCTURAL MODEL OF PRICES AND TRADES

The second approach to measuring informational efficiency follows Hasbrouck (1993) and is based on a model where the observed price is decomposed into an efficient price component (which is a random walk) and a pricing error. The magnitude of the pricing error, measured by its variance, has been proposed by Hasbrouck as an indicator of informational efficiency. The variance of the pricing error can be obtained by estimating a VAR model involving the variation in price, and trade characteristics. Precisely, the observed logarithm price, p_t, is assumed to be decomposed in $p_t=m_t+s_t$, where m_t is the efficient price corresponding to the expected value of the future payoffs -given all available information- and it is a random walk, with $m_t=m_{t-1}+w_t$; s_t is the deviation of the price from the fundamental value, denoted as pricing error. The pricing error captures market frictions which lead the price to deviate from a random walk: for example illiquidity issues, price discreteness, and inability to process available information. As in Hasbrouck (1993), we estimate the following VAR with five lags:

$$\begin{cases} r_t = a_1 r_{t-1} + a_2 r_{t-2} + \ldots + b_1 x_{t-1} + b_2 x_{t-2} + \ldots + v_{1,t} \\ x_t = c_1 r_{t-1} + c_2 r_{t-2} + \ldots + d_1 x_{t-1} + d_2 x_{t-2} + \ldots + v_{2,t} \end{cases} \quad (18)$$

where r_t is the difference in (log) prices p_t and x_t is a column vector of trade-related variables: the sign of the trade, signed trading volume, and the signed square root of trading volume to model concavity between prices and trades. The corresponding VMA representation is:

$$\begin{cases} r_t = a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} \ldots + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + \ldots \\ x_t = c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} \ldots + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + \ldots \end{cases} \quad (19)$$

Only the variance of the efficient price is exactly identified. To identify the variance of the pricing error we use the Beveridge and Nelson (1981) restriction. The pricing error can be written as:

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \ldots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \ldots \quad (20)$$

One can thus derive the variance of the random walk component of the price and that of the pricing error:

$$\sigma_w^2 = [\Sigma_{i=0}^{\infty} a_i^* \quad \Sigma_{i=0}^{\infty} b_i^*]\operatorname{cov}(v)[\Sigma_{i=0}^{\infty} a_i^* \quad \Sigma_{i=0}^{\infty} b_i^*]' \quad (21)$$

$$\sigma_s^2 = \Sigma_{j=0}^{\infty}[\alpha_j \quad \beta_j]\operatorname{cov}(v)[\alpha_j \quad \beta_j]' \quad (22)$$

where $\alpha_j = -\Sigma_{k=j+1}^{\infty} a_k^*$; $\beta_j = -\Sigma_{k=j+1}^{\infty} b_k^*$

We estimate the model with the returns computed on the midquotes corresponding to the trades; this implies that the pricing error is not affected by the bid-ask bounce. For a meaningful comparison, the variance of the pricing error is standardized on the variance of the logarithm of price.

The results show that the variance of the pricing error decreases after the reduction of the MTU but the variation is not significantly different from zero. The results are therefore similar to those found using random walk tests.

With the reduction of the MTU two opposite effects on informational efficiency can be distinguished. On the one hand if uninformed traders enter the market and submit more limit than market orders, market depth increases; the increase in depth leads to a decrease in the price impact of orders and therefore to a decrease in the deviation between the price and the fundamental value. On the other hand, according to the model´s predictions, when moving from an MTU to a no constraint regime, either a separating or a pooling equilibrium can occur. If the latter prevails, the frequency of large orders decreases, and because large orders are the most informative, informational efficiency can decrease. The results suggest that neither effect substantially prevails.

The model just described also allows us to quantify the extent of the conjectured decrease in the informativeness of orders submitted. Following Hasbrouck (1991b), we compute trade informativeness as the part of the variance of the efficient price that is explained by the trade components. This is the variance of the expected value of the efficient price innovation given the current trade and all the information available (Φ). It can be computed as (see Hasbrouck):

$$VAR(w,x) = Var(E[w_t \mid x_t - E[x_t \mid \Phi_{t-1}]]) = [\Sigma_{i=0}^{\infty} b_i^*]\text{cov}(v_x)[\Sigma_{i=0}^{\infty} b_i^*]' \qquad (23)$$

where $\text{cov}(v_x)$ is the variance-covariance matrix of v_2, v_3, v_4. We focus on a relative measure of trade informativeness, which is obtained as *VAR(w,x)* over the variance of the efficient price innovation: $R_w^2 = VAR(w,x)/VAR(w)$.

We find (Table 17, Panel B) that trade informativeness decreases after the reduction of the MTU. This is consistent with the view that with the reduction of the MTU a pooling equilibrium prevails where orders conveying less information are submitted. The results are also consistent with the documented decrease in adverse selection costs in the context of the Foster and Viswanathan (1993) model.

3.4. Stock splits vs. MTU reductions

Stock splitting is for some aspects analogous to a reduction in the MTU, as a split implies that the minimum transaction size decreases. A vast body of literature examines how market quality is affected by splits. In particular, most previous works (for example, Conroy, Harris and

Benet, 1990, Copeland, 1997, Michayluk and Kofman, 2001, Easley, O´Hara and Saar, 2001, Kunz and Majhensek, 2004) find a decrease in liquidity, measured by an increase in the bid-ask spread after splits. Furthermore, it has repeatedly been found that there is an increase in the participation of small traders, which is reflected by a substantial increase in the number of small trades (Muscarella and Vetsuypens, 1996; Kryzanowski and Zhang, 1996; and Schultz, 2000). At the same time, an increase in market valuation is generally documented (for example, Grinblatt, Masulis and Titman 1984, Conrad and Conroy 1994, Ikenberry et al. 1996, 2002). Our results also indicate an increase in the number of small traders in the market; in contrast to the findings on stock splitting, however, we find a liquidity improvement and no effect on stock prices.

Our analysis differentiates from this literature as stock splitting is voluntary, whereas the reduction in the MTU was exogenously deliberated by BIt and we are therefore able to isolate the effect of the microstructure change. Stock splits are the result of a firm choice and they can be used as a signaling method of good prospects (as argued, for example, by Brennan and Copeland, 1991; McNichols and Dravid, 1990; Brennan and Hughes, 1991, Prabhala, 1997, Nayak and Prabhala, 2001, Kadiyala and Vetsuuypens, 2002); if the market perceives them as such, they can be accompanied by an increase in stock valuation, and the induced variation in prices might also in turn affect liquidity.

We checked that there were no stock splits in the period under analysis. Therefore, our results only reflect the exogenous reduction in the MTU.

4. Conclusions

Should financial regulators remove constraints on the minimum trading unit (MTU)? What are the effects of a reduction of the minimum trade unit, and what is the optimal regulation of the minimum quote and transaction size? This paper addresses these questions by considering the unique natural experiment of Borsa Italiana (BIt), where in 2002 the MTU was reduced by the exchange to one unit for all the stocks. Unlike previous empirical works on MTU variations, and in contrast to the related literature on stock splitting, we are able to isolate the effect of this microstructure change, as it was exogenously deliberated by BIt.

We find a marked improvement in liquidity after the reduction of MTU, as measured by a decrease in the bid-ask spread and the price impact of orders, and by an increase in market depth. The results hold for all the five levels of the book available, suggesting that a decrease in transaction costs for small orders and for those larger orders walking up the book. We also find that the adverse selection component of the spread as well as trade informativeness decrease significantly after the MTU reduction; at the same time, informational efficiency does not change significantly.

The results are consistent with a theoretical framework where liquidity providers operate under asymmetric information. The model allows us to show how market quality varies under different regimes of transaction size regulation, and in particular gives predictions on how liquidity can change after the removal of the MTU. With a reduction of the MTU more traders have access to the market; hence the proportion of uninformed traders increases, adverse selection costs decrease and liquidity improves.

