Financial Management

Lot Size Constraints and Market Quality: Evidence from the Borsa Italiana

Arie E. Gozluklu, Pietro Perotti, Barbara Rindi, and Roberta Fredella*

Trading venues often impose a minimum lot size (minimum trade unit [MTU]) to facilitate order execution. We document changes in market quality associated with the reduction of the MTU to one share on the Italian stock exchange, the Borsa Italiana. We observe a substantial improvement in liquidity, with an average decrease in the relative spread of 10.2%, and more significant improvements for those firms for which the MTU constraint was more binding. We also show that the improvement in liquidity is mainly driven by a reduction in adverse selection; that informational efficiency is not significantly affected; and there is an increase in retail trading. We interpret our findings in light of a model of asymmetric information in which the MTU affects traders' choice of order size.

The optimal choice of the minimum number of shares that investors can trade with a single transaction—the lot size or minimum trade unit (MTU)—significantly affects the trading strategies of market participants and hence it is a relevant issue in market design (Huberman and Stanzl, 2005; Obizhaeva and Wang, 2013). Managers of exchanges and other trading platforms aim to standardize trading lots, so that the MTU is set at a size that is homogenous across stocks with different prices.

The average trade size has significantly decreased over the past 10 years (Securities and Exchange Commission (SEC) release 34-61358, 2010; Angel, Harris, and Spatt, 2013; O'Hara, Yao, and Ye, 2014), but most of the exchanges around the world still implement a variation of MTU regulation (see Table I). Although an odd-lot facility is provided in the majority of the exchanges with MTU regulation, odd-lot trading is different in nature compared to trading in standard lot sizes and is often subject to different regulation.[1] Because odd-lot trading has increased substantially in the recent years (e.g., O'Hara et al., 2014), it is becoming even more relevant to understand how a reduction of the MTU affects market quality and, in particular,

We thank Luisella Bosetti, Francesco Corielli, Wilma de Groot, Luca Filippa, Thierry Foucault, Suk-Joon Kim, Enrico Mandelli, Vikas Raman, and Andrea Resti for helpful comments. We are grateful to Borsa Italiana and Carol Gresse (DRM Finance, Université Paris-Dauphine) for providing the data. We thank the editor (Marc Lipson) and an anonymous reviewer for valuable suggestions. We also benefited from the comments of participants at the 2010 Forecasting Financial Markets conference (Hannover), the 2010 AFFI-Eurofidai International Paris Finance Meeting, the 2011 SGF Annual Conference (Zurich), the 2011 EFMA Annual Meeting (Braga), the 2012 FMA Annual Meeting (Istanbul), and the 2013 EAA Annual Meeting (Paris). We acknowledge financial support from CAREFIN, Bocconi University.

**Arie E. Gozluklu is an Assistant Professor of Finance at the University of Warwick in Coventry, England. Pietro Perotti is a Lecturer in Accounting and Finance at the University of Bath in Bath, England. Barbara Rindi is an Associate Professor at Bocconi University in Milan, Italy. Roberta Fredella currently works for DeusTechnology.*

[1] For example, even though the Securities and Exchange Commission (SEC) recently changed the post-trade reporting policy regarding odd lots in the United States, they are still subject to different pre-trade transparency requirements (SEC, 2014). Moreover, budget-constrained retail traders who have access to popular high-price stocks only through odd-lot trading, have a limited set of hedging instruments.

Table I. MTU Regulation around the World

This table reports the minimum trade unit (MTU in number of shares) that is greater than one share across various exchanges around the world. The data are collected from the World Federation of Exchanges and the individual websites of the exchanges. We report the market capitalization of each exchange (in USD billion in 2013), classify the MTU as being either constant, function of the trade price, or determined by the firm. The last column shows whether the exchange provides odd-lot trading facility.

Exchange	Market Cap 2013 (USD Billions)	MTU (No. of Shares)			Odd Lot
		Constant	Function of Trade Price	By the Firm	
Panel A. Americas					
BM&F BOVESPA	1,020		Discretionary: 1-10-100-1,000		√
Mexican Exchange	5,260		100: $P <$ Ps\$200; 5: $P >$ Ps\$200		√
NASDAQ OMX Nordic Exchange	1,269	100			√
Indonesia SE	347	100			√
NYSE	17,950	100			√
TMX Group	2,114		1,000: $P <$ 0.10\$; 500: \$0.10 $< P <$ \$1; 100: $P >$ \$1		√
Panel B. Asia-Pacific					
Bursa Malaysia	500	100			√
Hong Kong Exchanges	3,101			X	√
Indonesia SE	347	100			√
Japan - Osaka	238			X	
Japan - Tokyo	4,543			X	
National Stock Exchange India	1,113		10,000: $P < 14$, 8,000: $14 < P < 18$, 6,000: $18 < P < 25$, 4,000: $25 < P < 35$		
Philippine SE	217		1,000,000: $0.0001 < P < 0.0099$, 100,000: $0.0100 < P < 0.0490$, 10,000: $0.0500 < P < 0.2490$ 100: $0.2500 < P < 0.4950$		Odd-lot mkt
Shanghai SE	2,497	100			
Shenzhen SE	1,452	100			
Singapore Exchange	744	100			√
Taiwan SE Corp.	823	1,000			Odd-lot mkt
Stock Exchange of Thailand	354		100 for $P <$ TBH500; 50 for $P >$ TBH500		√
Panel C. Europe–Africa–Middle East					
BME Spanish Exchanges	1,117	100			
Johannesburg SE	943	100			√
NASDAQ OMX Nordic Exchange	1,269	100			√
Tel Aviv SE	203		75: $P =$ NIS5,000; 25: $P =$ NIS2,000		Only pre-opening/closing phases

liquidity.[2] To our knowledge, no theoretical literature and scant empirical evidence has been provided so far on the effects of an exogenous change in the MTU on market quality.[3] In this paper we examine a change in the MTU design by taking advantage of a unique natural experiment at Borsa Italiana (BIt), where, in 2002, the MTU was reduced to one share for all stocks.

Relying on intraday data, we document a liquidity improvement after the removal of the MTU constraint. Notably, the relative spread at the first level of the book decreases on average by 10.2% following the MTU change. The results hold using a variety of empirical models that 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 also show that our findings are not attributable to changes in global liquidity. The results are also robust to controlling for a local liquidity trend and for seasonality. We also document an increase in market depth and a reduction in the cost of executing a market order of different sizes. In the main analysis we focus on a post-event window covering the first 20 days after the MTU change; in further checks we show that the liquidity improvement is also observed in three post-event windows of 20 days spanning from one to four months after the event.

Interestingly, our results are stronger for those firms that had the highest percentage of trades at the MTU before the removal of the constraint, indicating that the MTU change mostly affects those firms for which the constraint was more binding before 2002. Specifically, we rank firms into terciles based on the extent to which the constraint was binding. We find that firms in the top tercile—with the most binding constraint—experience, on average, a 14.4% decrease in the relative spread. On the other hand, firms belonging to the first tercile experience a much smaller reduction, 7.9%, in the relative spread.[4] More precisely, we find that one standard deviation increase in the percentage of trades at the MTU prior to the MTU reduction results in a 4% decrease of the relative spread after the change. Overall these results indicate a substantial reduction in trading costs due to the MTU change.

