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Removing the Trade Size Constraint? Evidence from the Italian Market Design

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Abstract

Trading venues often impose a minimum trade unit constraint (MTUC) to facilitate order execution. This paper examines the effects of a natural experiment at Borsa Italiana where the exchange reduced the MTUC to one share for all stocks. After the removal of the MTUC, we observe a substantial improvement in liquidity, measured by a decrease in the bid-ask spread and an increase in market depth. The cross-sectional evidence shows that those firms for which the MTUC was more binding benefit the most from the microstructure change. These findings are consistent with a model of asymmetric information in which the MTUC affects traders' choice of order size. As the model predicts, liquidity improves following the reduction in adverse selection costs.

KEYWORDS: minimum trade unit constraint, limit order book, market liquidity, adverse selection costs

1. Introduction

The optimal choice of the minimum trade unit constraint (MTUC) is an important issue in market design as it significantly affects the trading strategies of market participants. Exchanges and trading platforms aim at standardizing trading lots so that the MTUC is set at a size which is both homogenous across stocks with different prices and consistent with traders' needs.[1]

As it has been recently documented (e.g., SEC release 34-61358, 2010, O'Hara, Yao and Ye, 2012, Angel, Harris and Spatt, 2013), the reduction of the average trade size is becoming increasingly relevant. It is therefore important to understand how the MTUC design may affect market quality, and in particular liquidity. To our knowledge, no theoretical literature and scant empirical evidence have so far been provided on the effects of an exogenous MTUC change on market quality. In this paper we examine these effects by taking advantage of a unique natural experiment at Borsa Italiana (BIt), where, in 2002, the MTUC was reduced to one share by the exchange, hence it was removed.

Relying on intra-day data - notably, at five book levels - we document a marked liquidity improvement, measured by both a decrease in the bid-ask spread and an increase in market depth. In particular, we show that the percentage spread on the first level of the book decreases on average by 10.2%. The results hold using a variety of models which control for the cross-sectional determinants of liquidity. Using a large panel of 15 countries and a matched sample analysis (Davies and Kim, 2009), we show that our findings are not attributable to changes in global liquidity.

Moreover, our results show that the MTUC removal mostly affects those firms which had a more binding MTUC before its change in 2002. Specifically, we rank firms into three terciles based on the extent to which the MTUC was binding. We find that firms in the top tercile - with the most binding MTUC hurdle - experience, on average, a 14.4% decrease in the percentage spread. Firms

[1] Examples of markets where a MTUC is imposed are the NASDAQ, the Toronto, Tokyo, Hong Kong and Tel Aviv stock exchanges. At the NYSE, while the round-lot for stocks is 100 shares, trading at a smaller size (odd-lots) is allowed, but it is subject to different reporting rules. Conversely, most European markets (for example Euronext, Xetra, and the Scandinavian and Baltic exchanges that use the OMX platform) have reduced the MTUC to one share.

belonging to the first tercile experience a much smaller reduction, 7.9%, in the percentage spread.[2] These results indicate a substantial reduction in trading costs. More precisely, we find that one standard deviation increase in the hurdle reduces the percentage spread by 4% (which corresponds to a 0.38 standard deviation decrease in the percentage spread change).

We interpret our results within the framework of a model with liquidity providers operating under asymmetric information, and in which traders can submit orders of different sizes. The model allows us to compare two regimes with and without a MTUC. When the MTUC is removed, those small liquidity traders that could not hedge their endowment shock in the former regime, can now perfectly hedge it and enter the market. The increased trading by these uninformed agents decreases adverse selection costs and induces liquidity providers to post smaller spreads. Accordingly, after the MTUC removal, we observe a decrease in adverse selection costs, measured by both the price impact of orders at different trade sizes, and model-based estimates (Glosten and Harris, 1988; Foster and Viswanathan, 1993). The predictions of the model regarding informational efficiency, though, depend crucially on the proportion of retail vs. institutional traders. Further analyses using random walk tests and the standard Hasbrouck (1993) model suggest that informational efficiency is not substantially affected by the MTUC removal.[3]

Two previous papers are closely related to our analysis. Amihud, Mendelson and Uno (1999) find that the voluntary reduction in the MTUC at the Tokyo Stock Exchange is associated with an increase in trading volume and in liquidity, measured, using daily data, by the Amihud's illiquidity ratio. At the Tokyo Stock Exchange, however, any MTUC change is deliberated by listed firms that can use it as a signalling device. Our paper differs from Amihud, Mendelson and Uno (1999) because the MTUC removal is imposed by BIt and hence it cannot be interpreted as a signalling mechanism. Hauser and Lauterbach (2003) look at an exogenous MTUC reduction at the Tel Aviv Stock

[2] The results are similar if we group the firms into two groups or quintiles.
[3] Although we do not have information on the exact proportion of retail traders, according to proprietary data provided by BIt, the proportion of online trading increased by approximately 16% in a period of one month around the MTUC change. This is in line with the model predictions of increased retail trading after the MTUC change.

Exchange, but concentrate on the effects on the stock value and do not examine market liquidity; furthermore, they only use daily data. We differ from Hauser and Lauterbach (2003) as we study the market quality rather than the valuation consequences of the MTUC removal. This paper is also related to the literature on stock splitting; splitting is in some aspects analogous to a reduction of the MTUC, as a split implies that the minimum transaction size decreases. See, for instance, Conroy, Harris and Benet, 1990, Copeland, 1979, Michayluk and Kofman, 2001, Easley, O´Hara and Saar, 2001, Kunz and Majhensek, 2004. Most of these works find a decrease in liquidity, measured by an increase in the bid-ask spread after the stock splits.[4] Our analysis differs from these studies in which stock splitting is voluntary and can be used as a signaling device to convey information to market participants. This may influence both valuation and liquidity, as argued by McNichols and Dravid, 1990; Brennan and Hughes, 1991, Prabhala, 1997, Nayak and Prabhala, 2001, Kadiyala and Vetsuuypens, 2002. We checked that there were no stock splits in the period under analysis.

The plan of the paper is as follows: section 2 presents a theoretical benchmark to assess the effect of varying transaction size design on market quality; section 3 examines the effect of the MTUC removal on BIt, and section 4 concludes.

2. Theoretical benchmark

To our knowledge there exists no theory that offers predictions on the design of the minimum trade size. Today, most financial trading platforms work like a limit order book (LOB), in which the provision of liquidity is endogenous as it is generated by the limit orders posted by market participants. The existing theoretical frameworks for LOBs, however, either do not embed asymmetric information (e.g., Foucalt, Kadan and Kandel, 2005 and Parlour, 1998), or are not

[4] It has also repeatedly been found that stock splits are followed by 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).

adequate to include the traders' choice between orders of different size (Rosu, 2009 and Pagnotta, 2010). For this reason, we derive our empirical implications by extending the standard adverse selection model of Glosten and Milgrom (1985) and Easley and O´Hara (1987).[5]

In our 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 the complementary probability, $1-\alpha$. The insider is risk-neutral and trades in order to exploit his private information, whereas liquidity traders trade in order to share risk.[6] To investigate the effects of different transaction size regimes, we assume that 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:

$$q = \frac{\mathrm{E}(\tilde{\mathrm{v}}) - \mathrm{p}}{\gamma \mathrm{VAR}(\tilde{\mathrm{v}})} - I \qquad (1)$$

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

[5] In essence, the Glosten and Milgrom (1985) framework can be viewed as a LOB model in which a continuum of liquidity providers offers liquidity at some levels of the book. Admittedly, in this model, the book can never be empty, but there are no reasons to believe that the reactions of liquidity providers in a model of LOB - that could also be empty - would differ from those described by the Glosten and Milgrom (1985) protocol. If the removal of the MTUC - in a hypothetical LOB model with asymmetric information and different order sizes - allowed uninformed investors to quote and execute orders for a smaller size, the existing liquidity providers would perceive less adverse selection costs and they would consequently drive competition for the provision of liquidity towards more aggressive spreads. Hence, what is crucial for the model predictions is not the perfect adherence of the protocol to the real working of a LOB, but rather the conjecture that retail traders are induced to enter the market when they are allowed to trade smaller sizes.

[6] For a textbook discussion of this model, see de Jong and Rindi (2009).

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 investors. We assume that competition brings dealers' quotes to the zero-profit level.

In this framework we analyze two different 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 regime with a minimum quote and transaction size (MQTS) of 2 shares, under which market makers cannot quote prices for a quantity smaller than the MQTS, and at the same time market participants cannot execute orders for a size smaller than the MQTS. This is the regime prevailing before the MTUC was eliminated in the Italian exchange: in the empirical analysis we compare this regime to the setting without a constraint. [7]

When there is no constraint, the model resembles Easley and O´Hara (1987). A priori, informed agents would like to submit large orders to exploit their information, but these large orders might themselves affect the price because 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 there is a relatively high proportion of large uninformed traders in the market who produce 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 choose 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, respectively:

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

$$A_1 = \frac{1}{2} \qquad \text{and} \qquad A_2 = \frac{\frac{1}{2}(1-\alpha)\beta + \alpha}{(1-\alpha)\beta + \alpha} \qquad \text{(2 and 3)}$$

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. As shown in the Appendix, in this context of pooling equilibrium the ask prices for one or two shares are:

$$A_1 = \frac{1}{2}[(1-\beta) + \alpha(1+\beta)] \qquad \text{and} \qquad A_2 = \frac{1}{4}[(3-\beta) + \alpha(1+\beta)] \qquad \text{(4 and 5)}$$

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 and hence the higher the spread associated with these trades.[8]

Now, let's consider the MQTS regime. 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. In this regime the ask price, A_{QT}, is equal to the one prevailing under the regime with no constraint and semi-separating equilibrium (equation 3). Under MQTS, insiders are only allowed to trade large quantities and hence the ask price, A_{QT} ,is the highest possible one because it reflects all the adverse selection costs.