Appendix

Proof of Proposition 1:

In order to show the validity of (7), notice that: $A_2 - A_Q = \dfrac{\frac{1}{4}(1-\alpha)^2(\beta^2-1)}{(-1+\alpha)\beta-\alpha-1} > 0$.

When insiders play pure strategies ($\mu = 1$) we obtain that $A_{QT} = A_2$.

Since, $\dfrac{\partial A_2}{\partial \mu} = -\dfrac{1}{2}\dfrac{\alpha\beta(\alpha-1)}{(-\beta+\alpha\beta-\alpha\mu)^2} > 0$, we have: $A_{QT} - A_2 > 0$

Moreover we get: $A_Q - A_1 = -\dfrac{1}{2}\dfrac{\alpha(\beta-1)(\alpha-1)}{(\beta-1)\alpha-\beta-1} + \dfrac{1}{2}(1-\alpha)\beta > 0 \quad \forall \alpha, \beta \in (0,1)$.

Analogous results can be obtained when measuring liquidity by the price impact of a trade:

$\dfrac{A_1 - E(v)}{1-0} < \dfrac{A_Q - E(v)}{1-0}$ for small trades and $\dfrac{A_{QT} - E(v)}{2-0} > \dfrac{A_2 - E(v)}{2-0} > \dfrac{A_Q - E(v)}{2-0}$

for large trades with $E(v) = \dfrac{1}{2}$.

Proof of Proposition 2:

Welfare - Notice that insiders´ expected profits under NC are equal to:

$E(\pi^I_{ASK})_{NC} = E(\pi^I_{ASK} \mid \overline{V})\Pr(\overline{V}) + E(\pi^I_{ASK} \mid \underline{V})\Pr(\underline{V}) =$
$= [\mu 2(1-A_2) + (1-\mu)(1-A_1)]\Pr(\overline{V}) = (1-A_2)$ and with MQS and MQTS they are:

$E(\pi^I_{ASK})_{Q,QT} = (1 - A_{Q,QT)})$. Since $A_{QT} \geq A_2 > A_Q$, we have $E(\pi^I_{ASK})_{QT} \leq E(\pi^I_{ASK})_{NC} < E(\pi^I_{ASK})_Q$

Large liquidity traders´ expected profits are equal to:

$E(\pi^U_{ASK}) = E(\pi^U_{ASK} \mid \overline{V})\Pr(\overline{V}) + E(\pi^U_{ASK} \mid \underline{V})\Pr(\underline{V}) =$

$= [2(1-A_{2,Q,QT})]\Pr(\overline{V}) + [2(0 - A_{2,Q,QT})]\Pr(\underline{V}) = 1 - 2A_{2,Q,QT}$

Since $A_{QT} \geq A_2 > A_Q$, it follows that $E(\pi^U_{ASK})_{QT} \leq E(\pi^U_{ASK})_{NC} < E(\pi^U_{ASK})_Q$.

Informational efficiency – Observe that:

$$E[VAR(\tilde{v} \mid q_i)] = 2\sum_{i=1}^{2}[(\overline{V} - E(\tilde{v} \mid q_i^A))^2 \Pr(\overline{V} \mid q_i^A) + (\underline{V} - E(\tilde{v} \mid q_i^A))^2 \Pr(\underline{V} \mid q_i^A)]\Pr(q_i^A)$$

For given values of the parameters α and β; informational efficiency under MQS and MQTS is the same. Comparing the informational efficiency under the regimes with and without constraint, we obtain:

$$IE_{NC} - IE_j =$$

$$= -4\frac{-\alpha\beta - \beta^2 + 3\alpha\beta^2 + \beta^3 - 2\alpha\beta^3 - \alpha^2\beta + 2\alpha^2 + \alpha^2\beta^3 - 2\alpha^2\beta^2}{(-2 + \beta - \beta^3 - 2\alpha + \alpha\beta^2 - \alpha\beta)(-1 + \alpha)(\beta + \alpha)}$$

with $j = Q;QT$.

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Table 1: Market quality under the three regimes - without constraints with pooling (*NC_{POOL}*) and separating equilibrium (*NC_{SEP}*), with minimum quote size (*MQS*) and with minimum quote and transaction size

This table presents the implications of the different regimes of transaction size regulation for the parameters of market quality. The notation ">" ("~") should be read as "preferred" ("indifferent"). Take as an example the results for liquidity of small trades; here the regime without constraint under separating equilibrium is preferred to the same regime under pooling equilibrium, which in turn is preferred to MQS (MQTS being the poorest in terms of liquidity). Notice that it has been assumed that liquidity can be measured by either the bid-ask spread or the inverse of the price impact of a trade, i.e. $(|\frac{P^{A,B}-E(v)}{1-0}|)^{-1}$.

Liquidity	
Liquidity (small trades)	*NC_{SEP}> NC_{POOL}> MQS>MQTS*
Liquidity (large trades)	*MQS> NC_{POOL}> NC_{SEP} ~MQTS*
Volumes and number of shares	
(sep.) $0<\alpha<1/3$	*MQS~ NC_{SEP} >MQTS*
(pool.) $1/3<\alpha\leq 2/3$	*MQS> NC_{POOL} >MQTS*
(pool.) $2/3<\alpha<1$	*MQS>MQTS> NC_{POOL}*
Welfare	
Retail small traders	*NC_{SEP} > NC_{POOL} >MQS>MQTS*
Institutional large traders and insiders	*MQS > NC_{POOL} > NC_{SEP} ~MQTS*

Table 2: Expected number of shares associated with different regimes of quote and transaction size regulation

NC_{POOL}	NC_{SEP}	MQS	$MQTS$
$(1-\alpha)1.5 + \alpha(1+\mu) = 1.67$; $\mu = \beta + \frac{\beta(1-\beta)}{\alpha(1+\beta)}$	$\frac{1}{2}(3+\alpha)$	$\frac{1}{2}(3+\alpha)$	$(1+\alpha)$

Table 3: Dataset

We consider the stocks belonging to the MIB30 and MIDEX indexes. We compare the 20-trading day period before (*PRE*: from December 10, 2001 to January 11, 2002) to the 20-trading day period after (*POST*: from January 15 to February 11, 2002) the reduction of the MTU to one unit for all the stocks listed on BIt (happened on January 14, 2002).

Stock	*Capitalization (Million of Euros)*	*Index*	*MTU (Pre)*
ACEA	1,687	MIDEX	100
AEM	4,032	MIB30	500
ALITALIA	1,638	MIDEX	1000
ALLEANZA	8,384	MIB30	50
AUTOGRILL	2,575	MIDEX	50
AUTOSTRADA TO-MI	946	MIDEX	50
AUTOSTRADE	8,779	MIB30	100
BANCA DI ROMA	3,421	MIB30	125
BANCA FIDEURAM	7,501	MIB30	50
BANCA MONTE PASCHI SIENA	7,580	MIB30	250
BANCA NAZ LAVORO	5,331	MIB30	250
BANCA POPOLARE BERGAMO	2,395	MIDEX	50
BANCA POP. COMM. IND.	968	MIDEX	50
BANCA POPOLARE LODI	1,246	MIDEX	50
BANCA POPOLARE MILANO	1,506	MIDEX	100
BANCA POPOLARE NOVARA	1,617	MIDEX	250
BANCA POPOLARE VERONA	2,411	MIDEX	50
BENETTON GROUP	2,179	MIDEX	50
BENI STABILI	903	MIDEX	2500
BIPOP-CARIRE	3,749	MIB30	250
BULGARI	2,772	MIB30	50
BUZZI UNICEM	983	MIDEX	250
CLASS EDITORI	356	MIDEX	50
CREDITO EMILIANO	1,472	MIDEX	100
ENEL	38,743	MIB30	125
ENI	52,536	MIB30	50
FIAT	6,815	MIB30	50
FINMECCANICA	8,222	MIB30	500
GENERALI	38,404	MIB30	25
HDP	2,428	MIB30	250
INTESABCI	15,935	MIB30	250
ITALCEMENTI	1,518	MIDEX	250
ITALGAS	3,485	MIB30	50
L´ESPRESSO (G.E.)	1,499	MIDEX	100
LA FONDIARIA	2,267	MIDEX	250
MEDIASET	9,875	MIB30	100
MEDIOBANCA	7,721	MIB30	50