We interpret our results within the framework of a model with liquidity providers operating under asymmetric information and in which both informed and uninformed traders can submit orders of different sizes. The model allows us to compare two regimes, one with and one without an MTU. When the constraint is removed, those small liquidity traders who could not hedge their endowment shock in the regime with an MTU, can now perfectly hedge it and enter the market. The increased trading activity of these uninformed agents leads to a reduction in adverse selection costs, which induces liquidity providers to lower the spread.

While BIt does not publicly release data on the proportion of retail versus institutional trading volume, we collect four pieces of evidence suggesting that retail trading increased after the event. First, we examine trade size distributions around the event. We find that when comparing the distribution of trades in the different size brackets, only the distribution of the smallest trades (less than €2,000) significantly changes (and has a higher average) after the MTU reduction, with an overall increase in trading volume. This result indicates that an important driver of the change in volume is the increase in the number of the smallest trades, which are likely to be originated by retail traders. Second, we examine online trading volume, which was an important channel through

[2] There is also an ongoing debate on the optimal minimum quote size for US over-the-counter (OTC) markets, following in particular a recent change in regulation (FINRA Rule 6433). While the discussion is certainly related, our primary focus is on minimum trade size in exchange trading rather than in OTC markets.

[3] Sparse anecdotal evidence suggests that the removal of the MTU constraint is beneficial for liquidity. For example, Xetra (Deutsche Boerse Press Release, August 1, 2002) reports that the bid-ask spread decreased on average by 10% for the midcap stocks belonging to the MDAX index after the MTU constraint was removed in March 2002 for these stocks.

[4] The results are similar if we group the firms into two groups or quintiles.

which the most active retail traders sent orders to the market in 2002. According to proprietary data provided by BIt, the proportion of online trading volume increases by approximately 16% in a period of one month around the MTU change and this increase is more pronounced in a window of one year, reflecting a structural change in the market. Third, when we measure retail trading activity using the method of Barber, Odean, and Zhu (2009), we find that it increases significantly after the MTU change. Furthermore, a difference-in-differences test using a matched sample of French companies traded on Euronext Paris suggests that the increase in retail trading activity mainly concentrates around the firms with the most binding MTU constraint before the MTU reduction. Fourth, we investigate the cumulative price impact of orders. Prior literature (e.g., Kraus and Stoll, 1972; Chan and Lakonishok, 1993; Jones and Lipson, 2005) indicates that informed traders' orders have a higher permanent price impact than uninformed traders' orders. Consistent with the conjectured increase in retail trading after the MTU reduction, we find a significant decrease in the cumulative price impact of small orders. Finally, we note that the increase in small-size trading after the MTU change cannot be attributed to trade-splitting by algorithmic or more generally by high-frequency traders for the following reason. When BIt dropped the MTU to one share in 2002, while high-frequency trading was already widespread in the US market (Barber et al., 2009), there were no high-frequency traders connected to the Italian trading platform.[5]

An increase in retail trading is consistent with our results on adverse selection costs. In line with the model's predictions, after the MTU change we observe a decrease in adverse selection costs, measured both by the price impact of trades (Hendershott, Jones, and Menkveld, 2011) and by the adverse selection component of the spread (Glosten and Harris, 1988; Foster and Viswanathan, 1993).

The predictions of the model regarding informational efficiency depend crucially on the proportion of retail versus institutional traders active in the market. By using random walk tests and the standard Hasbrouck (1993) model, we find that informational efficiency is not substantially affected by the MTU change; therefore, we observe that even if firms benefit from both an improvement in liquidity and a reduction in adverse selection costs, presumably due to an increase in uninformed trading, informational efficiency does not deteriorate.

Two previous papers are closely related to our analysis. Amihud, Mendelson, and Uno (1999) study the voluntary reduction of the MTU at the Tokyo Stock Exchange and using daily data they find that it is associated with an increase in price, trading volume, and liquidity, measured by the Amihud illiquidity ratio. At the Tokyo Stock Exchange, however, any MTU change is decided by the listed firms and may be endogenously determined and act as a strategic signaling device. Our paper differs from Amihud et al. (1999) because the MTU change that we study is decided by BIt and therefore cannot be used strategically by firms to signal the company's value. Hauser and Lauterbach (2003), on the other hand, look at an exogenous MTU reduction at the Tel Aviv Stock Exchange, but concentrate solely on stock valuation and do not examine market liquidity. We differ from Hauser and Lauterbach (2003) as we study the effects of the MTU change on market quality rather than on the traders' valuation of the company.

The plan of the paper is as follows: Section I presents a theoretical benchmark to assess the effect of varying transaction-size design on market quality; Section II examines the effect of the MTU reduction on BIt; and Section III concludes. We provide an online Appendix to present derivations and further robustness checks.[6]

[5] The list of the operators connected to the Mercato Telematico Azionario (MTA) in 2001 and in 2002 (BIt, Facts and Figures 2001 and 2002) does not include any proprietary trading firm active on own account in high-frequency mode.

[6] Available at https://dl.dropboxusercontent.com/u/7276469/GPRF%20%28Online%20Appendix%29.pdf.

I. 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., Parlour, 1998; Foucalt, Kadan, and Kandel, 2005), or are not adequate to include the traders' choice between orders of different size (Rosu, 2009; Pagnotta, 2013). 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).[7]

A. The Model

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 Figure 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.[8]

To investigate the effects of different transaction-size regimes, we assume that liquidity traders have a mean variance objective equal to:

$$\max_{q} \; E[(q + I)\tilde{v} - qp] - \frac{\gamma}{2}(q + I)^2 VAR(\tilde{v}), \tag{1}$$

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:

$$q = \frac{\mathrm{E}(\tilde{\mathrm{v}}) - \mathrm{p}}{\gamma \mathrm{VAR}(\tilde{\mathrm{v}})} - I. \tag{2}$$

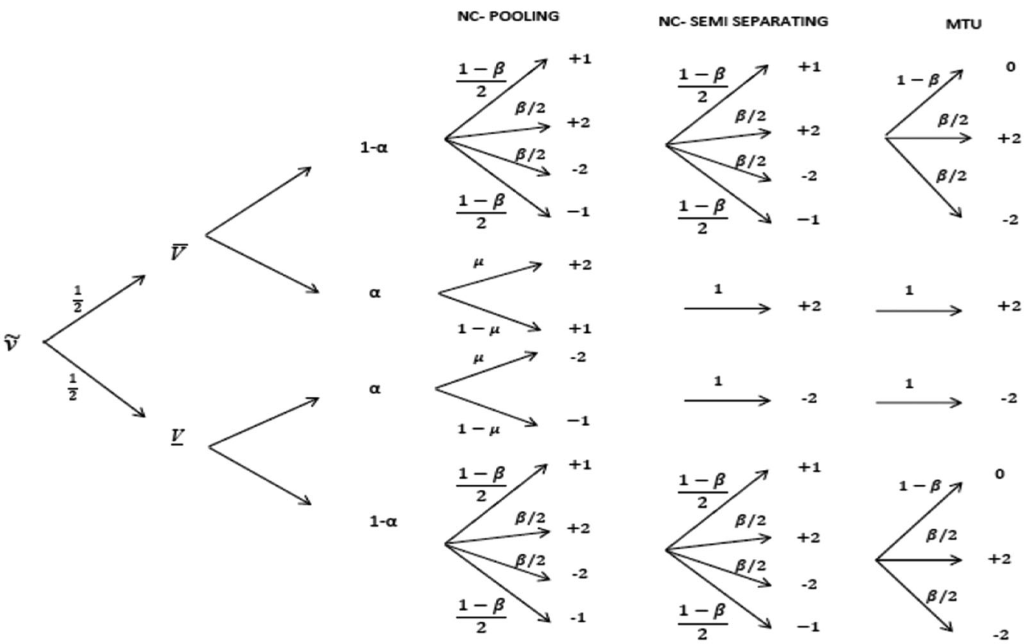
Assuming that liquidity traders are infinitely risk averse, that is, $\gamma \to \infty$, their trade is just the opposite of their inventory shock, $q = -I$. This is because they desire to fully share risk, whatever the price. Liquidity traders can have negative or positive inventory shocks with equal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

[7] 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—which could also be empty—would differ from those described by the Glosten and Milgrom (1985) protocol. If the removal of the MTU—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 toward 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.

