# Online Appendix of:
# "Lot Size Constraints and Market Quality: Evidence from the Borsa Italiana"

## A. Theoretical benchmark

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

$$\begin{cases} A_1 = E[\tilde{V} \mid +1] \\ A_2 = E[\tilde{V} \mid +2] \\ 2(\bar{V} - A_2) - (\bar{V} - A_1) = 0 \end{cases} \tag{A1}$$

***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:

$$IE = \left(E[VAR(\tilde{v} \mid \tilde{q}_{i)}]\right)^{-1} = \frac{1}{\sum_{i=1}^{2}[VAR(\tilde{v} \mid q_i^A)\Pr(q_i^A) + VAR(\tilde{v} \mid q_i^B)\Pr(q_i^B)]} \tag{A2}$$

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

$$E[VAR(\tilde{v} \mid \tilde{q}_i)] = 2\sum_{i=1}^{2}[(\overline{V} - E(\tilde{v} \mid q_i^A))^2 \Pr(\overline{V} \mid q_i^A) + (\underline{V} - E(\tilde{v} \mid q_i^A))^2 \Pr(\underline{V} \mid q_i^A)]\Pr(q_i^A) \tag{A3}$$

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

***Empirical predictions: Liquidity*** - The inside spread is the smallest with the NC semi-separating equilibrium and the largest with the MTU 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 MTU. 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 MTU, 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 MTU removal on informational efficiency hinges on the relative proportion of large uninformed trades. When the proportion of large uninformed traders is large, the regime under which informational efficiency is the highest depends on the parameter values. When instead the proportion of large uninformed traders is small, informational efficiency is the highest under the MTU regime. Numerical simulations, summarized in Figure 3, show that informational efficiency is higher under the MTU regime (dashed surface) than under the semi-separating regime (solid yellow surface) regardless of the proportion of informed traders. However, the difference is much more pronounced when small uninformed traders dominate the market. 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 MTU and the NC pooling regimes depends on the proportions of both insiders ($\alpha$) and of large liquidity traders ($\beta$). Hence, when switching from the MTU to the NC regime, the effect on informational efficiency depends on both the type of equilibrium that prevails, and on the parameters' value.

## B. Liquidity improvement and stock returns

We examine the cumulative abnormal returns (CARs) around the MTU change. CARs are defined as the sum of abnormal returns from 20 days before the event to 20 days after the event. 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. 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 MTU reduction, we regress CARs on the relative change in liquidity after the microstructure change. A similar approach is taken by Anand, Tanggard and Weaver (2009). We estimate the following model:

$$CAR_i = \beta_0 + \beta_1 \Delta_r L_i + \varepsilon_i \quad \text{(A4)}$$

where $\Delta_r L$ , is the relative change in liquidity after the MTU reduction. The results are reported in Table A-I. The coefficient of the relative change in liquidity is negative and highly significant for all the liquidity measures except for the quoted spread; thus, the stocks that experience a greater liquidity improvement exhibit larger returns. 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). It is also in line with prior evidence which documents an increase in price after an MTU reduction (Amihud, Mendelson and Uno 1999, Hauser and Lauterbach 2003).

Insert Table A-I here

## C. Sensitivity analysis on liquidity

In this section, we test whether our results on the liquidity improvement are sensitive to the empirical specification we choose and test alternative specifications addressing potential problems due to endogeneity and to correlated error terms. Then we try to alleviate concerns regarding the sample size, both time series and cross-section, and the timing of the event. To this end, we estimate an alternative low frequency spread measure suggested by Corwin and Schultz (2012) and check the robustness of our results along three dimensions: we extend the event window to 80 days around the MTU change, we include a larger set of stocks, and we test the effect of seasonality on our findings.

### C.1. Endogeneity and correlated error terms

We change the model specification in two directions to address possible concerns related to endogeneity and correlated error terms (Boehmer, Saar and Yu, 2005):

i) There might be an endogeneity problem in equations (7) and (8) if trading volume depends on the liquidity measure. Therefore, we estimate a two-equation model where liquidity is modeled simultaneously with volume. To identify the model, we include two exogenous variables in equation (8); following the approach used by Hasbrouck and Saar (2013) we employ, as instruments: the average liquidity of the stocks belonging to the same capitalization decile (excluding the stock under consideration), *IL*, and the average volume change of the stocks belonging to the same capitalization decile (excluding the stock under consideration), *IVLM*.[1] We then estimate the following model with three-stage least squares.[2] As in equation (8), there are 2,198 observations:

[1] For all the liquidity measures, we find that *IL* is positively and significantly correlated with *L* whereas it is not significantly correlated with *VLM*. Furthermore, *IVLM* is positively and significantly correlated with *VLM* whereas it is not significantly correlated with *L*. Boehmer, Saar and Yu (2005) use the standard deviation of daily inventory closing positions of specialists as instrument for the first equation, and the systematic component of volume as instrument for the second equation. As there are no specialists operating on the stocks in our sample, we are not able to use the instrument for the first equation suggested by Boehmer, Saar and Yu (2005). We also re-estimated the model using *IL* as instrument for the first equation and the systematic component of volume for the second equation and we obtained similar results.

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

$$\begin{cases} L_{it} = \alpha + \sum_{k=1}^{20}(\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \gamma_4 IL_{it} + \varepsilon_{it} \\ VLM_{it} = \delta + \sum_{k=1}^{20}(\kappa_k Day_{it}^k) + \phi_1 L_{it} + \phi_2 VLT_{it} + \phi_3 P_{it} + \phi_4 IVLM_{it} + \nu_{it} \end{cases} \quad \text{(A5)}$$

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 (for example, $L_t$ refers to the average $L$ on day $t$ across the 55 stocks in the sample) :

$$L_t = \beta_0 + \beta_1 POST_t + \beta_2 VLM_t + \beta_3 VLT_t + \beta_4 P_t + \varepsilon_t \quad \text{(A6)}$$

The results concerning the aforementioned models are presented in Table A-II. They are qualitatively analogous to the previous findings.

Insert Table A-II here

## C.2. High-low spread: low frequency alternative liquidity measure

Our intraday dataset consists of 55 stocks in the 40-day event window around the MTU reduction. We extend our robustness analysis by computing a daily bid-ask spread estimator developed by Corwin and Schultz (2012), which we denote as “high-low spread estimator”. This simple measure allows us to conduct the event study over a larger event window and with a larger set of stocks relying only on daily stock price data. First, we extend the event window to 80 days to check again whether our results are driven by a local market trend. Then, we expand our sample to the 137 Italian stocks which are available in DataStream and with a price greater than €1 at the time of the MTU change. Finally, we test whether our results are an artifact of any seasonal pattern in the data; to do this we collect ten years (1996-2007) of data in an 80-day event window around the MTU change date and measure the average *Pre* and *Post* spreads around the date to see whether there is a decrease in spreads in those months.[3]

The proposed high-low spread estimator is derived based on the intuition that the high-low price ratio consists of both variance and bid-ask spread components. Since only the variance component is proportional to the return interval, one can extract the spread component by measuring high-low ratios over a single day and two consecutive single days. In particular, the high low spread estimate is a function of two parameters, $\beta$ and $\gamma$

$$\beta = \sum_{j=0}^{1} \ln(\frac{H_{t+j}}{L_{t+j}})^2 \quad \text{(A7)}$$

where $H_t$ and $L_t$ are the daily high and low prices on day *t*, respectively.

$$\gamma = \left[ln\left(\frac{H_{t,t+1}}{L_{t,t+1}}\right)\right]^2 \quad \text{(A8)}$$

where $H_{t,t+1}$ and $L_{t,t+1}$ are the highest and lowest prices over two consecutive days *t* and *t*+1, respectively.

Then the spread estimator is a transformation of these two parameters

$$a = \frac{\sqrt{2\beta}-\sqrt{\beta}}{3-2\sqrt{2}} - \sqrt{\frac{\gamma}{3-2\sqrt{2}}} \quad \text{(A9)}$$

$$S = \frac{2(e^{a}-1)}{1+e^{a}} \quad \text{(A10)}$$

Following Corwin and Schultz (2012) we adjust the spread measure for overnight changes and days with infrequent trading.[4]

[3] The same analyses cannot be performed using daily bid-ask spreads based on DataStream because for most stocks the bid and ask prices are not available in the period around December 2001 and January 2002.
[4] When we compute the period averages, we only include the days with positive spreads and obtain comparable estimates with intraday data.