MEDIOLANUM	7,272	MIB30	50
MILANO	1,149	MIDEX	500
MONDADORI EDITORE	1,859	MIDEX	100
OLIVETTI	9,779	MIB30	250
PARMALAT FINANZIARIA	2,406	MIDEX	250
PIRELLI SPA	1,549	MIB30	250
RAS	9,905	MIB30	50
RINASCENTE	1,244	MIDEX	250
ROLO BANCA 1473	8,043	MIB30	50
SAI	939	MIDEX	50
SAIPEM	2,209	MIB30	250
SAN PAOLO IMI	17,289	MIB30	50
SEAT PAGINE GIALLE	10,536	MIB30	500
SNIA	744	MIDEX	1000
TELECOM ITALIA	50,037	MIB30	50
TIM	53,216	MIB30	250
TOD'S	1,426	MIDEX	25
UNICREDITO ITALIANO	21,154	MIB30	250

Table 4: Trading activity

The table compares cross-sectional averages of daily (obtained from intra-day observations) trading activity summary measures before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. We consider: the number of contracts; the number of shares traded; the Euro value of contracts executed; the average transaction price; the number of contracts at the MTU in the *PRE* period; the number of contracts at one unit; the proportion of contracts executed at the MTU; the proportion of contracts in the *POST* period with size less than the MTU in the *PRE* period; the first order autocorrelation of the series (it is equal to +1 for a buy and -1 for a sell) of buyer and seller initiated trades; the price range (the difference between the highest and a lowest price in a day); the realized volatility.

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
Number of contracts	1,492	1,730	238	4.4238***
Number of shares traded	5,519,236	5,887,091	367,855	3.8541***
Trading volume (Euro)	25,083,678	28,735,369	3,651,691	3.2760***
Price	8.2800	8.2821	0.0010	-0.2429
Number of contracts at MTU (PRE)	166.17	57.49	-108.68	-6.3174***
Number of contracts at 1 unit	-	24.28	-	-
Proportion of contracts at MTU	16.17%	1.78%	-14.39%	-6.4510***
Proportion of contracts at less than MTU	-	16.89%	-	-
Autocorrelation buy/sell	0.5019	0.5226	0.0207	3.6280***
Price Range	0.2089	0.1920	-0.0169	-3.7621***
Realized volatility	0.0319	0.0282	-0.0037	-5.3120***

Table 5: CAR around the MTU reduction

The table reports cross-sectional median values for CAR (cumulative abnormal returns) from 20 days before to 20 days after the reduction in the MTU. The measure is obtained from a market model by using COMIT index as the market return. The estimation period considers the 240 days before the event.

Day	*CAR*	*Wilcoxon-z*
-20	-0.0056	-2.7984***
-19	-0.0010	0.2848
-18	-0.0083	-2.6301***
-17	-0.0097	-2.8151***
-16	-0.0095	-1.8013*
-15	0.0020	0.1927
-14	-0.0083	-2.4800**
-13	-0.0030	-1.3489
-12	-0.0090	-2.7733***
-11	0.0052	0.2932
-10	-0.0053	-1.4159
-9	-0.0132	-1.7008*
-8	-0.0024	-1.7092*
-7	-0.0056	-0.8546
-6	-0.0108	-1.9354*
-5	-0.0143	-1.3992
-4	-0.0081	-0.3770
-3	0.0016	1.1143
-2	-0.0044	0.0670
-1	0.0043	1.2148
0	-0.0033	-0.1340
1	0.0004	1.0054
2	0.0035	0.2681
3	0.0057	0.5613
4	0.0064	0.6116
5	0.0072	0.4105
6	-0.0006	0.1005
7	0.0130	0.5781
8	0.0137	0.7708
9	0.0164	1.0138
10	0.0090	0.9048
11	0.0075	1.0389
12	0.0112	1.5332
13	0.0078	1.5081
14	0.0034	1.1227
15	0.0156	1.2986
16	0.0110	1.1478

17	0.0007	0.8043
18	0.0165	1.4746
19	0.0185	1.5081
20	0.0093	1.2316

Table 6: Bid-ask spread

The table compares the cross-sectional average of the daily (obtained as the daily average of intra-day observations) bid-ask spread at the five levels of the book before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. The % Spread is computed as the difference between the ask and the bid as a percentage of the midquote. We also consider a measure of the quoted bid-ask spread in level (denoted as Quoted spread - which is not standardized on the corresponding midquote). The significance level corresponding to a Wilcoxon signed rank test is reported.

		Pre	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
Level 1	*Quoted spread*	0.0202	0.0178	-0.0024***	-0.1040***
Level 1	*% Spread*	0.0024	0.0022	-0.0002***	-0.1017***
Level 2	*% Spread*	0.0059	0.0055	-0.0004***	-0.0623***
Level 3	*% Spread*	0.0093	0.0089	-0.0004***	-0.0524***
Level 4	*% Spread*	0.0128	0.0122	-0.0006***	-0.0485***
Level 5	*% Spread*	0.0163	0.0156	-0.0007***	-0.0451***

Table 7: Market depth

The table compares the cross-sectional average of daily (obtained as the daily average of intra-day observations) market depth at the five levels of the book before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. It is computed as the number of shares offered (or the corresponding Euro value) on the buy and on the sell side of the book. We analyze depth at the first 5 levels of the book. In addition, we compute cumulative depth (as the sum of depth at all the book levels). The significance level corresponding to a Wilcoxon signed rank test is reported.

		Pre	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
Level 1	*# of shares at Bid*	20,522	29,292	8,770***	0.4674***
Level 1	*# of shares at Ask*	21,395	29,507	8,112***	0.3286***
Level 1	*Total # of shares*	41,917	58,798	16,881***	0.3838***
Level 2	*# of shares at Bid*	29,526	41,681	12,155***	0.4846***
Level 2	*# of shares at Ask*	31,954	44,617	12,663**	0.4131***
Level 2	*Total # of shares*	61,480	86,298	24,818***	0.4336***
Level 3	*# of shares at Bid*	28,562	39,908	11,346***	0.4633***
Level 3	*# of shares at Ask*	31,637	43,314	11,677***	0.3798***
Level 3	*Total # of shares*	60,200	83,223	23,023***	0.4065***
Level 4	*# of shares at Bid*	27,840	37,142	9,302***	0.3526***
Level 4	*# of shares at Ask*	30,692	41,724	11,032***	0.3769***
Level 4	*Total # of shares*	58,532	78,866	20,334***	0.3586***
Level 5	*# of shares at Bid*	26,041	35,021	8,980***	0.3392***
Level 5	*# of shares at Ask*	30,621	40,437	9,816***	0.3348***
Level 5	*Total # of shares*	56,661	75,458	18,797***	0.3283***
Level 1	*Euro value at Bid*	96,028	129,925	33,897***	0.5191***
Level 1	*Euro value at Ask*	100,245	132,674	32,429***	0.3503***
Level 1	*Total Euro value*	196,273	262,599	66,326***	0.4172***
Level 2	*Euro value at Bid*	136,993	179,557	42,564***	0.5389***
Level 2	*Euro value at Ask*	147,447	194,951	47,504***	0.4376***
Level 2	*Total Euro value*	284,440	374,508	90,068***	0.4700***
Level 3	*Euro value at Bid*	129,930	168,639	38,709***	0.5126***
Level 3	*Euro value at Ask*	146,280	189,495	43,215***	0.3996***
Level 3	*Total Euro value*	276,209	358,135	81,926***	0.4383***
Level 4	*Euro value at Bid*	125,548	157,199	31,651***	0.3739***
Level 4	*Euro value at Ask*	142,002	183,362	41,360***	0.3979***
Level 4	*Total Euro value*	267,550	340,561	73,011***	0.3797***
Level 5	*Euro value at Bid*	119,261	147,218	27,957***	0.3582***
Level 5	*Euro value at Ask*	140,436	175,286	34,850***	0.3517***
Level 5	*Total Euro value*	259,698	322,504	62,806***	0.3460***
Cumulative (1-5)	# of shares at Bid	132,491	183,044	50,553***	0.4124***
Cumulative (1-5)	# of shares at Ask	146,299	199,599	53,300***	0.3641***
Cumulative (1-5)	*Total # of shares*	278,790	382,643	103,853***	0.3784***
Cumulative (1-5)	*Euro value at Bid*	607,759	782,539	174,780***	0.4499***
Cumulative (1-5)	*Euro value at Ask*	676,411	875,768	199,357***	0.3847***
Cumulative (1-5)	*Total Euro value*	1,284,170	1,658,308	374,138***	0.4058***