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

Figure 1.

This extensive form of the game shows the probability of the trading process under NC (pooling and semiseparating equilibria) and minimum trade unit (MTU). α is the probability that a trader is informed, $(1-\alpha)$ the probability he/she is uninformed; β is the probability an uninformed trader trades large orders and $(1-\beta)$ the probability that he/she trades small orders; μ and $(1-\mu)$ are the probabilities that informed traders submits small or large orders, respectively.



In this framework we analyze two different market regimes (Figure 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 of two shares (MTU), under which market makers cannot quote prices for a quantity smaller than the MTU, and at the same time market participants cannot execute orders for a size smaller than the MTU. This is the regime prevailing before the MTU was reduced to one share in the Italian exchange; in the empirical analysis we compare this regime to the setting without a constraint.[9]

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.

[9] In the case considered, in the empirical analysis the MTU constraint is also the minimum quote unit.

If the proportion of informed agents is not too high relative to liquidity traders placing large orders, that is, $\beta \geq \frac{\alpha}{1-\alpha}$, 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.

$$A_1 = \frac{1}{2} \quad \text{and} \quad A_2 = \frac{\frac{1}{2}(1-\alpha)\beta + \alpha}{(1-\alpha)\beta + \alpha}. \tag{3,4}$$

Because 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, that is, if $\beta < \frac{\alpha}{1-\alpha}$, they trade small and large orders with probability $\bar{V}$ and $(1-\mu)$, respectively. As shown in Appendix A, in this context of pooling equilibrium the ask prices for one or two shares are:

$$A_1 = \frac{1}{2}[(1-\beta) + \alpha(1+\beta)] \quad \text{and} \quad A_2 = \frac{1}{4}[(3-\beta) + \alpha(1+\beta)]. \tag{5,6}$$

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.[10]

Now, let us consider the MTU 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 4). Under MTU, 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:

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

with the equality holding when insiders play pure strategies. Figures 2 and 3 show the respective ask prices for the equilibria with pooling and separation of agent types.

B. Empirical Implications

Building on the model's results, we can derive testable empirical predictions (see Appendix A for a formal derivation) for the effect of the natural experiment of BIt, which in 2002 moved the MTU down to one share for all the Italian stocks. This microstructure change is equivalent to switching from the MTU regime to the NC regime.

Prediction 1. *Liquidity increases after the MTU reduction.*

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

[10] 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 5) or two shares at a worse price, A_2 (Equation 6).

Figure 2. Pooling Equilibrium

The figure compares the ask prices (vertical axes) corresponding to the NC regime (A_1 and A_2) and to the minimum trade unit (MTU) regime (A_{QT}). Notice that a pooling equilibrium prevails for the parameter values that satisfy $\beta < \alpha/(1 - \alpha)$.

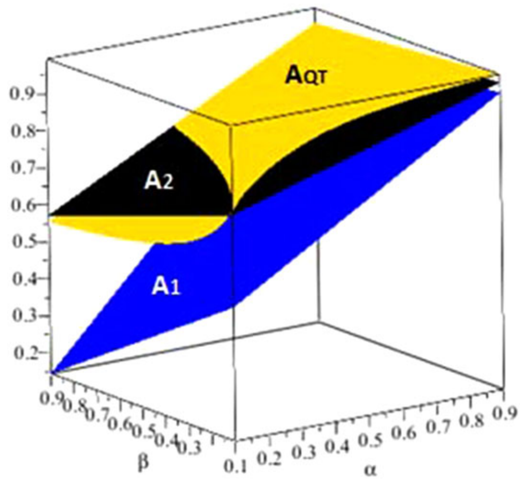


Figure 3. Semiseparating Equilibrium

The figure compares the ask prices (vertical axes) corresponding to the NC regime (A_1 and A_2), and to the minimum trade unit (MTU) regime (A_{QT}). Notice that a semiseparating equilibrium prevails for the parameter values that satisfy $\beta \geq \alpha/(1 - \alpha)$.

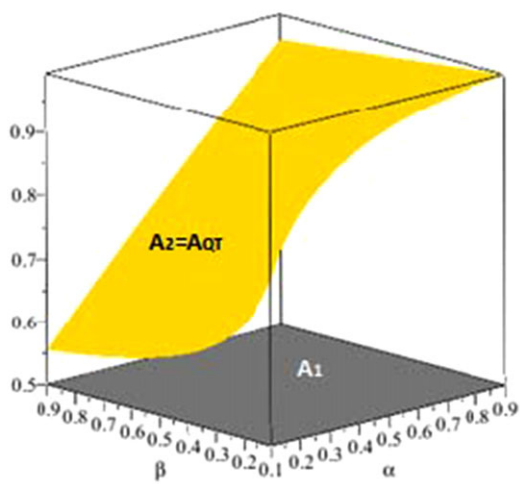
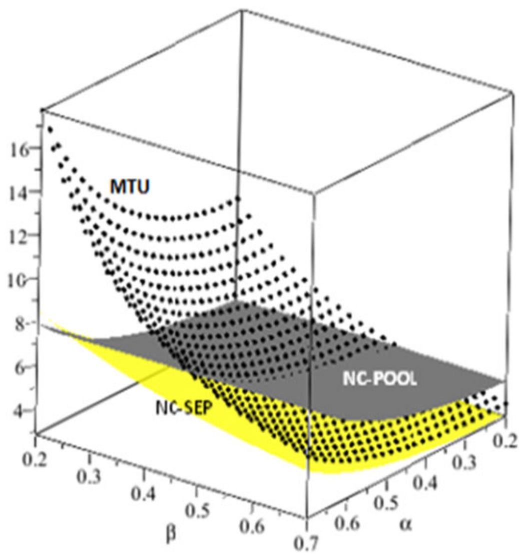


Figure 4. Informational Efficiency

The vertical axis presents informational efficiency (as defined in Appendix A) under the minimum trade unit (MTU) regime, the pooling NC regime (NC-POOL), and the separating NC regime (NC-SEP), respectively.



A direct implication of Prediction 1 is that those firms for which the MTU was more binding before the MTU reduction experience a larger increase in liquidity after the event.

Prediction 2. *Adverse selection costs decrease after the MTU reduction.*

The inside spread reflects adverse selection costs and it is the highest under the MTU regime (see also Figures 2 and 3) in which insiders trade only large orders and there are no small orders. Hence, we expect that adverse selection costs decrease when moving from the MTU to the NC regime.