Comparing the ask prices obtained above, we now get:

$$B_{QT} \leq B_2 < B_1 \leq A_1 < A_2 \leq A_{QT} \qquad (6)$$

[8] This framework 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).

with the equality holding when insiders play pure strategies. Figures 1 and 2 show the respective ask prices for the equilibria with pooling and separation of agent types.

Insert Figure 1 here

Insert Figure 2 here

2.1. Empirical implications on market quality

Building on the model's results we can derive testable empirical predictions (see the Appendix for a formal derivation) for the effect of the natural experiment of BIt, which in 2002 removed the MQTS (from now on MTUC) constraint for all the stocks. This microstructure change is equivalent to switching from the MQTS regime to the NC regime.

Prediction 1*: Liquidity increases after the removal of the MTUC.*

Moving from the MTUC to the NC regime the inside spread decreases because now quotes for smaller orders, which bear lower adverse selection costs, are posted to the book. This is true for both a semi-separating and a pooling equilibrium.

A direct implication of Prediction 1 is that *those firms for which the MTUC was more binding before, enjoy a larger increase in liquidity after the MTUC removal.*

Prediction 2*: Adverse selection costs decrease after the MTUC removal.*

The inside spread is due to adverse selection costs and it is the highest under the MTUC regime (see also Figures 1 and 2). Hence, we expect adverse selection costs to decrease after the MTUC removal.

A direct implication of Prediction 2 is that *those firms for which the MTUC was more binding before, enjoy a larger decrease in adverse selection costs after the MTUC removal.*

Prediction 3*: The variation in informational efficiency after the MTUC removal depends on both the proportion of insiders relative to uninformed traders, and the proportion of retail traders relative to institutional traders.*

The degree of informational efficiency changes along two parameters of the model, namely it depends on α, i.e., the probability of informed trading which affects the insiders' order submission strategy, and β, i.e., the probability of large institutional trading (see Figure 3). Figure 3 shows that after the MTUC change, informational efficiency decreases only for low values of β, along different values of α; whereas for high values of β the effect on informational efficiency depends on the equilibrium strategies of the insiders. Because we do not have direct estimates on the parameter values for our sample of stocks, it is an empirical issue whether we see any discernible variation in informational efficiency after the microstructure change.

Insert Figure 3 here

3. Empirical analysis

The empirical analysis investigates the effects of the MTUC removal on the quality of the limit order book for a sample of stocks listed on BIt. In the Italian exchange the MTUC indicates the minimum number of shares that can be executed in one trade; furthermore, the number of shares in one trade must be equal to a multiple of the MTUC. On January 14, 2002 the MTUC was reduced to one unit by the exchange for all stocks. The intention of the exchange official was to standardize trading lots of different sizes.[9] The previous policy of BIt was to revise the MTUC periodically to make exchange operations and order executions easier.[10]

[9] The MTUC has always been expressed in number of shares.

[10] In our sample, the MTUC for each firm was only significantly positively correlated with the average trade size, and not with other firm characteristics such as market value, price, market to book ratio, leverage or total assets. To economize space we do not report these results, which are available from the authors upon request.

We consider the stocks belonging to the MIB30 and MIDEX indices. At the time of the MTUC removal the MIB30 index included the 30 most capitalized and liquid stocks in the exchange. The MIDEX index included the following 25 stocks. Table 1 describes the stocks considered.

Insert Table 1 here

We compare different measures of market quality in the 20-trading-day period before the removal of the MTUC (denoted by *Pre*) and in the 20-trading-day period after (denoted by *Post*). During our sample period, trading took place during the following phases: an opening call auction (from 8:00 to 9:30 a.m.), a continuous trading phase (from 9:30 a.m. to 5:25 p.m.), and a closing call auction (pre closing from 5:25 to 5:35 p.m., and validation from 5:35 to 5:40 p.m.). We consider data during the continuous trading phase (from 9:30 a.m. to 5:00 p.m.).

During the continuous trading phase the market was organized as a pure limit order book. If the price variation exceeded a given threshold, a stock could be suspended from the continuous auction and trading could resume in an intra-day call auction; we remove observations from the intra-day call auctions. We use an intra-day dataset which includes quotes on the first five levels of the order book and trades. The analysis covers 5,093,542 records for quotes and 4,598,780 records for trades.[11] We also adjust prices for corporate actions that took place in the sample period.

First, we concentrate on the bid-ask spread and base our analysis on a dataset including the first five levels of the order book; this allows us to examine transaction costs also for large trades that walk up the book. In the main analysis, we focus on time-weighted quoted and percentage bid-ask spreads both in a univariate and in a multivariate analysis, controlling for firm characteristics; in further tests, we investigate changes in market depth. We control for a possible global liquidity trend by using a matched-sample approach with a large international panel. Next, we investigate adverse selection costs both by measuring the price impact of different trade size, and in the context of

[11] Data are not available for two stock/days in our sample: Fiat (December 10, 2001) and San Paolo IMI (December 18, 2001). We also replicated the analysis without these two stocks and the results are qualitatively unchanged.

Glosten and Harris (1988) and Foster and Viswanathan (1993) models.[12] Furthermore, we relate the variation in spreads and adverse selection costs to the cross-sectional differences in the MTUC hurdle. The MTUC hurdle for each stock is measured as the ratio of the average number of trades at the MTUC over the average number of trades executed in the *Pre* period for that stock. Finally, we examine informational efficiency by both performing random walk tests, and estimating the Hasbrouck (1993) model.

3.1. A first glance at trading activity

Table 2 summarizes our measures of market activity.[13] First, we observe that the removal of the MTUC has an important effect on trading activity. We find that, on average across the stocks, 16.89% of trades are executed at a size lower than the MTUC in the *Post* period (1.78% of trades are instead executed at the new MTUC i.e., one unit). This suggests that the MTUC was binding for market participants willing to trade small amounts. These small trades are likely to originate from retail traders, who play a crucial role in the Italian equity market.[14]

We note that the MTUC varies substantially across firms.[15] This allows us to test the cross-sectional differences on how the MTUC removal affects market quality. In line with our conjecture, we document a greater reduction in spreads for firms which were subject to a higher MTUC hurdle.

Insert Table 2 here

[12] The price impact has been used to measure information asymmetries in the previous literature (Saar and Yu, 2002, Collin-Dufresne and Fos, 2013). However, we acknowledge the fact that it might also be related to other factors unrelated to private information. We address this concern by measuring adverse selection costs within two widely used models.

[13] 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.

[14] BIt estimates that at the end of 1999 retail investors held more than 26% of total market capitalization (BIt Notes, 2001a and BIt Notes, 2001b).

[15] This variable is negatively correlated with market value of the firm, total assets, net debt, and price volatility (price range), but not correlated with stock price, trade size, market to book ratio or leverage.

Our theoretical benchmark predicts that the removal of the MTUC leads to the entrance of more uninformed traders. This is consistent with the increase in the proportion of on-line trading observed after the MTUC removal. Specifically, BIt estimates an increase in the proportion of online trading of approximately 16% in a period of one month around the event.[16]

The interpretation of the results as a greater participation of traders is supported by the significant increase in the number of trades (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 trades (by 4.13%), in particular for those stocks with lower average trade size. This can be due to the greater participation of small traders, who place orders following the market trend. It can also be explained by the increase in the number of orders which walk up the book when the MTUC is removed. Finally, it can be due to large traders taking advantage of the possibility to split their orders. This third explanation, however, seems unlikely, as the average value of the MTUC before the removal (808 Euro, the greatest value being 2,177 Euro) was already far smaller than the typical value of institutional traders' orders, worth at least 10,000 Euro according to BIt monitoring department.

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. Following Andersen, Bollerslev, Diebold and Labys (2003) we compute the realized volatility as the standard deviation of the midquote under the hypothesis that prices follow a Brownian motion.[17] The reduction in price volatility can be interpreted as a signal of possible reduction in adverse selection costs.

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[16] BIt provided us with proprietary monthly data around the event indicating the proportion of on-line trading. We excluded January 2002 and compared one-month before and after the event, i.e., December 2001 vs. February 2002.

[17] 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

Finally, we find that the removal of the MTUC does not have a significant effect on the price of the stocks. We examine the cumulative abnormal returns (CARs) around the event.[18] CARs are defined as the sum of abnormal returns from 20 days before the event to 20 days after the event. Average CARs are equal to 0.13% and they are not significantly different from zero (Wilcoxon-z=0.075). To further inquire into the valuation effect of the MTUC removal, we regress CARs on the relative change in liquidity after the microstructure change (the results are untabulated). The coefficient of the relative change in liquidity is negative and highly significant for all the liquidity metrics except for the quoted spread. This is in line with the interpretation that the liquidity improvement has a positive effect on stock prices (e.g., Amihud and Mendelson, 1986; Brennan and Subrahmanyam, 1996; Amihud, 2002). Overall, the results suggest that the MTUC removal does not have, on average, a significant effect on prices; yet, the cross-sectional differences in the price variation are significantly associated with the cross-sectional differences in the liquidity variation.