Table 8: Price impact of orders

The table compares the cross-sectional average of daily (obtained as the daily average of intra-day observations) price impact of orders before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. It is computed as the difference between the ask (for buy orders) or the bid price (for sell orders) and the midquote corresponding to the trade. In computing the price impact of an order that walks up the book, the difference is weighted on the quantities corresponding to the different trades. We also consider the price impact of orders as a percentage of the prevailing midquote. We compute the price impact of orders of different size (5,000 Euro/midquote; 10,000 Euro/midquote; 20,000 Euro/midquote; 30,000 Euro/midquote). The significance level corresponding to a Wilcoxon signed rank test is reported.

		Pre	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
5,000€/Midquote	*Buy order on Midquote*	0.0129	0.0117	-0.0012***	-0.0954***
5,000€/Midquote	*Sell order on Midquote*	0.0135	0.0121	-0.0014***	-0.1047***
5,000€/Midquote	*Buy order on Midquote (%)*	0.0015	0.0014	-0.0001***	-0.0928***
5,000€/Midquote	*Sell order on Midquote (%)*	0.0016	0.0014	-0.0002***	-0.1022***
10,000€/Midquote	*Buy order on Midquote*	0.0157	0.0140	-0.0017***	-0.1111***
10,000€/Midquote	*Sell order on Midquote*	0.0165	0.0146	-0.0019***	-0.1215***
10,000€/Midquote	*Buy order on Midquote (%)*	0.0019	0.0016	-0.0003***	-0.1078***
10,000€/Midquote	*Sell order on Midquote (%)*	0.0019	0.0016	-0.0003***	-0.1186***
20,000€/Midquote	*Buy order on Midquote*	0.0213	0.0183	-0.0030***	-0.1351***
20,000€/Midquote	*Sell order on Midquote*	0.0226	0.0199	-0.0027***	-0.1458***
20,000€/Midquote	*Buy order on Midquote (%)*	0.0025	0.0021	-0.0004***	-0.1312***
20,000€/Midquote	*Sell order on Midquote (%)*	0.0025	0.0021	-0.0004***	-0.1428***
30,000€/Midquote	*Buy order on Midquote*	0.0259	0.0220	-0.0039***	-0.1467***
30,000€/Midquote	*Sell order on Midquote*	0.0272	0.0242	-0.0030***	-0.1594***
30,000€/Midquote	*Buy order on Midquote (%)*	0.0030	0.0025	-0.0005***	-0.1423***
30,000€/Midquote	*Sell order on Midquote (%)*	0.0031	0.0026	-0.0005***	-0.1563***

Table 9: Bid-ask spread – Multivariate analysis

Panel A reports the results of specification (10) in section 3.2:

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i$$

We regress the variation (from *PRE* to *POST*) in the period-average daily level (obtained from intra-day observations) of the liquidity measures, *L*, of each stock, *i*, on: the variation in the period-average daily trading volume (the sum of trading volume in Euro in a day), *VLM*, the variation in the period-average daily volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, and the variation in the period-average daily transaction price (the average transaction price in a day), *P*. The regression involves 55 observations. We report a ***t***-test based on heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance matrix).

Panel B reports the results of specification (11) in section 3.2:

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it}$$

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intra-day data) on dummy variables for the days in *POST* (Day^k is equal to one for day *k* after the MTU reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,200 observations. We present a signed rank Wilcoxon test for the null hypothesis that the median of the 20 Day^k dummy variables is equal to zero.

		Panel A		**Panel B**	
		Intercept	*T-test*	*Median (Day)*	*Wilcoxon-z*
Level 1	*Quoted spread*	-0.0028	-5.8647***	-0.0019	-3.5839***
Level 1	*% Spread*	-0.0003	-6.4812***	-0.0003	-3.9199***
Level 2	*% Spread*	-0.0004	-4.5505***	-0.0003	-3.6586***
Level 3	*% Spread*	-0.0005	-3.7765***	-0.0004	-3.3973***
Level 4	*% Spread*	-0.0006	-3.6257***	-0.0006	-3.3226***
Level 5	*% Spread*	-0.0007	-3.4089***	-0.0007	-3.2479***

Table 10: Market depth – Multivariate analysis

Panel A reports the results of specification (10) in section 3.2:

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i$$

We regress the variation (from *PRE* to *POST*) in the period-average daily level (obtained from intra-day observations) of the liquidity measures, *L*, of each stock, *i*, on: the variation in the period-average daily trading volume (the sum of trading volume in Euro in a day), *VLM*, the variation in the period-average daily volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, and the variation in the period-average daily transaction price (the average transaction price in a day), *P*. The regression involves 55 observations. We report a *t*-test based on heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance matrix).

Panel B reports the results of specification (11) in section 3.2:

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it}$$

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intra-day data) on dummy variables for the days in *POST* (Day^k is equal to one for day *k* after the MTU reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,200 observations. We present a signed rank Wilcoxon test for the null hypothesis that the median of the 20 Day^k dummy variables is equal to zero.

		Panel A		**Panel B**	
		Intercept	*T-test*	*Median (Day)*	*Wilcoxon-z*
Level 1	*# of shares at Bid*	7,058	3.2418***	6,565	3.8453***
Level 1	*# of shares at Ask*	6,222	3.5767***	5,644	3.6586***
Level 1	*Total # of shares*	13,280	3.4374***	12,996	3.7706***
Level 2	*# of shares at Bid*	9,973	3.1220***	7,019	3.8079***
Level 2	*# of shares at Ask*	10,220	4.0358***	7,446	3.4719***
Level 2	*Total # of shares*	20,192	3.5759***	16,537	3.7706***
Level 3	*# of shares at Bid*	9,497	3.0745***	7,490	3.8079***
Level 3	*# of shares at Ask*	9,426	4.1347***	6,869	3.2479***
Level 3	*Total # of shares*	18,923	3.6162***	14,437	3.6959***
Level 4	*# of shares at Bid*	7,847	3.7410***	6,742	3.8453***
Level 4	*# of shares at Ask*	8,838	3.9416***	6,980	3.1359***
Level 4	*Total # of shares*	16,686	3.9181***	13,756	3.6959***
Level 5	*# of shares at Bid*	7,771	3.6599***	5,783	3.8453***
Level 5	*# of shares at Ask*	7,770	3.5328***	4,977	2.8000***
Level 5	*Total # of shares*	15,541	3.7309***	12,523	3.5093***
Level 1	*Euro value at Bid*	21,289	3.5310***	17,816	2.9119***
Level 1	*Euro value at Ask*	19,382	3.4739***	17,228	2.5013**
Level 1	*Total Euro value*	40,671	3.5724***	32,262	2.8373***
Level 2	*Euro value at Bid*	26,336	3.0370***	22,450	2.5013**
Level 2	*Euro value at Ask*	29,838	3.7013***	16,704	2.2773**
Level 2	*Total Euro value*	56,175	3.4580***	40,456	2.5760***
Level 3	*Euro value at Bid*	25,074	3.3479***	19,501	2.5386**
Level 3	*Euro value at Ask*	26,353	3.4241***	11,070	1.8666*
Level 3	*Total Euro value*	51,427	3.5282***	34,796	2.4266**
Level 4	*Euro value at Bid*	20,559	3.6315***	8,501	2.2773**
Level 4	*Euro value at Ask*	24,978	3.3966***	15,122	1.8293*
Level 4	*Total Euro value*	45,536	3.6046***	35,509	2.2026**