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

In the model, informational efficiency is proxied by the inverse of the variance of the asset value conditional on the information available to all traders, that is, the size of the trades. Intuitively, this measure captures the ability of market participants to infer the asset value conditional on what they learn by observing the trading process. The degree of informational efficiency changes along two parameters of the model, namely it depends on α, that is, the probability of informed trading which affects the insiders' order submission strategy, and β, that is, the probability of large institutional trading (see Figure 4). Figure 4 shows that after the MTU 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 these parameter values for our sample of stocks, we infer the model prediction by testing the changes in our empirical proxies of informational efficiency.

Prediction 4. *Retail participation increases after the MTU reduction.*

In the model, when the MTU constraint is removed, small liquidity traders who could not hedge their endowment shock in the MTU regime can now perfectly hedge it and enter the market. Therefore, a direct implication of the model should be an increase in retail trading activity. In particular, we expect that those firms for which the MTU was more binding before the MTU reduction experience a larger increase in retail participation.

II. Empirical Analysis

A. Institutional Background and Sample Description

1. BIt Characteristics and Structure

BIt is the firm that is responsible for the organization and management of the Italian stock exchange.[11] It is now part of the London Stock Exchange Group following a merger that took place in 2007. At the end of 2001, 294 companies were listed on BIt, for a total market capitalization equal to €592,319 million. The capitalization was approximately equal to 48.5% of the Italian 2001 gross domestic product (GDP). In terms of capitalization, at the end of 2001, BIt was the fourth largest stock exchange in Europe. In our main analysis we focus on the stocks covering 83.3% of total capitalization. In the calendar year 2001, 44,225,201 trades took place, which correspond to a volume of €658,041.5 million; the daily average number of trades was equal to 175,497, corresponding to €2,611.3 million.

During the sample period and for the stocks considered, trading took place in the following phases: an opening call auction (8:00 a.m. to 9:30 a.m.), a continuous trading phase (9:30 a.m. to 5:25 p.m.), and a closing call auction (preclosing 5:25 p.m. to 5:35 p.m. and validation 5:35 p.m. to 5:40 p.m.). In the continuous trading phase, the market was organized as a pure LOB. If the price variation exceeded a given threshold, a stock could be suspended from the continuous auction and trading could resume in an intraday call auction; we remove observations from the intraday call auctions.

2. Microstructure Change

In the Italian exchange the MTU indicates the minimum number of shares that can be executed in one trade and the number of shares in one trade must be equal to a multiple of the MTU. On January 14, 2002, the MTU was reduced to one unit by the exchange for all stocks. The intention of the exchange officials was to make corporate actions easier to manage and to attract retail traders.[12] The MTU change was also one of the elements included in the "European market model," an agreement signed by the major European stock exchanges in May 2000 that aimed

[11] BIt was founded in 1997 following the privatization of the Italian stock exchange and it has been operational since January 2, 1998.

[12] We thank Luca Filippa, head of BIt research and development (R&D) department at the time of the MTU change, for this insight. It is also worth noticing that BIt did not decide to reduce the MTU in order to increase the revenue from fees. Because fees depended on euro volume, an increase in the number of trades due to greater order-splitting would not necessarily lead to greater revenues from fees.

to achieve greater cross-country consistency in trading rules. The previous policy of BIt was to revise the MTU periodically to standardize lots of different size.[13]

The MTU reduction is different from stock-splitting as it is defined in number of shares rather than affecting the nominal price. In our sample, there are no stock splits which may confound the results.[14]

3. Sample Description

We consider the stocks belonging to the MIB30 and MIDEX indices. At the time of the MTU reduction the MIB30 index included the 30 most capitalized and liquid stocks in the exchange. The MIDEX index included the following 25 stocks. Table II reports the stocks considered.

We compare different measures of market quality in the 20–trading day period before the reduction of the MTU (denoted by *Pre*) and in the 20–trading day period after (denoted by *Post*). The *Pre* period goes from December 10, 2001 to January 11, 2002. The *Post* period goes from January 15 to February 11, 2002.

We consider data during the continuous trading phase (9:30 a.m. to 5:00 p.m.). We exclude the last 30 minutes of trading to ensure that our results are not influenced by the introduction of a closing call auction in BIt. Specifically, a closing call auction was introduced on December 3, 2001, and Kandel, Rindi, and Bosetti (2012) find that the closing auction introduction affected liquidity only in the last minutes of the continuous auction.

Our main analysis is based on an intraday data set which includes quotes on the first five levels of the order book and trades. We received this data set from BIt. The main analysis covers 5,093,542 records for quotes and 4,598,780 records for trades.[15] We adjust prices for corporate actions that took place in the sample period.

For additional analyses we obtain daily data from DataStream and intraday data from Thomson Reuters Tick History.

B. Overview of the Empirical Analysis

The empirical analysis investigates the effects of the MTU reduction on the quality of the LOB. First, we concentrate on the bid-ask spread and base our analysis on a data set 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 relative bid-ask spreads both in a univariate and in a multivariate analysis, controlling for firm characteristics. We control for a possible global liquidity trend by using a matched-sample approach with a large international panel. Furthermore, we relate the variation in liquidity to the cross-sectional differences in the MTU constraint. The MTU constraint for each stock is measured by the ratio of the average number of trades at the MTU over the average number of trades executed in the *Pre* period for that stock. We also examine the long-term effect of the MTU change on liquidity by considering a period that goes from one to four months after the change. Next, we investigate

[13] In our sample, the MTU 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.

[14] Stock-splitting implies a reduction in the nominal price of the stock and hence an increase in relative tick size (nominal tick size divided by price). As the model in Werner et al. (2015) shows, an increase in relative tick size caused by a reduction in stock price may affect market quality by reducing quoted spread and increasing proportional spread. These predictions on stock splitting are confirmed by the empirical evidence documented in Schultz (2000), Lipson (2001), and more recently in Yao and Ye (2015).

[15] 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.

Table II. Data Set

The table presents the Italian stocks belonging to the MIB30 and MIDEX indices during our sample period. The fourth column shows the minimum trade unit (MTU) of each firm before the MTU reduction on January 14, 2002. The MTU constraint, in the last column, is measured by the ratio of the average number of trades at the MTU over the average number of trades executed in the *Pre* period spanning from December 10, 2001 to January 11, 2002.