3.2. Liquidity

Our main liquidity metrics are based on the bid-ask spread at the best five levels of the order book. We concentrate on the percentage spread, which is defined as the difference between the ask and the bid prices as a proportion of the midquote. We also compute the quoted bid-ask spread.

The analysis takes daily averages (obtained from intra-day data) of the liquidity metrics as input. The metrics are obtained from the snapshot of the limit order book; they are all weighted by the time span between each quote revision generated by any limit or market order posted at any of the five levels of the book.

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interval considered. Because the time between two subsequent observations is not constant, we weight each observation by the duration (in seconds) between subsequent quote updates.

[18] Specifically, abnormal returns are estimated as the residuals from the market model. We take the 100 days before the event as the estimation period. We use the FTSE MIB index to obtain the market return. We also regress CARs on the relative change in liquidity after the microstructure change. We estimate the following equation (where $\Delta_r L$ refers to the relative change in average liquidity, and i refers to the stock): $CAR_i=\beta_0+ \beta_1\Delta_r L_i+\varepsilon_i$. A similar approach is taken by Anand, Tanggard and Weaver (2009). These results are untabulated.

Table 3 presents descriptive statistics for our liquidity metrics. We compute a Wilcoxon signed rank test for the null hypothesis that the cross-sectional median variation after the removal of the MTUC is equal to zero. Liquidity for small trades is measured by the bid-ask spread; liquidity for orders that walk up the book is assessed by looking at the bid-ask spread at further levels of the book. Overall, the results from the univariate analysis clearly highlight an increase in liquidity for all trade sizes. Notably, the percentage spread on the first level of the book decreases on average by 10.2%, which indicates a substantial reduction in trading costs.

Insert Table 3 here

To make sure that the documented improvement in liquidity is not due to a secular trend in the Italian market, we also examine the 20-trading-day period (we denote this period as *Pre1*) before the *Pre* period. We then compare our measures of spread in the *Pre1* and *Pre* periods. The results are reported in Panel B of Table 3: the median difference in the spread measures is not significantly different from zero. This result suggests that the improvement in liquidity after the MTUC removal cannot be attributed to a secular local market trend.

MULTIVARIATE ANALYSIS

The results of the univariate analysis are in line with our theoretical prediction which suggests a reduction in spreads. However, there is evidence that changes in liquidity are affected by other stock-specific attributes, such as volume, volatility and price level. Following the design proposed by Boehmer, Saar and Yu (2005), we examine liquidity in a multivariate setting by adding stock-specific controls. In particular, the analysis of the liquidity change after the event is based on two econometric specifications:

a) We firstly consider the *Pre* to *Post* variation in the period-average (*Pre* or *Post*) daily level of the liquidity measures, L, of each stock, i, with daily averages obtained from intra-day observations. We regress this variable 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):

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i \qquad (7)$$

We focus on the intercept value to assess the effect of the MTUC removal on liquidity. The regression involves 55 observations (as the number of stocks considered).

The results are presented in Panel A of Table 4. The coefficient of the intercept is negative and significantly different from zero for all the liquidity measures. Thus, there is a strong indication of an increase in liquidity. The magnitude of the average liquidity improvement (indicated by the intercept) is comparable to the results of the univariate analysis.

Insert Table 4 here

b) Because the MTUC removal happens for all the stocks at the same time, the error terms in specification (7) 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 stability of the results by considering the following specification:

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it} \qquad (8)$$

We here regress daily (*t* refers to the day considered) 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 MTUC removal and zero otherwise), and on trading volume, price volatility and 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.[19] The regression involves 2,198 observations corresponding to 55 stocks over 40 days.

The estimation results of specification (8) are presented in Panel B of Table 4. The median of the dummy coefficients is negative and it is significantly different from zero for all the liquidity measures, confirming the results of specification (7).[20] Moreover, the magnitude of the median liquidity improvement (indicated by the median of the dummy coefficients) is again comparable to the univariate results.

CONTROL FOR A GLOBAL LIQUIDITY TREND

As the MTUC removal involves all the stocks listed on BIt, there is no direct control sample within the Italian market. Moreover, one can argue that the reduction in spreads may coincide with a global liquidity trend. To alleviate these concerns, we conduct a matching sample analysis following Davies and Kim (2009). In particular, using a large panel of 15 countries,[21] we match each Italian stock one-to-one with a stock from each country based on market capitalization and share price (end of November 2001) and construct a global spread measure as an equally weighted percentage spread of each matched stock from each individual country. Such a measure controls for the liquidity trend of similar stocks from various countries without being affected by market-specific trends. Specifically, for each Italian stock $i \in F_I$, we select stock $j \in F_c$, from each country c that solves

$$\arg\min_{j_c \in F_c} \sum_k ((2(x_i^k - x_{j_c}^k))/(x_i^k + x_{j_c}^k))^2$$

where x_i^k is the stock characteristic k, i.e., market capitalization and share price, for stock i and $x_{j_c}^k$ is the stock characteristic k for stock j in country c. Then, we construct the global liquidity measure as

[19] 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, Boehmer, Saar and Yu, 2005).

[20] We also estimated specification (8) including firm fixed effects. The results – untabulated – are virtually unchanged.

[21] The number of countries is limited by data availability, i.e., closing bid and ask prices, in Thomson Datastream. The sample includes Australia, Denmark, Finland, France, Germany, Greece, Hong Kong, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, UK and US. US closing prices are obtained from TAQ intraday data.

$$L_i^G = \frac{1}{15}\sum_{c=1}^{15} L_{j_c} \text{ , } \forall\, i \in F_I \tag{9}$$

where L_{j_c} is the liquidity measure, i.e., percentage spread based on daily closing ask and bid prices, for each stock *j* in country *c*.

Then we repeat the previous analysis in equation (7) and (8) using the closing percentage spreads and controlling for the global liquidity variable.

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta L_i^G + \varepsilon_i \tag{7'}$$

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \gamma_4 L_{it}^G + \varepsilon_{it} \tag{8'}$$

The results are reported in Table 5. We report the coefficients for both specifications with and without the global liquidity trend. Note that unlike equations (7) and (8), which include the time-weighted spreads on the left-hand side of the equation, equations (7') and (8') test the effect on the daily closing spreads.[22] Controlling for the global liquidity trend does not have a major impact on spreads as the coefficients and their significance remain virtually unchanged.

Insert Table 5 here

MTUC HURDLE AND LIQUIDITY IMPROVEMENT

Our time-series analysis focuses on the average changes in liquidity around the MTUC removal. An alternative way to overcome the lack of a control group within the Italian market is to look at the cross-sectional implications of the MTUC removal. In particular, we test whether firms for which the MTUC was more binding before the MTUC removal face larger differences in liquidity after the removal. We sort the firms by the MTUC hurdle (MTUCH henceforth) before the change. We measure the MTUCH by the ratio of the average number of trades at the MTUC over the average

[22] The results using the time-weighted spread are unchanged with respect to the main analysis.

number of trades executed in the *Pre* period.[23] One would expect that firms with a more binding constraint witness a higher reduction in spreads. In fact, in Figure 4, where we plot the *Post-Pre* difference in the percentage spread against the MTUCH, we note that the reduction is much larger as the MTUCH increases.

Insert Figure 4 here

Hence we group the firms into three terciles based on the MTUCH and compare the reduction in percentage spreads. Figure 5 shows that the firms in the first tercile, i.e., with the least binding MTUC, benefit from a reduction of 1.3 *bp* in spreads, while the spreads for firms in the third tercile, with most binding MTUC, reduce by 4.8 *bp*. The latter amounts to a 14.4% decrease in the percentage spread after the MTUC removal. The difference between Tercile 3 and Tercile 1 is highly significant, with a Wilxocon z-value equal to 3.78***. We obtain similar results when we extend the analysis using the percentage spread at different levels of the book.

Insert Figure 5 here

Next, we also test the role of the MTUC on the change in liquidity in a multivariate setting. Specifically, we control for the MTUCH in equation (7) and we include additional firm characteristics (end of November 2001): market to book (MB) ratio, leverage (debt/asset ratio) and dividend yield.

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTUCH_i + \beta_5 cnt_i + \varepsilon_i \qquad (7'')$$

We report the results in Table 6. Panel A shows the coefficient estimates of the intercept β_0 and β_4 on the MTUCH while restricting the vector β_5 = [0, 0, 0].[24] We measure the changes in liquidity by the percentage spread at different levels of the book. Because we now analyze the cross-sectional implications of the MTUC removal, we focus on the percentage spread, which is suitable for comparison across stocks. We observe that the improvement in liquidity is mainly explained by the

[23] We repeat the same analysis with the Euro-value of the trades and the results are very similar.
[24] For the interpretation of our results we only report the intercept and the coefficient on the MTUCH to save space.

cross-sectional differences in the MTUCH, as reflected in the high significance of the β_4 estimates. This result is in line with the evidence provided in Figure 5. In Panel B we control for additional firm characteristics, and the results are robust to these additional controls. The cross-sectional evidence confirms the main prediction of the model that the reduction in spreads is mainly due to the MTUC removal rather than other factors that might affect the results.