Level 5	*Euro value at Bid*	18,463	3.4660***	9,702	1.8666*
Level 5	*Euro value at Ask*	19,980	2.9079***	6,279	1.7173*
Level 5	*Total Euro value*	38,444	3.2914***	29,642	1.9786**
Cumulative (1-5)	# of shares at Bid	42,146	3.3942***	34,012	3.8453***
Cumulative (1-5)	# of shares at Ask	42,476	3.9631***	31,087	3.2479***
Cumulative (1-5)	*Total # of shares*	84,622	3.7157***	62,066	3.7333***
Cumulative (1-5)	*Euro value at Bid*	111,721	3.4739***	90,765	2.6880***
Cumulative (1-5)	*Euro value at Ask*	120,531	3.4863***	66,833	2.0533**
Cumulative (1-5)	*Total Euro value*	232,253	3.5744***	175,544	2.4266**

Table 11: Price impact of orders – Multivariate analysis

Panel A reports the results of specification (10) in section 3.2:

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i$$

We regress the variation (from *PRE* to *POST*) in the period-average daily level (obtained from intra-day observations) of the liquidity measures, *L*, of each stock, *i*, on: the variation in the period-average daily trading volume (the sum of trading volume in Euro in a day), *VLM*, the variation in the period-average daily volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, and the variation in the period-average daily transaction price (the average transaction price in a day), *P*. The regression involves 55 observations. We report a *t*-test based on heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance matrix).

Panel B reports the results of specification (11) in section 3.2:

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it}$$

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intra-day data) on dummy variables for the days in *POST* (Day^k is equal to one for day *k* after the MTU reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,200 observations. We present a signed rank Wilcoxon test for the null hypothesis that the median of the 20 Day^k dummy variables is equal to zero.

		Panel A		**Panel B**	
		Intercept	*T-test*	*Median (Day)*	*Wilcoxon-z*
5,000€/Midquote	*Buy order on Midquote*	-0.0009	-2.5771**	-0.0008	-2.3520**
5,000€/Midquote	*Sell order on Midquote*	-0.0011	-2.3644**	-0.0008	-2.4640**
5,000€/Midquote	*Buy order on Midquote (%)*	-0.0002	-4.5237***	-0.0001	-3.5839***
5,000€/Midquote	*Sell order on Midquote (%)*	-0.0002	-4.4590***	-0.0002	-3.7333***
10,000€/Midquote	*Buy order on Midquote*	-0.0011	-2.1165**	-0.0010	-2.3146**
10,000€/Midquote	*Sell order on Midquote*	-0.0017	-2.9369***	-0.0012	-2.4266**
10,000€/Midquote	*Buy order on Midquote (%)*	-0.0002	-4.2969***	-0.0002	-3.6213***
10,000€/Midquote	*Sell order on Midquote (%)*	-0.0003	-4.7103***	-0.0003	-3.7333***
20,000€/Midquote	*Buy order on Midquote*	-0.0029	-4.1250***	-0.0020	-2.6880***
20,000€/Midquote	*Sell order on Midquote*	-0.0026	-3.3658***	-0.0023	-2.2773**
20,000€/Midquote	*Buy order on Midquote (%)*	-0.0004	-4.8285***	-0.0003	-3.6586***
20,000€/Midquote	*Sell order on Midquote (%)*	-0.0004	-5.1753***	-0.0004	-3.7706***
30,000€/Midquote	*Buy order on Midquote*	-0.0043	-4.7828***	-0.0023	-3.0239***
30,000€/Midquote	*Sell order on Midquote*	-0.0025	-2.1503**	-0.0018	-1.7173*
30,000€/Midquote	*Buy order on Midquote (%)*	-0.0005	-5.2028***	-0.0004	-3.5466***
30,000€/Midquote	*Sell order on Midquote (%)*	-0.0005	-4.9367***	-0.0005	-3.8453***

Table 12: Bid-ask spread – robustness checks

The table presents the results of robustness checks of the multivariate liquidity analysis. Panel A reports the results from the following simultaneous equation model (specification (12) in section 3.2):

$$\begin{cases} \Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta AC_i + \varepsilon_i \\ \Delta VLM_i = \chi_0 + \gamma_1 \Delta L_i + \gamma_2 \Delta VLT_i + \gamma_3 \Delta P_i + \gamma_4 \Delta SVOL_i + u_i \end{cases}$$

The model is estimated using three-stage least squares. The variation in the period-average daily liquidity measures, *L*, for each stock, *i*, is related to the variation in the period-average level of: daily trading volume (the sum of trading volume in Euro in a day), *VLM*, daily price volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, daily transaction price (i.e. the average transaction price in a day), *P*, the systematic component of volume, *SVOL*, and the adverse selection cost component of the bid-ask spread following the Glosten and Harrris (1988) model, *AC*. The total number of of observations is 55.

Panel B reports the results of the following cross-sectional average model (specification (13) in section 3.2)). We use one observation for each day, *t*, resulting in a total of 40 observations:

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t$$

		Panel A		**Panel B**	
		Intercept	*T-test*	*Post*	*t-test*
Level 1	*Quoted spread*	-0.0027	-3.3553***	-0.0018	-3.1941***
Level 1	*% Spread*	-0.0003	-4.1058***	-0.0002	-4.7873***
Level 2	*% Spread*	-0.0004	-2.9754***	-0.0003	-3.2128***
Level 3	*% Spread*	-0.0005	-2.5748**	-0.0003	-2.5851**
Level 4	*% Spread*	-0.0006	-2.4758**	-0.0003	-2.2964***
Level 5	*% Spread*	-0.0007	-2.3666**	-0.0004	-1.9416*

Table 13: Market depth – robustness checks

The table presents the results of robustness checks of the multivariate liquidity analysis. Panel A reports the results from the following simultaneous equation model (specification (12) in section 3.2):

$$\begin{cases} \Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta FC_i + \varepsilon_i \\ \Delta VLM_i = \chi_0 + \gamma_1 \Delta L_i + \gamma_2 \Delta VLT_i + \gamma_3 \Delta P_i + \gamma_4 \Delta SVOL_i + u_i \end{cases}$$

The model is estimated using three-stage least squares. The variation in the period-average daily liquidity measures, *L*, for each stock, *i*, is related to the variation in the period-average level of: daily trading volume (the sum of trading volume in Euro in a day), *VLM*, daily price volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, daily transaction price (i.e. the average transaction price in a day), *P*, the systematic component of volume, *SVOL*, and the fixed cost component of the bid-ask spread following the Glosten and Harrris (1988) model, *FC*. The total number of observations is 55.