Stock	Market Capitalization (Millions of Euros)	Index	MTU (Pre)	MTU Constraint
ACEA	1,687	MIDEX	100	0.30
AEM	4,032	MIB30	500	0.27
ALITALIA	1,638	MIDEX	1,000	0.46
ALLEANZA	8,384	MIB30	50	0.08
AUTOGRILL	2,575	MIDEX	50	0.12
AUTOSTRADA TO-MI	946	MIDEX	50	0.21
AUTOSTRADE	8,779	MIB30	100	0.11
BANCA DI ROMA	3,421	MIB30	125	0.10
BANCA FIDEURAM	7,501	MIB30	50	0.08
BANCA MONTE PASCHI SIENA	7,580	MIB30	250	0.11
BANCA NAZ LAVORO	5,331	MIB30	250	0.10
BANCA POPOLARE BERGAMO	2,395	MIDEX	50	0.16
BANCA POP. COMM. IND.	968	MIDEX	50	0.15
BANCA POPOLARE LODI	1,246	MIDEX	50	0.20
BANCA POPOLARE MILANO	1,506	MIDEX	100	0.14
BANCA POPOLARE NOVARA	1,617	MIDEX	250	0.23
BANCA POPOLARE VERONA	2,411	MIDEX	50	0.10
BENETTON GROUP	2,179	MIDEX	50	0.13
BENI STABILI	903	MIDEX	2,500	0.36
BIPOP-CARIRE	3,749	MIB30	250	0.15
BULGARI	2,772	MIB30	50	0.11
BUZZI UNICEM	983	MIDEX	250	0.39
CLASS EDITORI	356	MIDEX	50	0.11
CREDITO EMILIANO	1,472	MIDEX	100	0.23
ENEL	38,743	MIB30	125	0.09
ENI	52,536	MIB30	50	0.06
FIAT	6,815	MIB30	50	0.10
FINMECCANICA	8,222	MIB30	500	0.11
GENERALI	38,404	MIB30	25	0.06
HDP	2,428	MIB30	250	0.19
INTESABCI	15,935	MIB30	250	0.08
ITALCEMENTI	1,518	MIDEX	250	0.34
ITALGAS	3,485	MIB30	50	0.09
L'ESPRESSO (G.E.)	1,499	MIDEX	100	0.15
LA FONDIARIA	2,267	MIDEX	250	0.17
MEDIASET	9,875	MIB30	100	0.15
MEDIOBANCA	7,721	MIB30	50	0.06
MEDIOLANUM	7,272	MIB30	50	0.09
BANCA POPOLARE MILANO	1,149	MIDEX	500	0.29
MONDADORI EDITORE	1,859	MIDEX	100	0.19
OLIVETTI	9,779	MIB30	250	0.06

(Continued)

Table II. Data Set *(Continued)*

Stock	Market Capitalization (Millions of Euros)	Index	MTU (Pre)	MTU Constraint
PARMALAT FINANZIARIA	2,406	MIDEX	250	0.12
PIRELLI SPA	1,549	MIB30	250	0.11
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	0.22
SAN PAOLO IMI	17,289	MIB30	50	0.07
SEAT PAGINE GIALLE	10,536	MIB30	500	0.13
SNIA	744	MIDEX	1,000	0.44
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

adverse selection costs both by measuring the price impact of trades (Hendershott et al., 2011), and in the context of the Glosten and Harris (1988) and Foster and Viswanathan (1993) models. We then examine informational efficiency by both performing random walk tests and estimating the Hasbrouck (1993) model. Finally, we investigate retail trading activity around the MTU change. To this end, we follow four different empirical strategies, which focus on the distribution of trade size, the proportion of online trading, the proportion of buyer-initiated small trades (Barber et al., 2009), and the cumulative price impact of orders.

C. A First Glance at Trading Activity

Table III summarizes our measures of market activity.[16] First, we observe that the reduction of the MTU 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 MTU in the *Post* period (1.78% of trades are instead executed at the new MTU, i.e., one unit). This suggests that the MTU was binding for market participants willing to trade small amounts. As we discuss in more detail in Section II.1, these small trades are likely to originate from retail traders, who play a crucial role in the Italian equity market.[17] The average euro value of the MTU before the removal (€808, the greatest value being €2,177) was far smaller than the typical value of institutional traders' orders, worth at least €10,000 according to the BIt monitoring department; therefore, it is unlikely that trades at a size lower than the MTU originate from institutional traders.[18]

We note that the MTU varies substantially across firms. This allows us to test the cross-sectional differences on how the MTU reduction affects market quality. In line with our conjecture, we document a greater reduction in spreads for firms which were subject to a more binding MTU constraint.

[16] 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.

[17] BIt estimates that at the end of 1999 retail investors held more than 26% of total market capitalization (BIt Notes no. 2, 2001a and BIt Notes no. 3, 2001b).

[18] We thank Enrico Mandelli from BIt Trading Surveillance-Markets Supervision for providing us with this piece of information.

Table III. Trading Activity

The table presents cross-sectional averages of daily (obtained from intraday observations) trading activity summary measures before and after the reduction of the minimum trade unit (MTU). 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 MTU in the *Pre* period; the number of trades at one unit; the proportion of trades executed at the MTU; the proportion of trades in the *Post* period at a size less than the MTU in the *Pre* period; the number of trades with size greater than or equal to the MTU in the *Pre* period; the first order autocorrelation of the series (it is equal to +1 for a buy and –1 for a sell) of buyer- and seller-initiated trades; the price range (the difference between the highest and a lowest price in a day); the realized volatility. Number of trades, number of shares, and trading volume are in thousands.

	Pre	Post	Post-Pre	Wilcoxon-z
Number of trades	1.492	1.730	0.238	4.423***
Number of shares traded	5,519	5,887	368	3.854***
Trading volume	25,083	28,735	3,652	3.276***
Price	8.280	8.282	0.002	0.242
Number of trades at MTU	0.166	0.057	–0.109	–6.317***
Number of trades at one unit	—	0.024	—	—
Proportion of trades at MTU	0.162	0.178	–0.144	–6.451***
Proportion of trades at size < MTU	—	0.169	—	—
Number of trades at size ≥ MTU	1.492	1.498	0.006	0.570
Autocorrelation buy/sell	0.502	0.523	0.021	3.628***
Price range	0.209	0.192	–0.017	–3.762***
Realized volatility	0.032	0.028	–0.004	–5.312***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

We find a significant increase in the number of trades (by 15.95%) and trading volume (by 14.56%) after the event. The increase in the number of trades and trading volume without a significant change in prices is consistent with the prediction of greater participation of traders after the microstructure change. We also find a significant increase in the autocorrelation of the series of buy/sell trades (by 4.13%). This might either suggest an increase in trend-chasing behavior or an increase in the number of orders that walk up the book.

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 et al. (2003), we compute the realized volatility as the standard deviation of the midquote under the hypothesis that prices follow a Brownian motion.[19]

Finally, as mentioned earlier, the univariate tests indicate that the removal of the MTU does not have a significant effect on the average price of the stocks. We also examine the cumulative abnormal returns (CARs) around the event. CARs are defined as the sum of abnormal returns from 20 days before the event to 20 days after the event. These tests are described and reported in Appendix B. The results show that CARs are positively associated with the liquidity improvement,

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

Table IV. Bid-Ask Spread—Univariate Tests

Panel A of the table presents the cross-sectional average of the daily (obtained as the daily average of intraday observations) bid-ask spread at the five levels of the book before and after the reduction of the minimum trade unit (MTU). Specifically, individual stocks averages by periods are averaged across all the stocks. The Relative 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 intraday observations) bid-ask spread at the first level of the book in the *Pre* period and in the 20-day period before, that is, *Pre1* period which goes from November 12 to December 7, 2001. Reported levels of the bid-ask spread are multiplied by 10.