Insert Table 6 here

For robustness check, we also construct an alternative proxy for the MTUC hurdle. Specifically, we multiply the minimum trade units (shares) with the average stock price in the *Pre* period. We report this measure as MTUCV. We repeat the same cross-sectional analysis (Table 7) with the MTUCV and we find that the results confirm previous findings.

Insert Table 7 here

3.3. Liquidity: Further robustness analyses

In this section, we modify the model and test alternative specifications. Then, we consider market depth at different levels of the book as an alternative liquidity measure to the bid-ask spread.

ALTERNATIVE SPECIFICATIONS

We present two modifications of the model:

i) There might be an endogeneity problem in specifications (7) and (8) 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 (7): the adverse selection component of the bid-ask spread (obtained from the model of Glosten and Harris, 1988), *AC*, and the systematic component of volume, *SVOL*.[25] We then estimate the following model with three-stage least squares.[26] As in specification (7), there are 55 observations corresponding to the number of stocks:

$$\begin{cases} \Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta AC_i + \varepsilon_i \\ \Delta VLM_i = \chi_0 + \gamma_1 \Delta L_i + \gamma_2 \Delta VLT_i + \gamma_3 \Delta P_i + \gamma_4 \Delta SVOL_i + u_i \end{cases} \tag{10}$$

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 the variables and a dummy for the *Post* period. Here there are 40 observations corresponding to the number of days in the analysis:

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t \tag{11}$$

The results concerning the aforementioned alternative specifications are presented in Table 8. They are qualitatively analogous to the previous findings.

Insert Table 8 here

BOOK DEPTH AS ALTERNATIVE MEASURE OF LIQUIDITY

We repeat the previous analysis using the book depth measured as the number of shares offered (or the corresponding Euro value) at each of the first five levels of the book.[27] In addition, we compute cumulative depth as the sum of shares available at all these five book levels.

The univariate and multivariate results obtained using market depth are reported in Table 9 and Table 10, respectively. The findings show that market depth increases at all book levels.

[25] The estimation of the Glosten and Harris (1988) model is described in Section 3.4. The systematic component of volume is estimated as the predicted value from the market model using trading volume (in number of shares traded). We take the year before the event as the estimation period. We use the sum of volume of the stocks belonging to the COMIT Global index to obtain market volume. The systematic component of volume in *Pre* and *Post* is the average of the daily values in the two periods.

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

[27] We also examine market depth on the ask and on the bid side, separately. The results, untabulated, are very similar.

Therefore, the alternative measures further support the liquidity improvement documented by considering the bid-ask spread.

Taken together, these results confirm the first empirical prediction of our model, that liquidity increases after the removal of the MTUC.

Insert Tables 9 and 10 here

3.4. Adverse selection costs

According to the model's results, the significant improvement in liquidity observed after the removal of the MTUC is due to a reduction in adverse selection costs. Without a size constraint, small traders enter the market and the increased proportion of uninformed traders makes adverse selection costs smaller.

PRICE IMPACT

We first measure adverse selection costs by computing the price impact of orders 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 by the quantities corresponding to the different trades executed.[28] We also consider the price impact of orders as a proportion 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. We repeat the univariate and multivariate analysis in Section 3.2 and report results in Table 11 and Table 12, respectively. Firstly, note that in both specifications the price impact of orders of all different sizes decreases after the removal of the MTUC, suggesting a decrease in adverse selection costs. In

[28] 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*(17-14)]/300=2.333Euro.

Figure 6, we further plot, for the MTUCH terciles, the cross-sectional differences in the price impact of orders at different trade sizes. In line with the previous observation on bid-ask spreads, we show that the reduction in price impact after the MTUC removal is consistently and significantly higher for firms with a larger MTUCH.

Insert Tables 11, 12 and Figure 6 here

MODEL BASED ESTIMATION OF ADVERSE SELECTION

We now measure adverse selection costs parametrically relying on a microstructure model. We consider both Glosten and Harris (1988) and Foster and Viswanathan (1993) models to capture the adverse selection component of the spread. The former model separates the adverse selection cost, Z_t, from the order processing cost, C_t, and let both components be a linear function of trade size, q_t .

$$C_t = C_0 + C_1 q_t \text{ and } Z_t = Z_0 + Z_1 q_t \tag{12}$$

Hence the model implies the following reduced form specification for price changes (de Jong and Rindi, 2009)

$$\Delta p_t = C_0 \Delta D_t + C_1 \Delta x_t + Z_0 D_t + Z_1 x_t + U_t \tag{13}$$

where p_t is the price, D_t is the sign of the trade (it is equal to +1 for buyer-initiated trades and to -1 for seller initiated trades) and $x_t = q_t D_t$ is the signed trade size. [29]

The adverse selection component of the spread is estimated as: $AC=2(Z_0+Z_1)\bar{q}$; while the fixed cost (order processing/inventory holding) component of the spread is obtained as: $FC=2(C_0+C_1)\bar{q}$; where $\bar{q}$ is the average q (trade size) in the estimation period. We focus on the adverse selection component as a proportion of the spread which is calculated as: $AC/(AC+FC)$. We report the estimation results in Panel A of Table 13. In line with the evidence on the spread reduction, both

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

components of the spread decrease significantly after the MTUC removal. More importantly, in line with the theoretical model's prediction, the proportion of the adverse selection component over the spread reduces.

Alternatively, we measure adverse selection costs by estimating 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 τ is the residual from a regression relating trade size, q_t, to 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) trade.

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

The results of the estimation are given in Panel B of Table 13. As expected, the adverse selection component of the spread significantly decreases after the removal of the MTUC, confirming again our second empirical prediction on adverse selection costs. Furthermore, in line with the findings on the increase in market depth, the absolute value of ψ significantly decreases, indicating that illiquidity decreases after the MTUC removal. 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 generates a reduction of the midquote.[30]

Insert Table 13 here

3.5. Informational efficiency

RANDOM WALK TESTS

As a first approach to studying informational efficiency, we examine the autocorrelation of intra-day returns and intra-day variance ratios. See, for example, Campbell, Lo, MacKinley (1997), Boehmer, Saar and Yu (2005), and O´Hara and Ye (2011). 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. Following Chordia, Roll and Subrahmanyam (2005), we take 5, 10, 15, 20 and 30 minute returns. Furthermore, we exclude overnight returns. The results of the informational efficiency tests are presented in Table 14.

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 MTUC removal. Moreover, the sign of the variation is highly dependent on the choice of the lag.

[30] We have also checked the cross-sectional differences in parameter estimates. Both parameters indicate that the reduction in adverse selection costs and the reduction in illiquidity are higher for firms with larger MTUCH. However, these results are not statistically significant.

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 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. The magnitude of the pricing error, measured by its variance, has been proposed by Hasbrouck (1993) 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.

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, we focus on the ratio of the standard deviation of the pricing error to the standard deviation of the logarithm of price, denoted by σ_s/σ_p. The derivation of the measure is described in Appendix B. The results, reported in Table 14, show that the magnitude of the pricing error decreases after the MTUC removal but the variation is not significantly different from zero. The results are therefore similar to those found using random walk tests and confirm that the MTUC removal did not significantly impact informational efficiency.

In terms of the model's predictions, these results are consistent with a value of the parameter β lying in the middle-range, where the model does not predict a substantial improvement in price efficiency, regardless of the proportion of informed traders. With a MTUC, insiders are constrained to trade large quantities and the effect of insider trading on informational efficiency depends on the proportion of large vs. small uninformed traders. When the proportion of institutional traders is very small, with a MTUC informational efficiency is higher compared to no constraint regime. When instead the proportion of institutional investors is very large the effect depends on the equilibrium strategies under the no constraint regime. Intuitively, with few institutional traders in the market it is relatively easy to make inference on the fundamental value of the asset by observing large orders, the opposite is true when the market is populated by many institutional investors. When instead the proportion of institutional to retail traders is balanced, the model has no sharp predictions on the effect of the MTUC on informational efficiency.

4. Concluding Remarks

An important market design question is whether the minimum trade unit constraint (MTUC) imposed on traders affects market quality in terms of liquidity, adverse selection costs and informational efficiency. This paper addresses this question by considering a natural experiment of Borsa Italiana (BIt), where in 2002 the exchange reduced the minimum trade unit constraint to one unit for all listed stocks (i.e., the MTUC was removed).

We find a marked improvement in liquidity after the MTUC removal, measured by a decrease in the bid-ask spread and in depth at the first five levels of the book. This result suggests a decrease in transaction costs both for small orders, and for larger orders walking up the book. We also observe a substantial reduction in adverse selection costs, measured by the price impact of orders at different sizes, as well as by model-based estimates. These results are not driven by any local or global liquidity trend. Importantly, we show that the cross-sectional variation in the size of the MTUC hurdle has a significant impact on liquidity and adverse selection costs. Firms which were subject to a more binding MTUC before the removal of the constraint benefit from a greater improvement in liquidity and adverse selection costs after the change in the market design. This finding provides further support to the claim that the change in market quality is due to the removal of the MTUC.

The results are in line with the empirical predictions of a theoretical framework in which traders can choose their order size and liquidity providers operate under asymmetric information. The model compares different regimes of minimum transaction size design and offers empirical predictions for the effects of a removal of the MTUC on liquidity, adverse selection costs and informational efficiency. With the removal of the MTUC more traders have access to the market; hence the proportion of uninformed traders increases, adverse selection costs decrease and liquidity improves. However, we do not find any evidence that informational efficiency changes after the MTUC removal.