Panel B reports the results of the following cross-sectional average model (specification (13) in section 3.2)). We use one observation for each day, *t*, resulting in a total of 40 observations:

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t$$

		Panel A		**Panel B**	
		Intercept	*T-test*	*Post*	*t-test*
Level 1	*# of shares at Bid*	13,451	2.9679***	7,298	6.4184***
Level 1	*# of shares at Ask*	11,789	3.0326***	6,616	5.9620***
Level 1	*Total # of shares*	25,240	3.0399***	13,915	7.3217***
Level 2	*# of shares at Bid*	18,687	3.0543***	9,603	5.4363***
Level 2	*# of shares at Ask*	17,848	3.6010***	10,262	4.8272***
Level 2	*Total # of shares*	36,535	3.3599***	19,865	6.5195***
Level 3	*# of shares at Bid*	17,841	3.0324***	8,824	5.3463***
Level 3	*# of shares at Ask*	16,765	3.8378***	8,988	4.1234***
Level 3	*Total # of shares*	34,607	3.4747***	17,812	6.4816***
Level 4	*# of shares at Bid*	14,499	3.5300***	5,887	3.8593***
Level 4	*# of shares at Ask*	15,798	3.6977***	8,844	4.1973***
Level 4	*Total # of shares*	30,296	3.6961***	14,731	5.8339***
Level 5	*# of shares at Bid*	13,750	3.5164***	5,580	3.7672***
Level 5	*# of shares at Ask*	13,664	3.4732***	8,343	3.8137***
Level 5	*Total # of shares*	27,415	3.6348***	13,923	5.4019***
Level 1	*Euro value at Bid*	37,211	2.6349**	23,659	4.2777***
Level 1	*Euro value at Ask*	34,432	2.3768**	22,651	4.1241***
Level 1	*Total Euro value*	71,643	2.5490**	46,309	4.7205***
Level 2	*Euro value at Bid*	52,329	2.9896***	26,016	2.9459***
Level 2	*Euro value at Ask*	56,810	3.0487***	33,106	3.5640***
Level 2	*Total Euro value*	109,139	3.1172***	59,122	3.8229***
Level 3	*Euro value at Bid*	52,746	3.4114***	23,161	2.8989***
Level 3	*Euro value at Ask*	55,108	3.4808***	29,886	3.0772***
Level 3	*Total Euro value*	107,854	3.6921***	53,047	3.7377***
Level 4	*Euro value at Bid*	48,473	3.7539***	14,494	1.9078*
Level 4	*Euro value at Ask*	54,061	3.5269***	29,391	3.1549***
Level 4	*Total Euro value*	102,534	3.8830***	43,885	3.2881***
Level 5	*Euro value at Bid*	46,162	3.6294***	9,681	1.4071
Level 5	*Euro value at Ask*	46,461	3.2468***	26,119	2.7496***

Level 5	*Total Euro value*	92,623	3.8140***	35,800	2.8288***
Cumulative (1-5)	# of shares at Bid	78,228	3.2435***	37,192	5.2793***
Cumulative (1-5)	# of shares at Ask	75,864	3.6132***	43,054	4.6960***
Cumulative (1-5)	*Total # of shares*	154,092	3.4811***	80,246	6.6771***
Cumulative (1-5)	*Euro value at Bid*	236,922	3.3830***	97,011	2.7610***
Cumulative (1-5)	*Euro value at Ask*	246,871	3.2133***	141,153	3.4021***
Cumulative (1-5)	*Total Euro value*	483,793	3.4517***	238,164	3.7501***

Table 14: Price impact of orders – robustness checks

The table presents the results of robustness checks of the multivariate liquidity analysis. Panel A reports the results from the following simultaneous equation model (specification (12) in section 3.2):

$$\begin{cases} \Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta AC_i + \varepsilon_i \\ \Delta VLM_i = \chi_0 + \gamma_1 \Delta L_i + \gamma_2 \Delta VLT_i + \gamma_3 \Delta P_i + \gamma_4 \Delta SVOL_i + u_i \end{cases}$$

The model is estimated using three-stage least squares. The variation in the period-average daily liquidity measures, *L*, for each stock, *i*, is related to the variation in the period-average level of: daily trading volume (the sum of trading volume in Euro in a day), *VLM*, daily price volatility (measured by the price range, i.e. the difference between the highest and the lowest transaction price in a day), *VLT*, daily transaction price (i.e. the average transaction price in a day), *P*, the systematic component of volume, *SVOL*, and the adverse selection cost component of the bid-ask spread following the Glosten and Harrris (1988) model, *AC*. The total number of observations is 55.

Panel B reports the results of the following cross-sectional average model (specification (13) in section 3.2)). We use one observation for each day, *t*, resulting in a total of 40 observations:

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t$$

		Panel A		**Panel B**	
		Intercept	*T-test*	*Post*	*T-test*
5,000€/Midquote	*Buy order on Midquote*	-0.0012	-2.4595**	-0.0008	-1.8901*
5,000€/Midquote	*Sell order on Midquote*	-0.0015	-2.8495***	-0.0004	-0.8267
5,000€/Midquote	*Buy order on Midquote (%)*	-0.0002	-3.1197***	-0.0001	-3.3043***
5,000€/Midquote	*Sell order on Midquote (%)*	-0.0002	-3.6530***	-0.0001	-2.4911**
10,000€/Midquote	*Buy order on Midquote*	-0.0018	-2.1841**	-0.0011	-2.0343**
10,000€/Midquote	*Sell order on Midquote*	-0.0022	-3.1558***	-0.0007	-0.8929
10,000€/Midquote	*Buy order on Midquote (%)*	-0.0003	-2.9433***	-0.0002	-3.4461***
10,000€/Midquote	*Sell order on Midquote (%)*	-0.0003	-3.7329***	-0.0002	-2.5608**
20,000€/Midquote	*Buy order on Midquote*	-0.0035	-2.7561***	-0.0022	-2.6874**
20,000€/Midquote	*Sell order on Midquote*	-0.0033	-4.0864***	-0.0008	-0.6089
20,000€/Midquote	*Buy order on Midquote (%)*	-0.0005	-3.1403***	-0.0003	-3.8187***
20,000€/Midquote	*Sell order on Midquote (%)*	-0.0005	-4.2483***	-0.0002	-2.5724**
30,000€/Midquote	*Buy order on Midquote*	-0.0047	-3.1367***	-0.0029	-2.9154***
30,000€/Midquote	*Sell order on Midquote*	-0.0036	-4.5199***	-0.0005	-0.3480
30,000€/Midquote	*Buy order on Midquote (%)*	-0.0006	-3.2903**	-0.0004	-4.1220***
30,000€/Midquote	*Sell order on Midquote (%)*	-0.0007	-4.3912***	-0.0003	-2.7515***

Table 15: Adverse selection costs and informativeness of trades

This table summarizes the cross-sectional averages of the measures of adverse selection costs and informativeness of trades. Both models are estimated, for each stock separately, using all the observations in the *PRE* or in the *POST* periods (this results is one observation regarding ψ, λ, *SD(w), VAR(w,x)*, *R^2(w)* for each stock in both periods). Panel A reports the results of the estimation of the Foster and Viswanathan (1993) model, as described in section 3.2. Panel B reports the results of the estimation of trade informativeness, following Hasbrouck (1991b), as described in section 3.3; *SD(w)* refers to the standard deviation of the efficient price innovation, *w*.

Panel A

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
ψ	-0.0022	-0.0020	0.0002	5.5130***
λ * 10,000	0.0022	0.0012	-0.0010	-2.2450**

Panel B

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
SD(w)	0.0006	0.0005	-0.0001	-5.9907***
VAR(w,x) * 10,000	0.0017	0.0012	-0.0006	-5.9111***
R^2(w)	0.3980	0.3781	-0.0199	-2.0109**

Table 16: Control for a trend in liquidity

Panel A presents the results of the analysis used to control for a secular trend in the Italian market. It compares the cross-sectional average of the daily (obtained as the daily average of intra-day observations) bid-ask spread at the first level of the book in the *PRE* period and in the 20-day period before. Specifically, individual stocks averages by periods are averaged across all the stocks. The *PRE1* period goes from November 12 to December 7, 2001. The % Spread is computed as the difference between the ask and the bid as a percentage of the midquote. We also consider a measure of the quoted bid-ask spread in level (denoted as Quoted spread – which is not standardized on the corresponding midquote).