Panel A

		Pre	Post	Post-Pre	(Post-Pre)/Pre
Level 1	*Quoted spread*	0.202	0.178	−0.024***	−0.104***
Level 1	*Relative spread*	0.024	0.022	−0.002***	−0.102***
Level 2	*Relative spread*	0.059	0.055	−0.004***	−0.062***
Level 3	*Relative spread*	0.093	0.089	−0.004***	−0.052***
Level 4	*Relative spread*	0.128	0.122	−0.006***	−0.049***
Level 5	*Relative spread*	0.163	0.156	−0.007***	−0.045***

Panel B

		Pre1	Pre	Pre-Pre1	(Pre-Pre1)/Pre1
Level 1	*Quoted spread*	0.206	0.202	−0.004	0.021
Level 1	*Relative spread*	0.024	0.024	0.000	0.010

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

consistent 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). These findings suggest that although on average prices do not change after the MTU change, the MTU reduction does have an effect on valuation: the higher the liquidity improvement after the MTU change the higher the returns. This is coherent with prior evidence on the effects of MTU changes (Amihud et al., 1999; Hauser and Lauterbach, 2003).

D. Liquidity

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

The analysis takes daily averages (obtained from intraday data) of the liquidity measures as input. The measures are obtained from the snapshot of the LOB; 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.

Panel A of Table IV presents descriptive statistics for our liquidity measures. We compute a Wilcoxon signed rank test for the null hypothesis that the cross-sectional median change after the reduction of the MTU is equal to zero. Liquidity for small trades is measured by the difference between the best ask and the best bid prices, which corresponds to the bid-ask spread at the first level of the book; 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 highlight an increase in liquidity for all trade sizes. Notably, the relative spread on the first level of the book decreases on average by 10.2%, which indicates a substantial reduction in trading costs.

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 IV: the median difference in the spread measures is not significantly different from zero. This result suggests that the improvement in liquidity after the MTU reduction cannot be attributed to a secular local market trend.

1. 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 the two following specifications:

(a) First, we consider the *Pre* to *Post* change in the period-average (*Pre* or *Post*) daily level of the liquidity measures, L, of each stock, i, with daily averages obtained from intraday observations. We regress this variable on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), VLM, the change 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 change in the period-average daily transaction prices, P (the average transaction price in a day):[20]

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \varepsilon_i. \tag{8}$$

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

The results are presented in panel A of Table V. 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.

(a) Because the MTU reduction happens for all the stocks at the same time, the error terms in Equation (8) might be cross-correlated. This would not affect the consistency of the ordinary

[20] We also repeated the analysis using the relative price range, that is, the price range standardized by average transaction price. The results are unchanged.

Table V. Bid-Ask Spread—Multivariate Analysis

Panel A reports the results of Model (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 change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of the liquidity measures, L, of each stock, i, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), VLM, the change 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 change 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 Model (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 intraday data) on dummy variables for the days in *Post* (Day^k is equal to one for day k after the minimum trade reduction (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 of the 20 Day^kdummy variables is equal to zero. Reported coefficients are multiplied by 10.

		Panel A		*Panel B*	
		w	***t*-stat**	**Median (β_k)**	**Wilcoxon-*z***
Level 1	*Quoted spread*	−0.028	−5.864***	−0.019	−3.583***
Level 1	*Relative spread*	−0.003	−6.481***	−0.003	−3.919***
Level 2	*Relative spread*	−0.004	−4.550***	−0.003	−3.658***
Level 3	*Relative spread*	−0.005	−3.776***	−0.004	−3.397***
Level 4	*Relative spread*	−0.006	−3.625***	−0.006	−3.322***
Level 5	*Relative spread*	−0.007	−3.408***	−0.007	−3.247***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

least squares (OLS) coefficients but would imply the standard errors to be biased. Therefore, we check the stability of the results by considering the following specification:

$$L_{it} = \alpha + \sum_{k=1}^{20} \left(\beta_k Day_{it}^k\right) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \varepsilon_{it}. \tag{9}$$

We here regress daily (t refers to the day considered) liquidity measures (obtained, as before, from intraday data) on dummy variables for the days in *Post* (Day^k is equal to one for day k after the MTU change l and 0 otherwise), and on trading volume, price volatility, and transaction price. We estimate the model using all the days in the *Pre* and *Post* periods and we focus on the 20 coefficients of the postevent dummies. To assess their statistical significance, we use a Wilcoxon signed rank test to test the hypothesis that the median across the 20 coefficients is equal to zero.[21] The regression involves 2,198 observations corresponding to 55 stocks over 40 days.

The estimation results of Equation (9) are presented in panel B of Table V. The median of the dummy coefficients is negative and it is significantly different from zero for all the liquidity measures, confirming the results of Equation (8).[22] Moreover, the magnitude of the median liquidity improvement (indicated by the median of the dummy coefficients) is again comparable to the univariate results.

We finally run a sensitivity analysis on liquidity. Following Boehmer et al. (2005), we test alternative specifications addressing potential problems due to endogeneity and to correlated error terms; the results are similar to those from our main analysis. Furthermore, using an alternative low-frequency spread measure suggested by Corwin and Schultz (2012), we show that our results are robust to controlling for seasonality effects and to extending the sample to all the stocks for which daily data are available. All these robustness checks are described and reported in Appendix C.

2. Control for a Global Liquidity Trend

One could argue that the reduction in spreads may coincide with a global liquidity trend. To alleviate this concern, we conduct a matching sample analysis following Davies and Kim (2009). In particular, using a large panel of 15 countries, 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 relative spread of each matched stock from each individual country.[23] 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:

$$\arg\min_{j_c \in F_c} \sum_k \left(\left(2\left(x_i^k - x_{j_c}^k\right)\right)/\left(x_i^k + x_{j_c}^k\right)\right)^2, \tag{10}$$

where x_i^k is the stock characteristic *k*, that is, 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:

$$L_i^G = \frac{1}{15} \sum_{c=1}^{15} L_{j_c}, \ \forall\, i \in F_I, \tag{11}$$

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

[21] 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 Boehmer et al., 2005).

[22] We also estimated Specification (9) including firm fixed effects. The results, untabulated, are virtually unchanged.

[23] The number of countries is limited by data availability, that is, closing bid and ask prices, in DataStream. The sample includes Australia, Denmark, Finland, France, Germany, Greece, Hong Kong, Japan, the Netherlands, Norway, Spain, Sweden, Switzerland, United Kingdom, and United States. US closing prices are obtained from Trade and Quote (TAQ) intraday data.

Table VI. Bid-Ask Spread—Global Liquidity Trend

Panel A reports the results of Model (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 change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of the liquidity measures, *L*, of each stock, *i*, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), *VLM*, the change 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 change in the period-average daily transaction price (the average transaction price in a day), *P*, and the change in the global liquidity measure defined in Equation (11). 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 Model (8′):

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

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intraday data) on dummy variables for the days in *Post* (Day^k is equal to one for day *k* after the minimum trade unit (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 is equal to zero. Reported coefficients are multiplied by 10.