Our analysis focuses on the MTUC and its implications on market quality. Today, this issue is becoming increasingly relevant for a larger set of market participants due to the widespread adoption of algorithmic and high frequency trading, which substantially reduced the average trade size in most financial markets (SEC, 2010). In a high frequency trading environment (Kozhan and Tham, 2012) minimum trade size restrictions are relevant as they may crowd out arbitrageurs. Furthermore, as mentioned by O'Hara, Yao and Ye (2012), small orders may be useful for large traders to detect hidden liquidity, and, specifically for the US market, orders smaller than the MTUC and not included in the consolidated tape, may allow investors to elude reporting requirements. The removal of the MTUC may facilitate all these practices. Investigating this is a potentially interesting extension of our analysis which we leave for future work.

Appendix A: Theoretical benchmark

***Equations (4), (5)* -** Equation (4) and (5) can be obtained by solving for A_1, A_2 and β the following system of the quoted prices and the condition for insiders' mixed strategies:

$$\begin{cases} A_1 = E[\tilde{V} \mid +1] \\ A_2 = E[\tilde{V} \mid +2] \\ 2(\bar{V} - A_2) - (\bar{V} - A_1) = 0 \end{cases}$$

***Equation (6)* -** In order to show the validity of (6), notice that when insiders play pure strategies $(\mu = 1)$ we obtain that $A_{QT} = A_2$.

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

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

$$\frac{A_{QT} - E(v)}{2-0} > \frac{A_2 - E(v)}{2-0}$$

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

***Measure of informational efficiency* -** To measure informational efficiency, we use the following indicator:

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

with i=1 for small and i=2 for large trades, and

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

We run numerical simulations for this indicator computed for the NC and MQTS regimes (Figure 3).

Empirical predictions: Liquidity - The inside spread is the smallest with the NC semi-separating equilibrium and the largest with the MQTS equilibrium. The results on liquidity are simply explained by inequality (6), which shows that the inside spread is the smallest under the NC semi-separating equilibrium, and the widest under MQTS. With the semi-separating equilibrium the inside spread coincides with the spread associated with small orders, which bears no adverse selection costs and hence it is equal to zero. Under MQTS, instead, the inside spread coincides with that of large orders, which reflect all the adverse selection costs.

***Empirical predictions: Informational efficiency* -** The effect of the MTUC removal on informational efficiency hinges on the relative proportion of large informed trades. When the proportion of insiders is large, the regime under which informational efficiency is the highest depends on the parameters' values. When instead the proportion of insiders is small, informational efficiency is the highest under the regimes with MQTS. Numerical simulations, summarized in Figure 3, show that informational efficiency is higher under the MQTS regime (solid surface) than under the semi-separating regime (dashed surface). This result derives from the assumption that only insiders possess private information and that the presence of small uninformed traders in the semi-separating regime can add noise to the process of price discovery. The comparison between the MQTS and the NC pooling regimes depends on the proportions of both insiders (α) and of large liquidity traders (β). Hence, when switching from the MQTS to the NC regime, the effect on informational efficiency depends on both the type of equilibrium that prevails, and on the parameters' value.

Appendix B: Estimation of informational efficiency: The magnitude of the pricing error (following Hasbrouck, 1993)

The observed logarithm of 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.

To obtain an estimate of the variance of the pricing error, the variation in price and a set of trade characteristics are assumed to follow a VAR with five lags:

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

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:

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

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

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + \dots + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + \dots$$

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

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

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

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. The measure of informational efficiency is the ratio of the standard deviation of the pricing error to the standard deviation of the logarithm of price.

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Table 1: Dataset

We consider the stocks belonging to the MIB30 and MIDEX indices. 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 MTUC to one share for all the stocks listed on BIt (happened on January 14, 2002). The MTUC hurdle, in the last column, is measured by the ratio of the average number of trades at the MTUC over the average number of trades executed in the *Pre* period.

Stock	*Capitalization (Millions of Euros)*	*Index*	*MTUC (Pre)*	*MTUC Hurdle*
ACEA	1,687	MIDEX	100	0.30
AEM	4,032	MIB30	500	0.27
ALITALIA	1,638	MIDEX	1000	0.12
ALLEANZA	8,384	MIB30	50	0.08
AUTOGRILL	2,575	MIDEX	50	0.21
AUTOSTRADA TO-MI	946	MIDEX	50	0.11
AUTOSTRADE	8,779	MIB30	100	0.46
BANCA DI ROMA	3,421	MIB30	125	0.13
BANCA FIDEURAM	7,501	MIB30	50	0.08
BANCA MONTE PASCHI SIENA	7,580	MIB30	250	0.08
BANCA NAZ LAVORO	5,331	MIB30	250	0.15
BANCA POPOLARE BERGAMO	2,395	MIDEX	50	0.11
BANCA POP. COMM. IND.	968	MIDEX	50	0.10
BANCA POPOLARE LODI	1,246	MIDEX	50	0.36
BANCA POPOLARE MILANO	1,506	MIDEX	100	0.10
BANCA POPOLARE NOVARA	1,617	MIDEX	250	0.11
BANCA POPOLARE VERONA	2,411	MIDEX	50	0.39
BENETTON GROUP	2,179	MIDEX	50	0.23
BENI STABILI	903	MIDEX	2500	0.11
BIPOP-CARIRE	3,749	MIB30	250	0.09
BULGARI	2,772	MIB30	50	0.06
BUZZI UNICEM	983	MIDEX	250	0.15
CLASS EDITORI	356	MIDEX	50	0.10
CREDITO EMILIANO	1,472	MIDEX	100	0.17
ENEL	38,743	MIB30	125	0.11
ENI	52,536	MIB30	50	0.06
FIAT	6,815	MIB30	50	0.19
FINMECCANICA	8,222	MIB30	500	0.09
GENERALI	38,404	MIB30	25	0.34
HDP	2,428	MIB30	250	0.06
INTESABCI	15,935	MIB30	250	0.09
ITALCEMENTI	1,518	MIDEX	250	0.29
ITALGAS	3,485	MIB30	50	0.19
L´ESPRESSO (G.E.)	1,499	MIDEX	100	0.15
LA FONDIARIA	2,267	MIDEX	250	0.06
MEDIASET	9,875	MIB30	100	0.11
MEDIOBANCA	7,721	MIB30	50	0.16
MEDIOLANUM	7,272	MIB30	50	0.15

BANCA POPOLARE MILANO	1,149	MIDEX	500	0.20
MONDADORI EDITORE	1,859	MIDEX	100	0.14
OLIVETTI	9,779	MIB30	250	0.23
PARMALAT FINANZIARIA	2,406	MIDEX	250	0.12
PIRELLI SPA	1,549	MIB30	250	0.10
RAS	9,905	MIB30	50	0.10
RINASCENTE	1,244	MIDEX	250	0.24
ROLO BANCA 1473	8,043	MIB30	50	0.12
SAI	939	MIDEX	50	0.15
SAIPEM	2,209	MIB30	250	0.44
SAN PAOLO IMI	17,289	MIB30	50	0.13
SEAT PAGINE GIALLE	10,536	MIB30	500	0.07
SNIA	744	MIDEX	1000	0.22
TELECOM ITALIA	50,037	MIB30	50	0.04
TIM	53,216	MIB30	250	0.17
TOD'S	1,426	MIDEX	25	0.21
UNICREDITO ITALIANO	21,154	MIB30	250	0.08

Table 2: 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 MTUC. Specifically, individual stocks averages by periods are averaged across all the stocks. We consider: the number of trades; the number of shares traded; the Euro value of trades executed; the average transaction price; the number of trades at the MTUC in the *Pre* period; the number of trades at one unit; the proportion of trades executed at the MTUC; the proportion of trades in the *Post* period with size less than the MTUC 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
Number of trades	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 trades at MTUC (Pre)	166.17	57.49	-108.68	-6.3174***
Number of trades at 1 unit	-	24.28	-	-
Proportion of trades at MTUC	16.17%	1.78%	-14.39%	-6.4510***
Proportion of trades at less than MTUC	-	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 3: Bid-ask spread – Univariate tests

The Panel A of 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 MTUC. 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 proportion 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. Panel B 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, i.e. *Pre1* period which goes from November 12 to December 7, 2001. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A		*Pre*	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
Level 1	*Quoted Spread*	0.0202	0.0178	-0.0024***	-10.4%***
Level 1	*% Spread*	0.0024	0.0022	-0.0002***	-10.2%***
Level 2	*% Spread*	0.0059	0.0055	-0.0004***	-6.2%***
Level 3	*% Spread*	0.0093	0.0089	-0.0004***	-5.2%***
Level 4	*% Spread*	0.0128	0.0122	-0.0006***	-4.9%***
Level 5	*% Spread*	0.0163	0.0156	-0.0007***	-4.5%***

Panel B		*Pre1*	*Pre*	*Pre-Pre1*	*(Pre-Pre1)/Pre1*
Level 1	*Quoted Spread*	0.0206	0.0202	-0.0004	2.1%
Level 1	*% Spread*	0.0024	0.0024	0.0000	1.0%

Table 4: Bid-ask spread – Multivariate analysis

Panel A reports the results of specification (7):

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

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 (8):

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

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 MTUC reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A		**Panel B**	
		Intercept	*T-stat*	*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 5: Bid-ask spread – Global liquidity trend

Panel A reports the results of specification (7'):

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta L_i^G + \varepsilon_i$$

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*, the variation in the period-average daily transaction price (the average transaction price in a day), *P and* the variation in the global liquidity measure defined in equation (9). 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 (8'):

$$L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \gamma_4 L_{it}^G + \varepsilon_{it}$$

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 MTUC reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A		**Panel B**	
		Intercept	*T-stat*	*Median (Day)*	*Wilcoxon-z*
Level 1	*% (closing) Spread no global trend*	-0.0003	-3.0193***	-0.0003	-2.9119***
Level 1	*% (closing) Spread with global trend*	-0.0002	-2.2297***	-0.0003	-2.9493***

Table 6: Bid-ask spread – MTUC hurdle and liquidity improvement

Panel A reports the results of specification (7'')

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTUCH_i + \varepsilon_i$$

Panel B reports the results of specification (7'') with additional firm characteristics, market to book ratio (MB), leverage (debt to asset ratio) and dividend yield as of end of November 2001.