Panel B reports the results of the regression used to control for a global liquidity trend, as described in section 3.2:

$$\Delta S_{BIT,t} = \alpha + \beta_1 \Delta S_{G,t} + \beta_2 \Delta S_{G,t-1} + \beta_3 \Delta S_{G,t+1} + \delta_1 RET_{G,t} + \delta_2 RET_{G,t-1} + \delta_3 RET_{G,t+1} + \delta_4 \Delta VLT_{BIT,t} + \varepsilon_t$$

where *S* is the % Spread; *RET* is the daily return; *VLT* is the difference between the highest and the lowest transaction price; Δ refers to the percentage variation from day *t*-1 to day *t*; the subscript *BIT* refers to the Italian sample (i.e. S_{BIT} and VLT_{BIT} are the equal-weighted average across the 55 firms in the Italian sample of the spread and of volatility, respectively); the subscript *G* refers to a global sample of 29 countries (i.e. S_G and RET_G are the equal-weighted average across all the firms in the global sample of the spread and of daily return, respectively). The model is estimated using the 41 days including the *PRE* period, the event day and the *POST* period.

Panel A

	Pre1	*Pre*	*Pre-Pre1*	*Wilcoxon-z*
% Spread	0.002431	0.002437	0.000006	-0.2850
Quoted spread	0.020560	0.020249	-0.000310	-1.2150

Panel B

	Coeff.	*T-test*
Intercept	0.0002	0.0200
$\Delta S_{G,t}$	0.0444	0.1400
$\Delta S_{G,t-1}$	-0.1302	-0.4000
$\Delta S_{G,t+1}$	0.3448	1.0400
$\Delta R_{G,t}$	-0.0420	-1.6100
$\Delta R_{G,t-1}$	-0.0001	0.0000
$\Delta R_{G,t+1}$	0.0357	1.6900
$\Delta VLT_{BIT,t}$	0.0667	1.1800
R^2	0.2102	
N	40	

Table 17: Informational efficiency

The table compares the cross-sectional averages of the informational efficiency measures before and after the reduction of the MTU. We measure informational efficiency by: the absolute value of daily first order return autocorrelation at different lags; the absolute value of daily variance ratio (*VR*) deviations from 1 at different lags (as described in section 3.3); the pricing error standardized by the standard deviation of the logarithm of price, *SD(s)/SD(ln_p),* (following Hasbrouck, 1993, as described in section 3.3). To obtain the reported autocorrelation and variance ratios, individual stocks averages by periods are averaged across all the stocks. The pricing error variance is computed, for each stock separately, using all the days in the *PRE* or *POST* periods (this results in one observation regarding *SD(s)/SD(ln_p)* for each stock in both periods).

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
|*Return Autocorrelation (5 min.)*|	0.1294	0.1344	0.0050	1.2652
|*Return Autocorrelation (10 min.)*|	0.1498	0.1587	0.0089	1.5081
|*Return Autocorrelation (15 min.)*|	0.1809	0.1851	0.0042	1.0389
|*Return Autocorrelation (20 min.)*|	0.2000	0.2018	0.0019	0.0503
|*Return Autocorrelation (30 min.)*|	0.2451	0.2413	-0.0038	-0.5446
|*VR(30 min.,10 min.)-1*|	0.3301	0.3260	-0.0040	-0.5697
|*VR(30 min.,15 min.)-1*|	0.2787	0.2797	0.0010	0.0168
|*VR(20 min.,10 min.)-1*|	0.2331	0.2268	-0.0063	-1.0725
SD(s)/SD(ln_p)	0.1566	0.1489	-0.0077	-0.6954

Diagram 1

This diagram shows the probability of the trading process under NC (pooling equilibrium), MQS and MQTS. α is the probability a trader is informed, $(1-\alpha)$ the probability he is uninformed; β is the probability an uninformed trader trades large, $(1-\beta)$ the probability he trades small; μ and $(1+\mu)$ are the probabilities that informed traders submits small or large orders respectively. With separating equilibrium, the informed only trade large and $\mu = 1$.

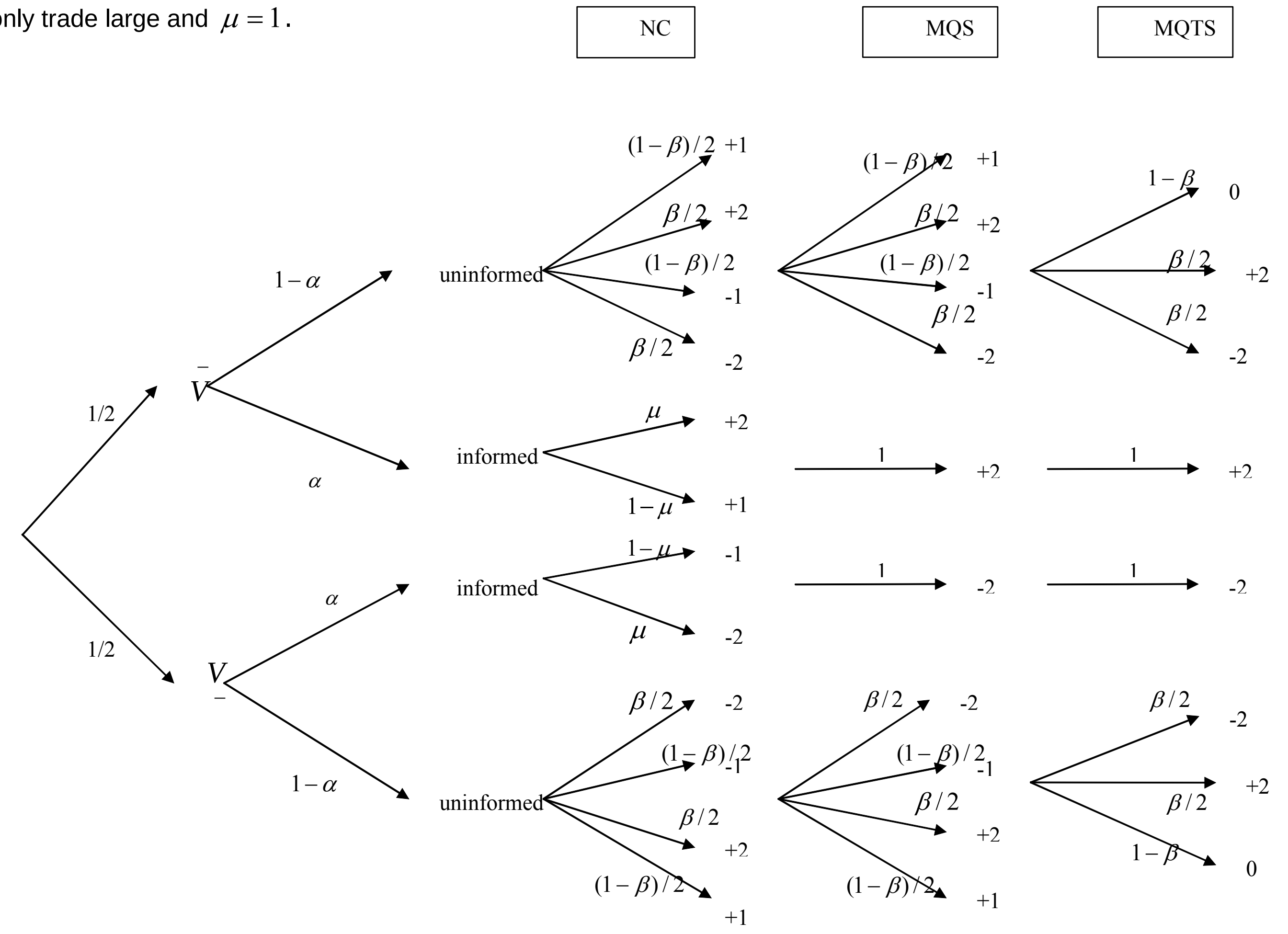

Figure 1: Pooling equilibrium

The vertical axis shows the equilibrium ask prices when the condition for insiders playing mixed strategies is satisfied. With $\beta = 1/2$, α on the horizontal axis goes from 0.33 to 1. From below A_1, A_Q, A_2 and A_{QT} are plotted over α.