		Panel A		*Panel B*	
		β_0	***t*-stat**	**Median (β_k)**	**Wilcoxon-*z***
Level 1	*Relative spread (no global trend)*	−0.003	−3.019***	−0.003	−2.911***
Level 1	*Relative spread (with global trend)*	−0.002	−2.229***	−0.003	−2.949***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

We then repeat the previous analysis in Equations (8) and (9) using the closing relative spreads and controlling for the global liquidity variable:

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 \Delta L_i^G + \varepsilon_i, \tag{8′}$$

$$L_{it} = \alpha + \sum_{k=1}^{20} \left(\beta_k Day_{it}^k\right) + \gamma_1 VLM_{it} + \gamma_2 VLT_{it} + \gamma_3 P_{it} + \gamma_4 L_{it}^G + \varepsilon_{it}. \tag{9′}$$

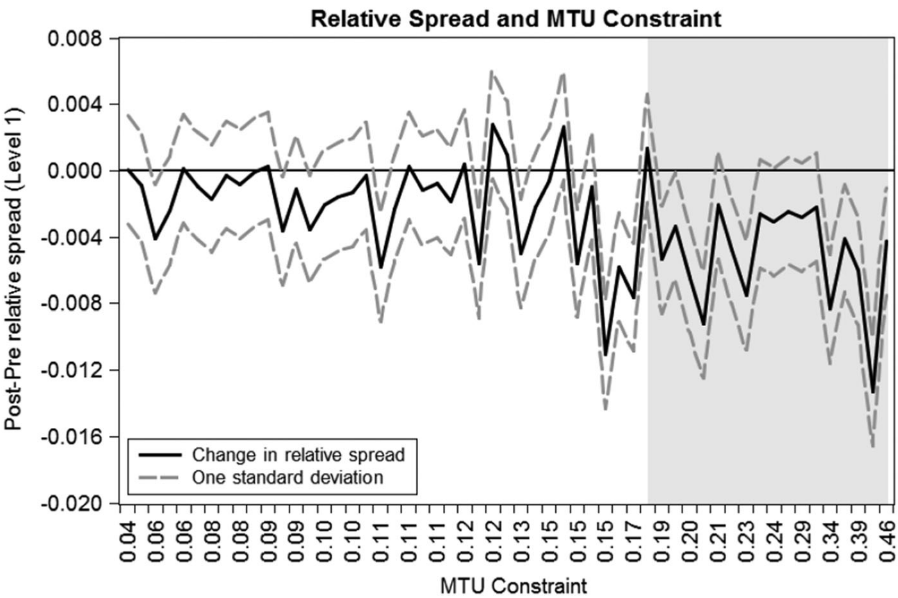
The results are reported in Table VI. We report the coefficients for both specifications with and without the global liquidity trend. Note that unlike Equations (8) and (9), which include the time-weighted spreads on the left-hand side of the equation, Equations (8′) and (9′) test the effect on the daily closing spreads.[24] Controlling for the global liquidity trend does not have a major impact on spreads as the coefficients and their significance remain virtually unchanged.[25]

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

[25] As a robustness check, we also collected TAQ data for the S&P500 companies and conducted a matched-sample analysis. We find that our results are robust to the inclusion of this control sample.

Figure 5. Liquidity and MTU Constraint

This figure plots the Post-Pre difference in first-level relative spread. The *x*-axis shows the minimum trade unit (MTU) constraint for each firm, which is measured as the average number the trades at the MTU over the average number of trades in the Pre period. The solid black line shows the Post-Pre change in relative 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 MTU constraint is most binding. Reported level of the relative spread is multiplied by 10.



3. MTU Constraint and Liquidity Improvement

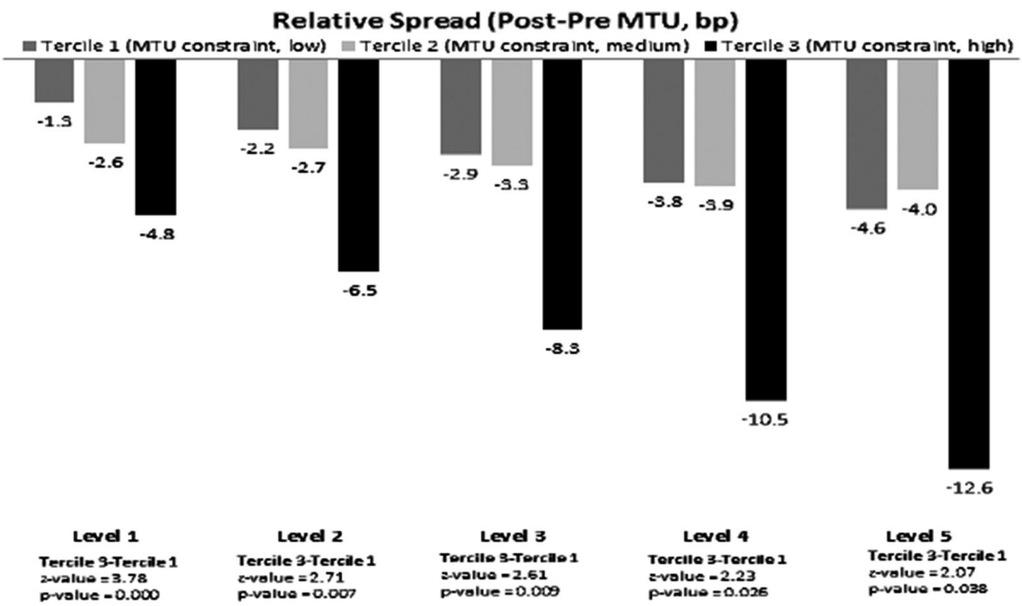
Our time-series analysis focuses on the average changes in liquidity around the MTU reduction. Here, we also look at the cross-sectional implications of the MTU change. In particular, we test whether firms for which the MTU constraint was more binding before the MTU reduction face larger differences in liquidity after the removal. We sort firms by the severity of the MTU constraint prior to the change, which is captured by the ratio of the average number of trades at the MTU over the average number of trades executed in the *Pre* period.[26] One would expect that firms with a more binding constraint witness a higher reduction in spreads. Accordingly, in Figure 5, where we plot the *Post*-*Pre* difference in the relative spread against the MTU constraint, we note that the reduction is much larger as the MTU constraint becomes more binding.

Hence, we group the firms into three terciles based on the MTU constraint and compare the reduction in relative spreads. Figure 6 shows that the firms in the first tercile, that is, with the least binding MTU constraint, benefit from a reduction of 1.3 bp in spreads, while the spreads for firms in the third tercile, with the most binding MTU constraint, reduce by 4.8 bp. The latter amounts to a 14.4% decrease in the relative spread after the MTU reduction. The difference

[26] We repeat the same analysis with the euro-value of the trades and we obtain similar results.

Figure 6. Cross-Sectional Differences in the Bid–Ask Spread

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



between Tercile 3 and Tercile 1 is highly significant (at the 1% level), with a Wilcoxon z-value equal to 3.78. We obtain similar results when we extend the analysis using the relative spread at different levels of the book.

Next, we test the role of the MTU constraint on the change in liquidity in a multivariate setting. Specifically, we control for the MTU constraint in Equation (8) and we include additional firm characteristics:market-to-book (MB) ratio, leverage (debt/asset ratio), and dividend yield measured at the end of 2001 (we refer to these additional control variables as *cnt* in the following equation).

$$\Delta L_i = \beta_0 + \beta_1 \Delta VLM_i + \beta_2 \Delta VLT_i + \beta_3 \Delta P_i + \beta_4 MTU_i + \beta_5 cnt_i + \varepsilon_i. \qquad (8'')$$

We report the results in Table VII. Panel A shows the estimates of the intercept, β_0, and of the coefficient of MTU, β_4, while restricting the vector $\beta_5 = [0, 0, 0]$.[27] We measure the changes in liquidity by the relative spread at different levels of the book. Because we now analyze the

[27] For the interpretation of our results, we report only the intercept and the coefficient on the MTU to save space.