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTUCH_i + \beta_5 cnt_i + \varepsilon_i$$

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*, the variation in the period-average daily transaction price (the average transaction price in a day), *P*, and the MTUC hurdle, MTUCH, measured as the number of trades at the MTUC over the average number of trades in the *Pre* period. 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). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A

		Intercept	*T-stat*	β_4	*T-stat*
Level 1	*% Spread*	0.0000	0.0409	-0.0017	-3.6533***
Level 2	*% Spread*	0.0000	0.4661	-0.0026	-3.6337***
Level 3	*% Spread*	0.0001	0.5272	-0.0034	-3.7491***
Level 4	*% Spread*	0.0001	0.4497	-0.0042	-3.5734***
Level 5	*% Spread*	0.0002	0.4989	-0.0051	-3.5148***

Panel B

		Intercept	*T-stat*	β_4	*T-stat*
Level 1	*% Spread*	-0.0000	-0.2625	-0.0017	-3.5896***
Level 2	*% Spread*	-0.0000	-0.0824	-0.0025	-3.5028***
Level 3	*% Spread*	-0.0000	-0.0944	-0.0032	-3.5150***
Level 4	*% Spread*	-0.0001	-0.2612	-0.0039	-3.2608***
Level 5	*% Spread*	-0.0002	-0.3206	-0.0047	-3.2105***

Table 7: Bid-ask spread –MTUC hurdle (based on value) and liquidity improvement

Panel A reports the results of specification (7'') modified using *MTUCV*:

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTUCV_i + \varepsilon_i$$

Panel B reports the results of specification (7'') with additional firm characteristics, market to book ratio (MB), leverage (debt to asset ratio) and dividend yield as of end of November 2001.

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTUCV_i + \beta_5 cnt_i + \varepsilon_i$$

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*, the variation in the period-average daily transaction price (the average transaction price in a day), *P*, and the MTUC hurdle (based on value), MTUCV, measured as the MTUC (number of shares) times average stock price in the *Pre* period (normalized by 1/10000). 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). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A

		Intercept	*T-stat*	β_4	*T-stat*
Level 1	*% Spread*	0.0000	-1.0674	-0.0025	-2.4666**
Level 2	*% Spread*	0.0000	-0.4979	-0.0036	-2.1913**
Level 3	*% Spread*	0.0000	-0.3726	-0.0046	-2.0089**
Level 4	*% Spread*	0.0000	-0.3027	-0.0060	-1.9769*
Level 5	*% Spread*	0.0000	-0.1681	-0.0077	-1.9964*

Panel B

		Intercept	*T-stat*	β_4	*T-stat*
Level 1	*% Spread*	-0.0002	-1.2215	-0.0024	-2.2439**
Level 2	*% Spread*	-0.0002	-0.8271	-0.0036	-2.1198**
Level 3	*% Spread*	-0.0003	-0.7621	-0.0046	-2.0170**
Level 4	*% Spread*	-0.0004	-0.8340	-0.0059	-2.0230**
Level 5	*% Spread*	-0.0004	-0.7960	-0.0076	-2.0967**

Table 8: Bid-ask spread – Alternative specifications

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 9):

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

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 (see footnote 25), *SVOL*, and the adverse selection cost component of the bid-ask spread following the Glosten and Harrris (1988) model (see Section 3.4), *AC*. The total number of of observations is 55.

Panel B reports the results of the following cross-sectional average model (specification 10). *POST* is a dummy variable for the *Post* period. We use one observation for each day, *t*, resulting in a total of 40 observations:

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

In both models, we report a *t*-test based on heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance matrix). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A		**Panel B**	
		Intercept	*T-test*	*POST*	*T-test*
Level 1	*Quoted spread*	-0.0027	-3.3553***	-0.0018	-3.2810***
Level 1	*% Spread*	-0.0003	-4.1058***	-0.0002	-5.6203***
Level 2	*% Spread*	-0.0004	-2.9754***	-0.0003	-3.6597***
Level 3	*% Spread*	-0.0005	-2.5748**	-0.0003	-2.8245***
Level 4	*% Spread*	-0.0006	-2.4758**	-0.0003	-2.5177**
Level 5	*% Spread*	-0.0007	-2.3666**	-0.0004	-2.1387**

Table 9: Market depth – Univariate tests

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 MTUC. 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 five 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Pre	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
Level 1	*Total # of shares*	41,917	58,798	16,881***	38.4%***
Level 2	*Total # of shares*	61,480	86,298	24,818***	43.4%***
Level 3	*Total # of shares*	60,200	83,223	23,023***	40.7%***
Level 4	*Total # of shares*	58,532	78,866	20,334***	35.9%***
Level 5	*Total # of shares*	56,661	75,458	18,797***	32.8%***
Level 1	*Total Euro value*	196,273	262,599	66,326***	41.7%***
Level 2	*Total Euro value*	284,440	374,508	90,068***	47.0%***
Level 3	*Total Euro value*	276,209	358,135	81,926***	43.8%***
Level 4	*Total Euro value*	267,550	340,561	73,011***	38.0%***
Level 5	*Total Euro value*	259,698	322,504	62,806***	34.6%***
Cumulative (1-5)	*Total # of shares*	278,790	382,643	103,853***	37.8%***
Cumulative (1-5)	*Total Euro value*	1,284,170	1,658,308	374,138***	40.6%***

Table 10: Market depth – Multivariate analysis

Panel A reports the results of specification (7):

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

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 (8):

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

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 MTUC reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A		**Panel B**	
		Intercept	*T-test*	*Median (Day)*	*Wilcoxon-z*
Level 1	*Total # of shares*	13,280	3.4374***	12,996	3.7706****
Level 2	*Total # of shares*	20,192	3.5759***	16,537	3.7706****
Level 3	*Total # of shares*	18,923	3.6162***	14,437	3.6959****
Level 4	*Total # of shares*	16,686	3.9181***	13,756	3.6959****
Level 5	*Total # of shares*	15,541	3.7309***	12,523	3.5093****
Level 1	*Total Euro value*	40,671	3.5724***	32,262	2.8373****
Level 2	*Total Euro value*	56,175	3.4580***	40,456	2.5760****
Level 3	*Total Euro value*	51,427	3.5282***	34,796	2.4266***
Level 4	*Total Euro value*	45,536	3.6046***	35,509	2.2026***
Level 5	*Total Euro value*	38,444	3.2914***	29,642	1.9786***
Cumulative (1-5)	*Total # of shares*	84,622	3.7157***	62,066	3.7333****
Cumulative (1-5)	*Total Euro value*	232,253	3.5744***	175,544	2.4266***

Table 11: Price impact of orders – Univariate tests

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 MTUC. 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 proportion 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Pre	*Post*	*Post-Pre*	*(Post-Pre)/Pre*
5,000€/Midquote	*Buy order on Midquote*	0.0129	0.0117	-0.0012***	-9.5%***
5,000€/Midquote	*Sell order on Midquote*	0.0135	0.0121	-0.0014***	-10.5%***
5,000€/Midquote	*Buy order on Midquote (%)*	0.0015	0.0014	-0.0001***	-9.3%***
5,000€/Midquote	*Sell order on Midquote (%)*	0.0016	0.0014	-0.0002***	-10.2%***
10,000€/Midquote	*Buy order on Midquote*	0.0157	0.0140	-0.0017***	-11.1%***
10,000€/Midquote	*Sell order on Midquote*	0.0165	0.0146	-0.0019***	-12.2%***
10,000€/Midquote	*Buy order on Midquote (%)*	0.0019	0.0016	-0.0003***	-10.8%***
10,000€/Midquote	*Sell order on Midquote (%)*	0.0019	0.0016	-0.0003***	-11.9%***
20,000€/Midquote	*Buy order on Midquote*	0.0213	0.0183	-0.0030***	-13.5%***
20,000€/Midquote	*Sell order on Midquote*	0.0226	0.0199	-0.0027***	-14.6%***
20,000€/Midquote	*Buy order on Midquote (%)*	0.0025	0.0021	-0.0004***	-13.1%***
20,000€/Midquote	*Sell order on Midquote (%)*	0.0025	0.0021	-0.0004***	-14.3%***
30,000€/Midquote	*Buy order on Midquote*	0.0259	0.0220	-0.0039***	-14.7%***
30,000€/Midquote	*Sell order on Midquote*	0.0272	0.0242	-0.0030***	-15.9%***
30,000€/Midquote	*Buy order on Midquote (%)*	0.0030	0.0025	-0.0005***	-14.2%***
30,000€/Midquote	*Sell order on Midquote (%)*	0.0031	0.0026	-0.0005***	-15.6%***