*EXTENDING THE TIME SAMPLE AND THE NUMBER OF STOCKS*

The first row in Table A-III shows the change in the high-low spread in an 80-day event window around the date of the MTU change. It is based on the 55 Italian firms included in the main analysis, whereas the second row extends the sample to the 137 Italian stocks available in DataStream. We first note that by using the low-frequency estimator we still observe a substantial decrease in equally weighted spreads across firms, in line with the results reported in the main analysis. The results are similar once we extend our sample to 137 stocks.

Insert Table A-III here

*CONTROLLING FOR A SEASONAL PATTERN*

One might be concerned that this shift only reflects a seasonal pattern in the Italian market, i.e., larger spreads in the last months of the year relative to the first months when our event takes place. To address this concern, we compute the 10-year average (1996-2007, excluding the event year) of the bid-ask spread in a window of 80 days around the date of the MTU change, January 14. Specifically, in each year and for each firm, we compute the average spread in the 40-day period before and in the 40-day period after January 14. The average is computed including the 30 firms that have complete data over 10 years. The last row in Table A-III shows that there is no such a downward seasonal pattern in spread. On the contrary, over the ten years, the spreads, on average, increase in the period considered.

### D. 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 change in price and a set of trade characteristics are assumed to follow a VAR with five lags:

$$\begin{cases} r_t = a_1 r_{t-1} + a_2 r_{t-2} + ... + b_1 x_{t-1} + b_2 x_{t-2} + ... + v_{1,t} \\ x_t = c_1 r_{t-1} + c_2 r_{t-2} + ... + d_1 x_{t-1} + d_2 x_{t-2} + ... + v_{2,t} \end{cases} \quad \text{(A11)}$$

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:

$$\begin{cases} r_t = a_0^* v_{1,t} + a_1^* v_{1,t-1} + a_2^* v_{1,t-2} ... + b_0^* v_{2,t} + b_1^* v_{2,t-1} + b_2^* v_{2,t-2} + ... \\ x_t = c_0^* v_{1,t} + c_1^* v_{1,t-1} + c_2^* v_{1,t-2} ... + d_0^* v_{2,t} + d_1^* v_{2,t-1} + d_2^* v_{2,t-2} + ... \end{cases} \quad \text{(A12)}$$

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:

$$s_t = \alpha_0 v_{1,t} + \alpha_1 v_{1,t-1} + ... + \beta_0 v_{2,t} + \beta_1 v_{2,t-1} + ... \quad \text{(A13)}$$

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

$$\sigma_w^2 = [\Sigma_{i=0}^{\infty} a_i^* \quad \Sigma_{i=0}^{\infty} b_i^*] \operatorname{cov}(v) [\Sigma_{i=0}^{\infty} a_i^* \quad \Sigma_{i=0}^{\infty} b_i^*]' \quad \text{(A14)}$$

$$\sigma_s^2 = \Sigma_{j=0}^{\infty} [\alpha_j \quad \beta_j] \operatorname{cov}(v) [\alpha_j \quad \beta_j]' \quad \text{(A15)}$$

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.

**E. Probability of informed trading and arrival rate of informed and uninformed traders (Easley et al., 1996)**

We also estimate the model of Easley et al. (1996). The model allows us to have an estimate of the probability of informed trading (*PIN*) and of the arrival rates of informed and uninformed traders in the market.

The probability of informed trading, as derived by Easley et al. (1996) and in many modifications, has been widely used in different fields of financial economics. The model is akin to our theoretical benchmark, as it can be seen as an extension of Easley and O'Hara (1987). In a market for a single risky asset, a competitive market maker receives orders from informed and uninformed traders. The market game is repeated over *T* days. At the beginning of each day an information event occurs with probability $\alpha$; the event is good news with probability $(1-\delta)$ and bad news with probability $\delta$. Informed traders know whether the event is good or bad news; uninformed traders trade for liquidity reasons. Orders from informed and uninformed traders follow a Poisson process with daily intensity $\mu$ and $\varepsilon$, respectively. The probability of observing *B* buys and *S* sells on day *t*, conditional on the parameters of the model ($\Theta \equiv [\mu, \varepsilon, \beta, \delta]$), can be derived as:

$$\Pr[y_t = (B,S) \mid \Theta] = \alpha(1-\delta)e^{-(\mu+2\varepsilon)} \frac{(\mu-\varepsilon)^B \varepsilon^S}{B!S!} + \\ + \alpha\delta e^{-(\mu+2\varepsilon)} \frac{(\mu+\varepsilon)^S \varepsilon^B}{B!S!} + (1-\alpha)e^{-2\varepsilon} \frac{\varepsilon^{B+S}}{B!S!} \tag{A16}$$

where $y_t$ contains the number of buys and sells on day *t*.