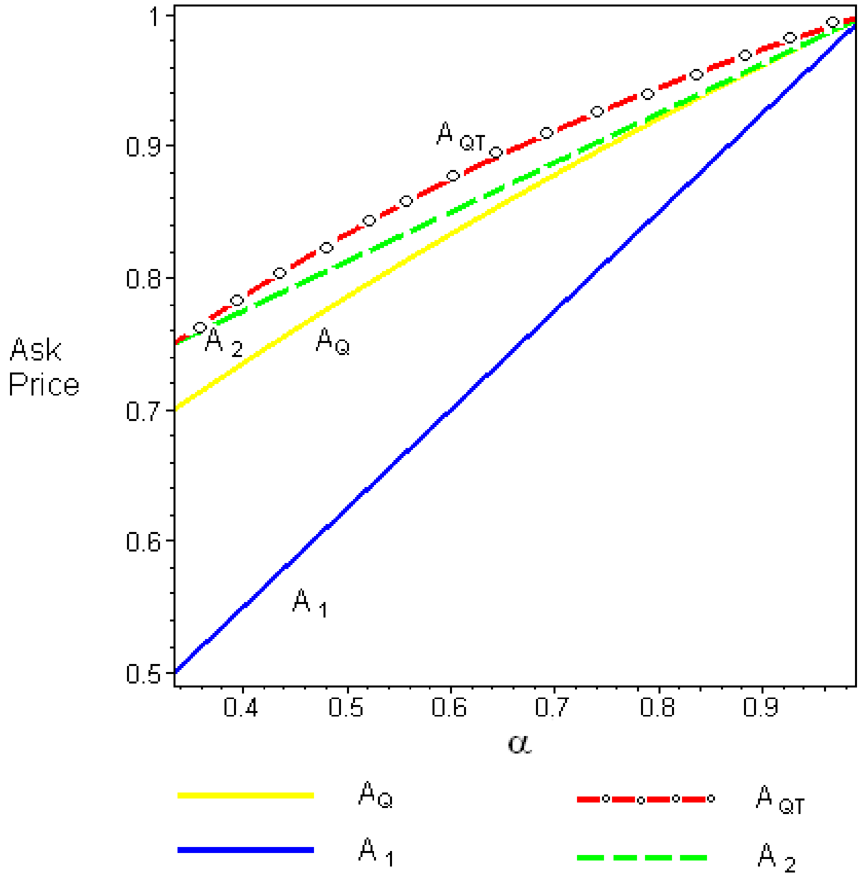

Figure 2: Semi-separating equilibrium
The vertical axis shows the equilibrium ask prices when the condition for insiders playing pure strategies is satisfied, i.e. when $\beta \geq \frac{\alpha}{1-\alpha}$. For simplicity sake let's assume that $\beta = 1/2$, which implies that $\alpha \leq 0.33$; this explains why α goes from 0 to 0.33 on the horizontal axis. Working up from the bottom, one can observe A_1; A_Q and A_2; the last being equal to A_{QT} when insiders buy only large quantities.

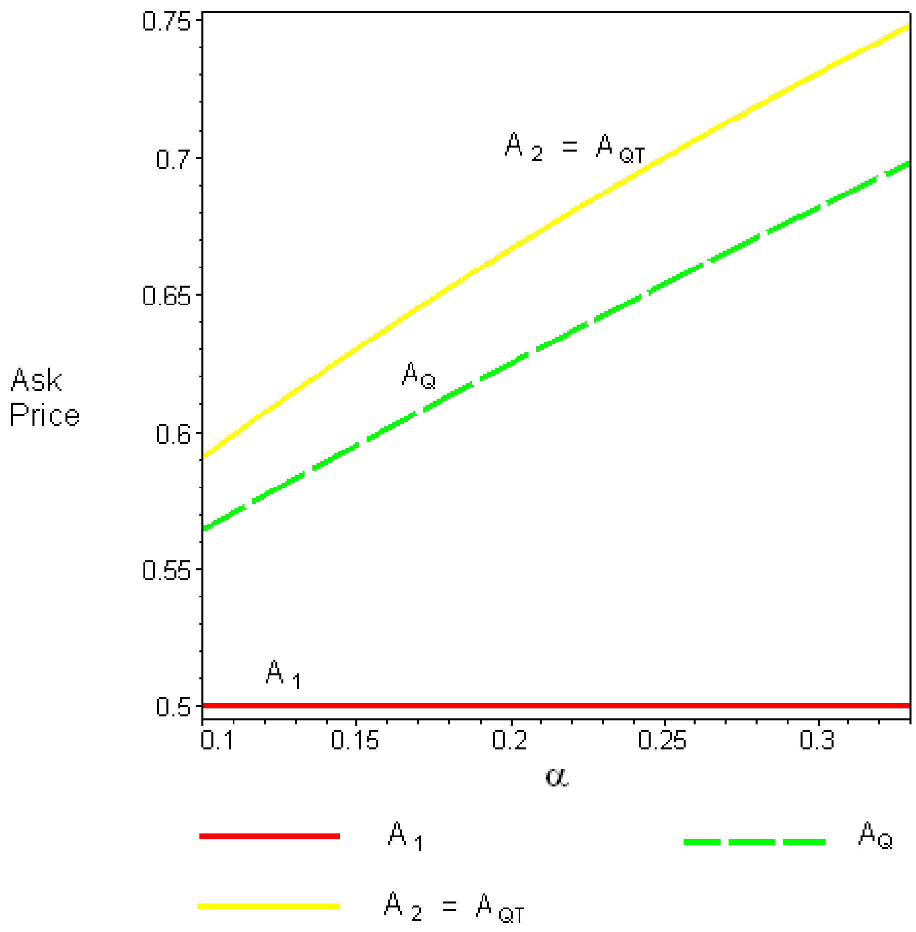

Figure 3: Price pattern around the MTU reduction
The figure reports the value of indexes (MIB30 and MIDEX) to which the stocks in the sample belong from 20 days before to 20 days after the reduction of the MTU.

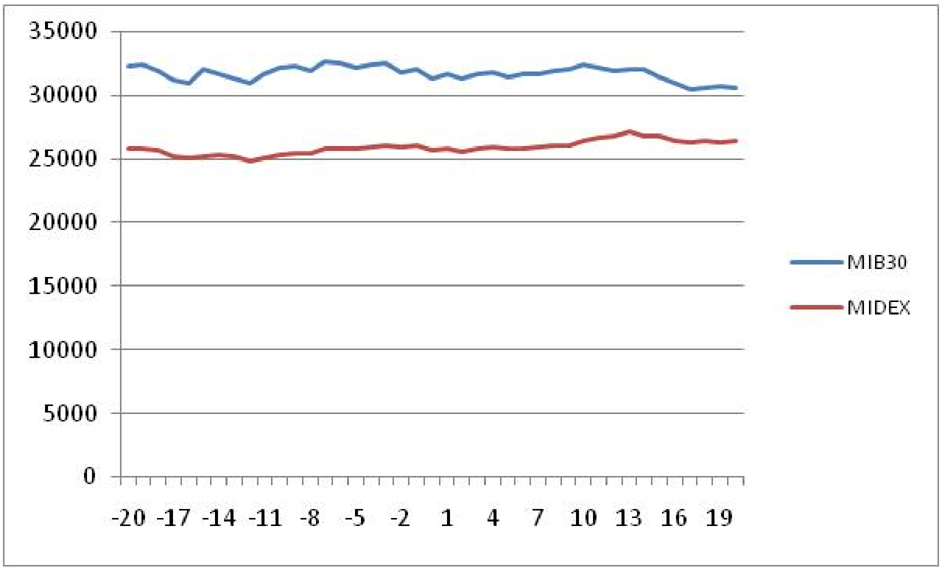

Figure 4:
This figure graphically represents the example described in section 3.2 (*adverse selection costs*). A_t(# of shares), B_t(# of shares) and M_t refer to the best ask, the best bid and the midquote at time *t*. The figure shows the evolution of the transaction price (dashed arrows) and of the midquote (solid arrows) when three unitary market buy orders (MO_1B) followed by a limit buy order (LO_1B) are submitted.