Table 12: Price impact of orders – Multivariate analysis

Panel A reports the results of specification (7):

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

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 (8):

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

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 MTUC reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 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. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

		Panel A		**Panel B**	
		Intercept	*T-stat*	*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 13: Adverse selection cost

This table reports the results of the estimation of the Glosten and Harris (1988, Panel A) and Foster and Viswanathan (1993, Panel B) models, as described in section 3.4. The reported values are averages across the 55 firms in the sample. The models are estimated, for each stock separately, using all the observations in the *Pre* or in the *Post* periods (this results in one observation regarding *AC*, *FC*, *AC* proportion, ψ and λ (multiplied by 10,000) for each stock in both periods). In the Glosten and Harris (1988) model, *AC* and *FC* refer to the adverse selection and to the fixed costs components of the spread, respectively; *AC* proportion refers to the adverse selection component as a proportion of the spread. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Panel A: Glosten and Harris (1988)

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
AC	0.0045	0.0043	-0.0002	-4.6330***
FC	0.0079	0.0072	-0.0007	-2.1030**
AC proportion	0.3496	0.3238	-0.0258	-4.2400***

Panel B: Foster and Viswanathan (1993)

	Pre	*Post*	*Post-Pre*	*Wilcoxon-z*
ψ	-0.0022	-0.0020	0.0002	5.5130***
λ	0.0022	0.0013	-0.0010	-2.2450**

Table 14: Informational efficiency

The table compares the cross-sectional averages of the informational efficiency measures before and after the reduction of the MTUC. 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 standard deviation of the pricing error divided by the standard deviation of the logarithm of price, σ_s/σ_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 standard deviation is computed, for each stock separately, using all the days in the *Pre* or *Post* periods (this results in one observation regarding σ_s/σ_p for each stock in both periods). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

	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
σ_s/σ_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-α) the probability he is uninformed; β is the probability an uninformed trader trades large orders, (1-β) the probability he trades small orders; μ and (1-μ) are the probabilities that informed traders submits small or large orders respectively. With separating equilibrium, the informed only trade large and μ=1.

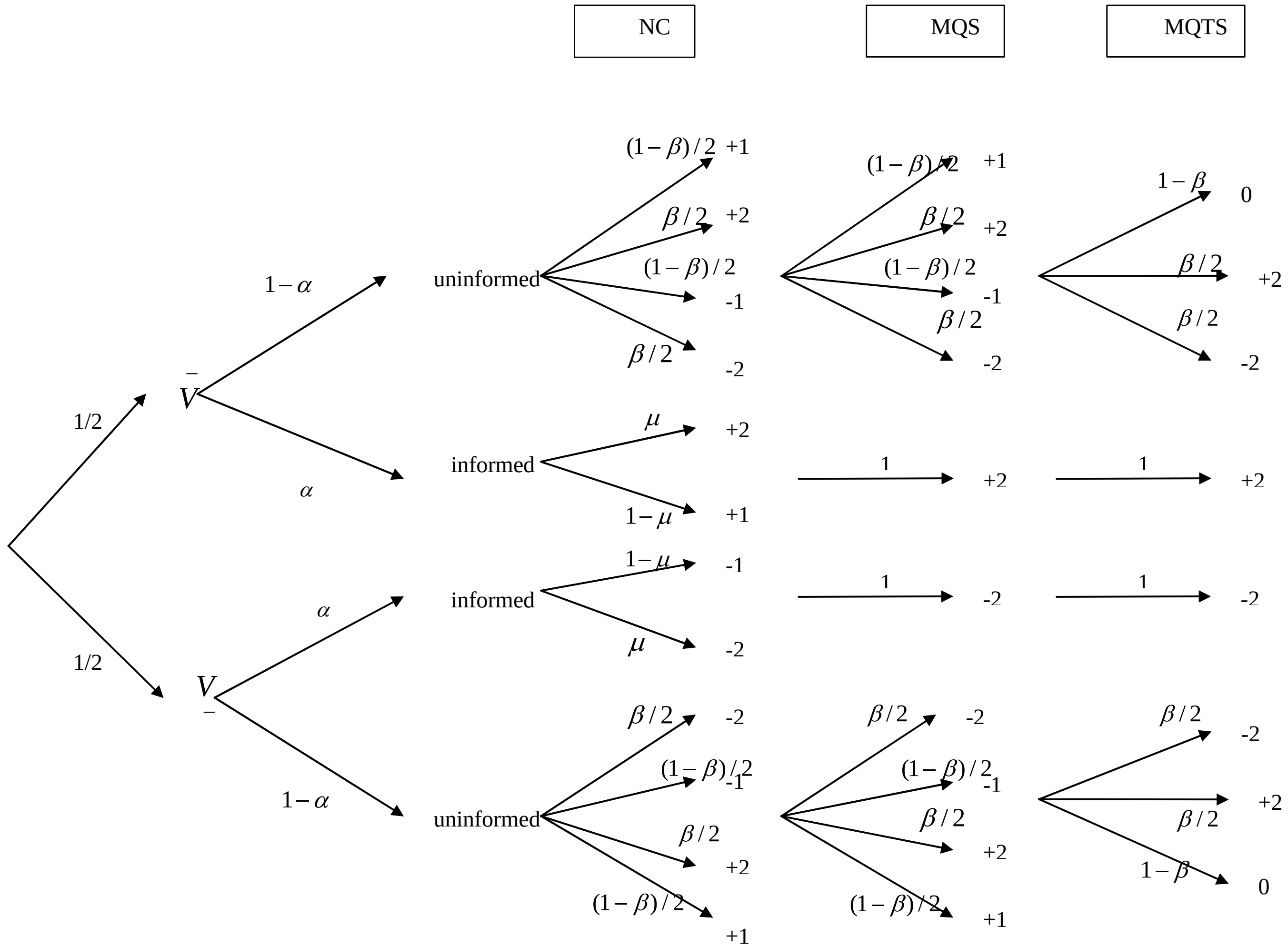

Figure 1: Pooling equilibrium

The vertical axis shows the ask prices that characterize the regime with insiders playing mixed strategies. The figure compares the ask prices corresponding to the NC regime (A_1 and A_2), to the MQS regime (A_Q), and to the MQTS regime (A_{QT}). Notice that a pooling equilibrium prevails for the parameter values that satisfy $\beta < \alpha/(1-\alpha)$.

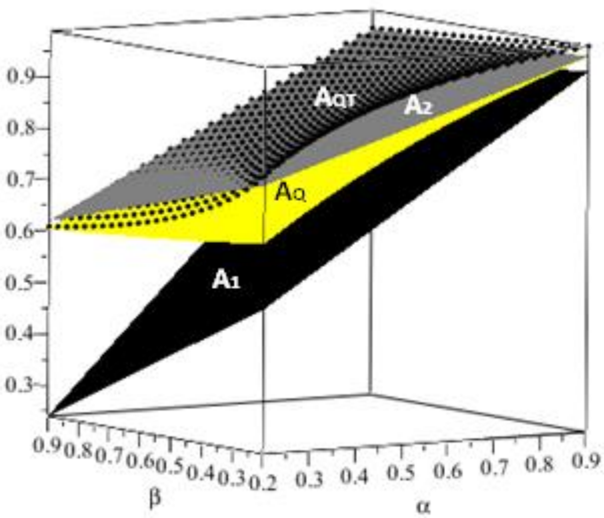

Figure 2: Semi-separating equilibrium

The vertical axis shows the ask prices that characterize the regime with insiders playing pure strategies. The figure compares the ask prices corresponding to the NC regime (A_1 and A_2), to the MQS regime (A_Q), and to the MQTS regime (A_{QT}). Notice that a Semi-separating equilibrium prevails for the parameter values that satisfy $\beta \geq \alpha/(1-\alpha)$.

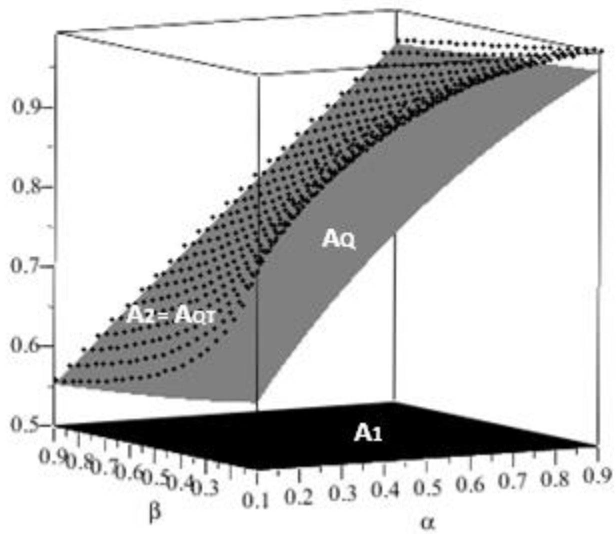

Figure 3: Informational efficiency
The vertical axis presents informational efficiency (as defined in the Appendix) under the MQTS regime, the pooling NC regime (NC-POOL), and the separating NC regime (NC-SEP).