By assuming that $\{y_t\}_{t=1}^T$ are i.i.d, the likelihood function can then be computed:

$$L[(B,S) \mid \Theta] = (1-\delta)e^{-(\varepsilon T)} \frac{(\varepsilon T)^B}{B!} e^{-(\varepsilon T)} \frac{(\varepsilon T)^S}{S!} + \\ + (\alpha\delta)e^{-(\varepsilon T)} \frac{(\varepsilon T)^B}{B!} e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^S}{S!} + \alpha(1-\delta)e^{-(\mu+\varepsilon)T} \frac{[(\mu+\varepsilon)T]^B}{B!} e^{-(\varepsilon T)} \frac{(\varepsilon T)^S}{S!} \tag{A17}$$

The probability of informed trading is defined as the ratio of the arrival rate of informed orders to the arrival rate of all orders:

$$PIN = \frac{\alpha\mu}{\alpha\mu + 2\varepsilon} \qquad \text{(A18)}$$

To estimate *PIN* and the parameters of the model, only the number of buys and sells in each day in the sample is needed.[5] As in the prior analyses we classify trades as buys or sells by comparing the transaction price to the preceding midquote.

Table A-VI reports the results of the estimation. First, we note that *PIN* decreases after the MTU change and the median decrease is significantly different from zero. The decrease in the probability of informed trading is an indication that the proportion of uninformed traders decreases. If retail traders' orders are uninformed, the decrease in *PIN* may be a piece of evidence in line with the conjectured increase in retail trading activity after the MTU reduction.

Insert Table A-VI here

Furthermore, we examine the parameters of *PIN*. Both $\mu$ (number of informed traders per day) and $\varepsilon$ (number of uninformed traders per day) increase. This is consistent with the increase in trading volume documented in Table III. However, only the increase in the number of uninformed traders is significantly different from zero. Because retail traders are likely to be uninformed, this result may further support the conjecture that retail trading increases after the MTU reduction.

We note that the results of the model of Easley et al. (1996) have to be taken with caution as we are not able to assess what portion of uninformed orders are originated from retailers and from institutional traders.

[5] We maximize the likelihood function numerically by using the NLMIXED procedure in SAS. The maximization converges for 44 stocks in both the *Pre* and *Post* periods; therefore, we report the results only for these 44 stocks in Table A-VI. We also repeated the analysis for the remaining 11 stocks by excluding, for each stock/period, the days with the minimum number of trades, until convergence is achieved. The results obtained using 55 stocks are untabulated; inference is unchanged.

## References

Anand, A., C. Tanggaard, and D. Weaver (2009). Paying for market quality. *Journal of Financial and Quantitative Analysis* 44, 1427-1457.

Beveridge, S., and C. Nelson (1981). A new approach to the decomposition of economic time series into permanent and transitory components with particular attention to the measurement of the business cycle. *Journal of Monetary Economics* 7, 151-174.

Hasbrouck, J., and G. Saar (2013). Low-latency trading. *Journal of Financial Markets* 16, 646-679.

**Table A-I: Association between cumulative abnormal returns and the liquidity improvement**
This table reports the results of the following model:

$$CAR_i = \beta_0 + \beta_1 \Delta_r L_i + \varepsilon_i$$

We regress cumulative abnormal returns, *CAR*, of each stock, *i*, on relative change (from *PRE* to *POST*) in the period-average daily level (obtained from intra-day observations) of the liquidity measures, $\Delta_r L$, i.e., $(L_{i,POST}-L_{i,PRE})/L_{i,PRE}$. Abnormal returns are estimated as the residuals from the market model; we take the 100 days before the MTU reduction as the estimation period. We use the FTSE MIB index to obtain the market return. *CARs* are defined as the sum of abnormal returns from 20 days before the event to 20 days after the event. The regression involves 55 observations. As measures of liquidity we use the quoted spread (*QS*) and the relative spread (*RS*). We report a *t*-test based on heteroskedasticity consistent standard errors (we use the Huber-White estimator of the variance-covariance). Reported coefficients are multiplied by 10. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | *QS* *Level 1* | *RS* *Level 1* | *RS* *Level 2* | *RS* *Level 3* | *RS* *Level 4* | *RS* *Level 5* |
|---|---|---|---|---|---|---|
| *Intercept* | 0.179 | -0.378* | -0.286 | -0.248 | -0.238 | -0.227 |
| | (0.881) | (-1.725) | (-1.532) | (-1.421) | (-1.405) | (-1.369) |
| $\Delta_r L$ | 0.159 | -0.385** | -0.480*** | -0.499*** | - 0.518*** | -0.532*** |
| | (1.151) | (-2.620) | (-2.789) | (-2.873) | (-2.928) | (-2.893) |
| $R^2$ | 0.021 | 0.136 | 0.165 | 0.174 | 0.182 | 0.186 |

**Table A-II: 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 (equation A5):

$$\begin{cases} L_{it} = \alpha + \sum_{k=1}^{20} (\beta_k Day_{it}^k) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \gamma_4 IL_{it} + \varepsilon_{it} \\ VLM_{it} = \delta + \sum_{k=1}^{20} (\kappa_k Day_{it}^k) + \phi_1 L_{it} + \phi_2 VLT_{it} + \phi_3 P_{it} + \phi_4 IVLM_{it} + \nu_{it} \end{cases}$$

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intra-day data) on dummy variables for the days in *Post* ($Day^k$ is equal to one for day *k* after the MTU reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 observations. We present a signed rank Wilcoxon test for the null hypothesis that the median coefficient of the 20 $Day^k$ dummy variables in the first equation is equal to zero.

Panel B reports the results of the following cross-sectional average model (equation A6). *POST* is a dummy variable for the *Post* period. We use one observation for each day, *t*, resulting in a total of 40 observations:

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

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

| | | **Panel A** | | **Panel B** | |
|---|---|---|---|---|---|
| | | *Median ( $\beta_k$ )* | *Wilcoxon-z* | $\beta_1$ | *t-stat* |
| *Level 1* | *Quoted spread* | -0.017 | -3.471*** | -0.018 | -3.281*** |
| *Level 1* | *Relative spread* | -0.002 | -3.919*** | -0.002 | -5.620*** |
| *Level 2* | *Relative spread* | -0.002 | -3.322*** | -0.003 | -3.659*** |
| *Level 3* | *Relative spread* | -0.002 | -2.762*** | -0.003 | -2.824*** |
| *Level 4* | *Relative spread* | -0.003 | -2.688*** | -0.003 | -2.517** |
| *Level 5* | *Relative spread* | -0.003 | -2.464** | -0.004 | -2.138** |

**Table A-III: High-low spread around the MTU change**

The table compares the cross-sectional average of the high-low spread (HL-Spread, calculated following Corwin and Schultz, 2012) in a 80-days window around the date of the MTU change. Specifically, individual stocks averages by periods are (equally weighted) averaged across all the stocks. The first row includes the 55 firms included in the main analysis. The second row extends the analysis to the 137 Italian firms with available data in DataStream. In the first two rows, *Pre* and *Post* refer to the 40 trading days before and after the MTU reduction (January 14, 2002), respectively. The third row reports the 10-year average (1996-2007, excluding the event year) of bid-ask spreads around the date of the MTU change (*Pre* and *Post* refer to the 40 trading days in each year before and after January 14, respectively); it includes the 30 firms which have complete data over 10 years. Reported levels of the high-low spread are multiplied by 10. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, based on Wilcoxon signed rank test.

| | *Sample* | *Pre* | *Post* | *Post-Pre* | *(Post-Pre)/Pre* |
|---|---|---|---|---|---|
| *HL Spread* | 55 firms | 0.127 | 0.114 | -0.013 | -0.102*** |
| *HL Spread* | 137 firms | 0.125 | 0.118 | -0.007 | -0.056*** |
| *10-year Avg. HL Spread* | 30 firms | 0.118 | 0.127 | 0.009 | 0.076 |