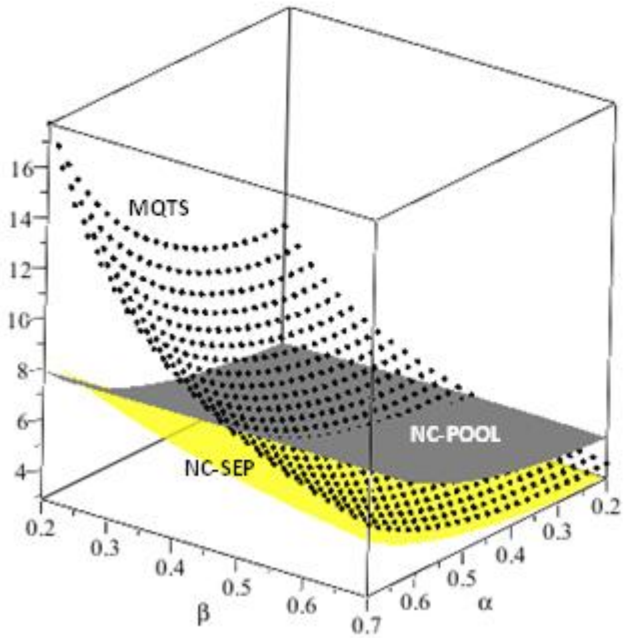

Figure 4: Liquidity and MTUC Hurdle

This figure plots the *Post-Pre* difference in first level percentage spread. The x-axis shows the MTUC hurdle for each firm, which is measured as the average number the trades at the MTUC over the average number of trades in the *Pre* period. The solid black line shows the *Post-Pre* change in percentage spread and the gray dashed lines show the one standard deviation band. The shaded area indicates the third tercile of the firms for which the MTUC is most binding.

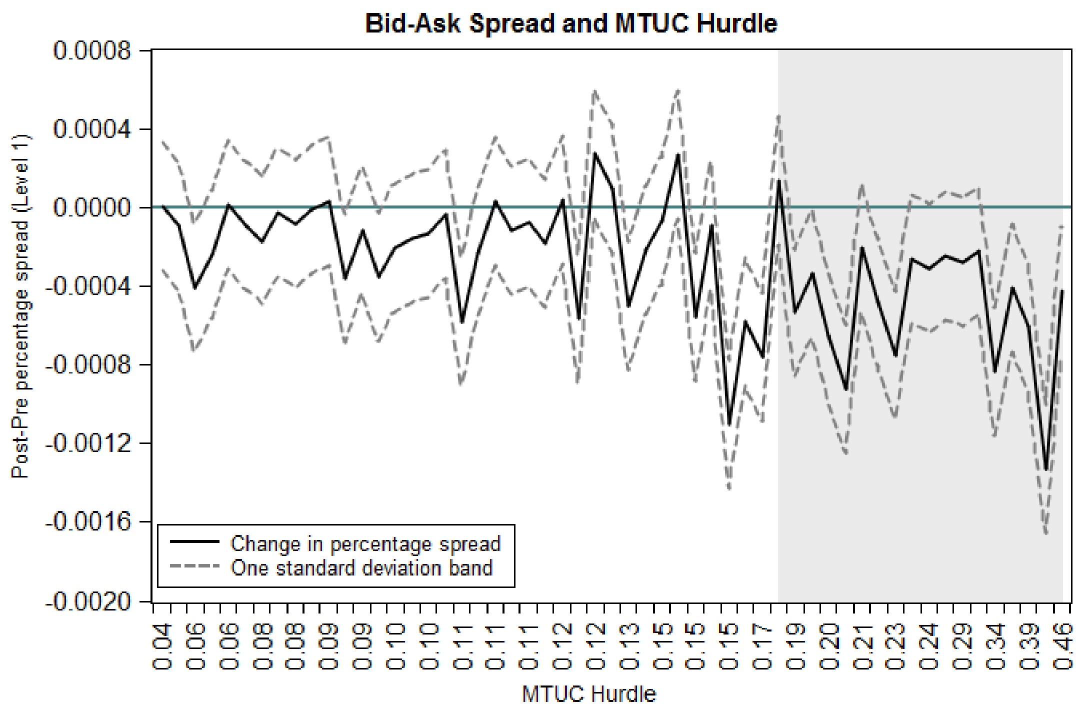

Figure 5: Cross-sectional differences in the bid – ask spread

This figure groups the firms into three terciles based on the MTUC hurdle and plots the *Post-Pre* difference in percentage spreads at the first five levels of the book. The MTUC hurdle is measured as the average number of trades at the MTUC over the average number of trades in the *Pre* period. The firms in the first tercile are subject to smaller MTUC, while the MTUC is most binding for the firms in the third tercile. In the figure we also report the average percentage spread change (in basis points, bp) for each tercile and the paired sample signed-rank Wilxocon z-value and associated p-values for the equality of medians between the third and the first tercile.

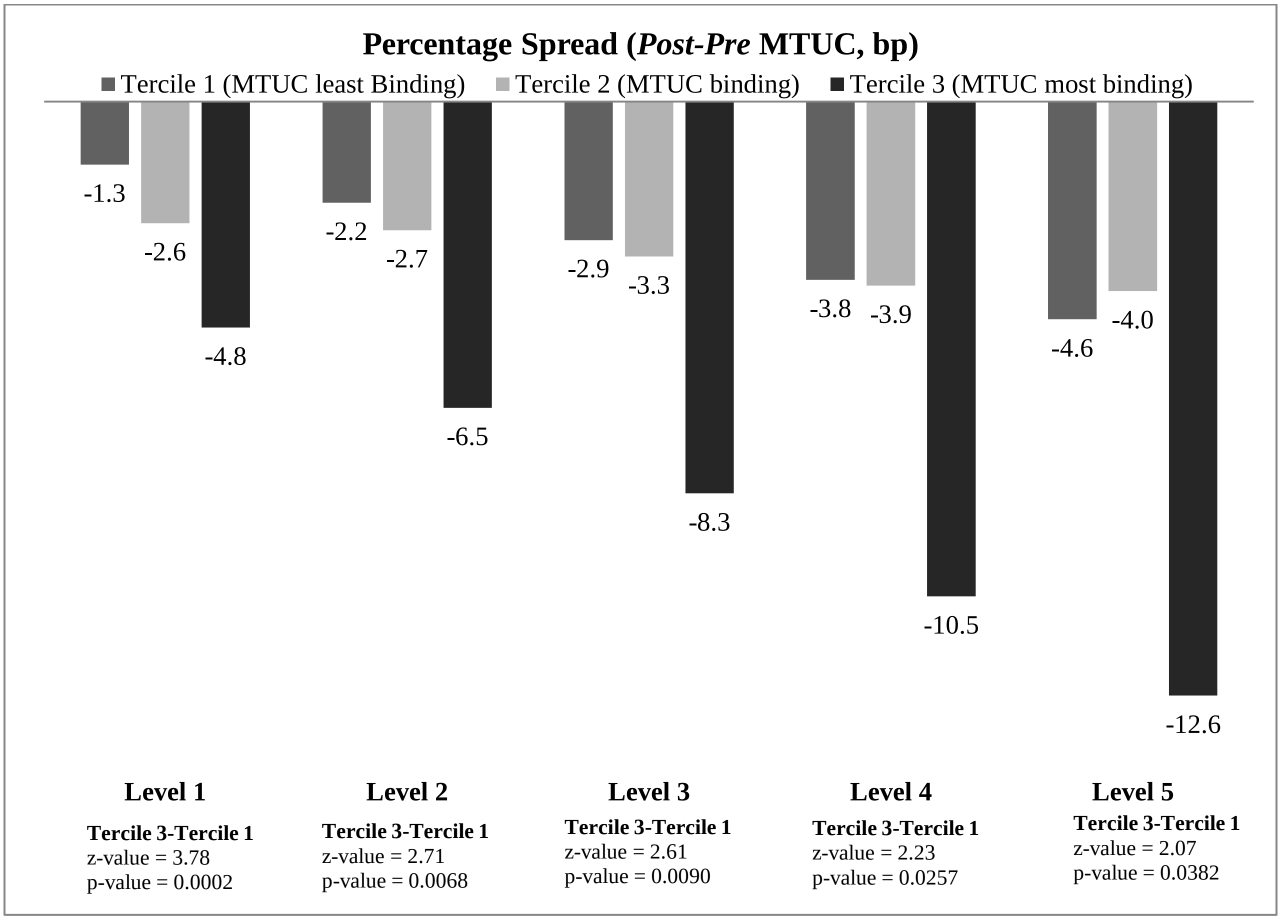

Figure 6: Cross-sectional differences in the price impact

This figure groups the firms into three terciles based on the MTUC hurdle and plots the *Post-Pre* difference in the price impact of orders at different size. The MTUC hurdle is measured as the average number of trades at the MTUC over the average number of trades in the *Pre* period. The price impact is computed as the difference between the bid price (for sell orders) and the midquote corresponding to the trade as a proportion of the prevailing midquote. 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 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). In the figure we report the average change in the price impact (in basis points, bp) for each tercile and the paired sample signed-rank Wilxocon z-value and associated p-values for the equality of medians between the third and the first tercile.