**Table A-IV: 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 MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. It is computed as the number of shares offered (or the corresponding Euro value) on the buy and on the sell side of the book. We analyze depth at the first 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*** | 0.384*** |
| *Level 2* | *Total # of shares* | 61,480 | 86,298 | 24,818*** | 0.434*** |
| *Level 3* | *Total # of shares* | 60,200 | 83,223 | 23,023*** | 0.407*** |
| *Level 4* | *Total # of shares* | 58,532 | 78,866 | 20,334*** | 0.359*** |
| *Level 5* | *Total # of shares* | 56,661 | 75,458 | 18,797*** | 0.328*** |
| *Level 1* | *Total Euro value* | 196,273 | 262,599 | 66,326*** | 0.417*** |
| *Level 2* | *Total Euro value* | 284,440 | 374,508 | 90,068*** | 0.470*** |
| *Level 3* | *Total Euro value* | 276,209 | 358,135 | 81,926*** | 0.438*** |
| *Level 4* | *Total Euro value* | 267,550 | 340,561 | 73,011*** | 0.380*** |
| *Level 5* | *Total Euro value* | 259,698 | 322,504 | 62,806*** | 0.346*** |
| *Cumulative (1-5)* | *Total # of shares* | 278,790 | 382,643 | 103,853*** | 0.378*** |
| *Cumulative (1-5)* | *Total Euro value* | 1,284,170 | 1,658,308 | 374,138*** | 0.406*** |

**Table A-V: Cost of executing a market order – Univariate analysis**

The table compares the cross-sectional average of daily (obtained as the daily average of intra-day observations) cost of executing market orders measures before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. The cost of a market order 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 cost of a market order that walks up the book, the difference is weighted on the quantities corresponding to the different trades. We also consider the cost of a market order as a proportion of the prevailing midquote. We compute the cost of a market order 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. Reported levels of the cost of executing a market order are multiplied by 10. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| *Order size (€ thousand divided by midquote)* | *Order direction* | *Pre* | *Post* | *Post-Pre* | *(Post-Pre)/Pre* |
|---|---|---|---|---|---|
| *5* | *Buy* | 0.129 | 0.117 | -0.012*** | -0.095*** |
| *5* | *Buy* | 0.135 | 0.121 | -0.014*** | -0.105*** |
| *5* | *Sell* | 0.015 | 0.014 | -0.001*** | 0.093*** |
| *5* | *Buy (mq)* | 0.016 | 0.014 | -0.002*** | -0.102*** |
| *5* | *Sell (mq)* | 0.157 | 0.140 | -0.017*** | -0.111*** |
| *10* | *Buy* | 0.165 | 0.146 | -0.019*** | -0.122*** |
| *10* | *Sell* | 0.019 | 0.016 | -0.003*** | -0.108*** |
| *10* | *Buy (mq)* | 0.019 | 0.016 | -0.003*** | -0.119*** |
| *10* | *Sell (mq)* | 0.213 | 0.183 | -0.030*** | -0.135*** |
| *20* | *Buy* | 0.226 | 0.199 | -0.027*** | -0.146*** |
| *20* | *Sell* | 0.025 | 0.021 | -0.004*** | -0.131*** |
| *20* | *Buy (mq)* | 0.025 | 0.021 | -0.004*** | -0.143*** |
| *20* | *Sell (mq)* | 0.259 | 0.220 | -0.039*** | -0.147*** |
| *30* | *Buy* | 0.272 | 0.242 | -0.030*** | -0.159*** |
| *30* | *Sell* | 0.030 | 0.025 | -0.005*** | -0.142*** |
| *30* | *Buy (mq)* | 0.031 | 0.026 | -0.005*** | -0.156*** |

**Table A-VI: *PIN* and arrival rate of informed and uninformed traders**

This table compares the average (across stocks) parameters of the Easley et al. (1996) model and the average (across stocks) probability of informed trading (*PIN*) in the *Pre* and *Post* periods. The model and the estimation procedure is described in Appendix E. $\alpha$ refers to the probability of an information event; $\delta$ is the probability that the event is bad news; $\varepsilon$ is the rate of arrival of uninformed orders; $\mu$ is the rate of arrival of informed orders. The table presents the results for the 44 stocks for which the maximization procedure converges in both periods. A Wilcoxon signed-rank test for the null hypothesis that the median change is zero is reported. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

| | *Pre* | *Post* | *Post-Pre* | *Wilcoxon-Z* |
|---|---|---|---|---|
| *PIN* | 0.183 | 0.157 | -0.027 | 2.182** |
| $\alpha$ | 0.487 | 0.452 | -0.035 | 0.870 |
| $\delta$ | 0.537 | 0.479 | -0.057 | 1.126 |
| $\varepsilon$ | 570.591 | 644.800 | 74.210 | -3.373*** |
| $\mu$ | 440.181 | 453.520 | 13.339 | -1.342 |