Table VII. Bid-Ask Spread—MTU Constraint and Liquidity Improvement

Panel A reports the results of Model (7″):

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

Panel B reports the results of Model (7″) with additional firm characteristics (referred to as *cnt* in the following equation), market to book ratio (MB), leverage (debt to asset ratio), and dividend yield as of end of November 2001.

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

We regress the change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of the liquidity measures, *L*, of each stock, *i*, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), *VLM*, the change in the period-average daily volatility (measured by the price range, that is, the difference between the highest and the lowest transaction price in a day), *VLT*, the change in the period-average daily transaction price (the average transaction price in a day), *P*, and the minimum trade unit (MTU) constraint, *MTU*, measured as the number of trades at the MTU 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). Reported coefficients are multiplied by 10.

		β_0	*t*-stat	β_4	*t*-stat
		Panel A			
Level 1	*Relative spread*	0.000	0.040	−0.017	−3.653***
Level 2	*Relative spread*	0.000	0.466	−0.026	−3.633***
Level 3	*Relative spread*	0.001	0.527	−0.034	−3.749***
Level 4	*Relative spread*	0.001	0.449	−0.042	−3.573***
Level 5	*Relative spread*	0.002	0.498	−0.051	−3.514***
		Panel B			
Level 1	*Relative spread*	−0.000	−0.262	−0.017	−3.589***
Level 2	*Relative spread*	−0.000	−0.082	−0.025	−3.502***
Level 3	*Relative spread*	−0.000	−0.094	−0.032	−3.515***
Level 4	*Relative spread*	−0.001	−0.261	−0.039	−3.260***
Level 5	*Relative spread*	−0.002	−0.320	−0.047	−3.210***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

cross-sectional implications of the MTU reduction, we focus on the relative spread, which is a better measure for comparison across stocks. We observe that the improvement in liquidity is mainly explained by the cross-sectional differences in the MTU constraint, as reflected in the high significance of the β_4 estimates. This result is in line with the evidence provided in Figure 6. In panel B we control for additional firm characteristics, and the results are robust to these additional controls. This cross-sectional evidence further confirms that consistent with the main prediction of the model, the reduction in spreads is due to the MTU change.

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

Table VIII. Bid-Ask Spread—MTU Constraint (Based on Value) and Liquidity Improvement

Panel A reports the results of model (7′′) modified using *MTUV*:

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

Panel B reports the results of model (7′′) with additional firm characteristics (referred to as *cnt* vector in the following equation), market-to-book ratio (MB), leverage (debt-to-asset ratio), and dividend yield as of end of November 2001.

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

We regress the change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of the liquidity measures, *L*, of each stock, *i*, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), *VLM*, the change 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 change in the period-average daily transaction price (the average transaction price in a day), *P*, and the minimum trade unit (MTU) constraint (based on value), *MTUV*, measured as the MTU (number of shares) times average stock price in the *Pre* period (normalized by 1/10,000). 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). Reported coefficients are multiplied by 10.

		β_0	*t*-stat	β_4	*t*-stat
		Panel A			
Level 1	*Relative spread*	0.000	−1.067	−0.025	−2.466**
Level 2	*Relative spread*	0.000	−0.497	−0.036	−2.191**
Level 3	*Relative spread*	0.000	−0.372	−0.046	−2.008**
Level 4	*Relative spread*	0.000	−0.302	−0.060	−1.976*
Level 5	*Relative spread*	0.000	−0.168	−0.077	−1.996*
		Panel B			
Level 1	*Relative spread*	−0.002	−1.221	−0.024	−2.243**
Level 2	*Relative spread*	−0.002	−0.827	−0.036	−2.119**
Level 3	*Relative spread*	−0.003	−0.762	−0.046	−2.017**
Level 4	*Relative spread*	−0.004	−0.834	−0.059	−2.023**
Level 5	*Relative spread*	−0.004	−0.796	−0.076	−2.096**

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

E. Long-Term Effect of the MTU Change on Liquidity

In the main analysis we examine a period of 20 trading days after the MTU reduction to investigate the effects of the microstructure change. We choose a short period of time to minimize the probability that the results are contaminated by concurrent confounding effects.

In this section, we investigate whether the effects of the MTU reduction persist. To do this, we examine three further periods after the *Post* period, spanning from one to four months after the event. We consider three periods of 20 trading days as follows: *Post1* covers the 20 trading days starting one month after the MTU change (February 15 to March 14, 2002); *Post2* covers the 20 trading days starting two months after the MTU change (March 15 to April 16, 2002);

Post3 covers the 20 trading days starting three months after the MTU change (April 15 to May 13, 2002).

For this extension of the main analysis, we use data from Thomson Reuters Tick History. From this database, we obtain tick-by-tick updates on the quotes on the first five levels of the book and on transactions (price, quantity). We also check the consistency of the data with those provided by BIt; in the overlapping periods, the data common to both databases are virtually identical.

We replicate both the univariate analysis and the multivariate analysis (which were presented in Section II.D) comparing the *Pre* period to the *Post1*, *Post2*, and *Post3* periods. The results are reported in Tables IX and X. Both sets of results clearly show that the decrease in the bid-ask spread is sustained in the further periods examined. At all five levels and in all three periods after *Post*, there is a significant decrease in the spread. In the *Post1* period, that is, between one and two months after the MTU change, the improvement in liquidity is similar to that observed in the *Post* period. In the *Post2* period, that is, between two and three months after the MTU change, the improvement in liquidity is higher than in the *Post1* period. In the *Post3* period, that is, between three and four months after the MTU change, the improvement in liquidity is lower in magnitude than in the other periods considered; however, the change in the bid-ask spread is highly significant.

Overall, these results suggest that the improvement in liquidity after the MTU reduction is structural. The spread decrease is sustained up to four months after the microstructure change; this brings further support to the interpretation that the MTU reduction is beneficial for market participants.

F. Other Dimensions of Liquidity: Book Depth and Measures of Execution Costs Based on Effective Spread

So far we have focused on only one dimension of liquidity, namely the bid-ask spread at different book levels. The bid-ask spread measures the tightness of the book. A complementary aspect of liquidity is depth (e.g., Kyle, 1985; Harris, 2003). In this section, we first examine the amounts offered, which indicate how deep the book is; next, we investigate the cost of executing a market order, which reflects both the tightness and the depth of the book.

1. Book Depth

We repeat the previous analysis using book depth, measured as the number of shares offered (or the corresponding euro value) at each of the first five levels of the book.[28] In addition, we compute cumulative depth as the sum of shares available at all the five book levels.

The univariate and multivariate results obtained using market depth are reported in Table A-IV (Appendix) and Table XI, respectively. The results show that market depth increases at all book levels, which reflects higher participation and liquidity provision to the LOB. Evidence on reduced spreads together with increased market depth at the top levels of the book suggest that the entrance of the new liquidity tradersmight have triggered competition among existing liquidity traders and resultin aggressive liquidity provision after the MTU change.

These results further confirm the first empirical prediction of our model that liquidity increases after the reduction of the MTU.

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

Table IX. Long-Term Effect of the MTU Change on Liquidity—Univariate Analysis

This table reports the effect of the minimum trade unit (MTU) change on liquidity. We compare the *Pre* period to three periods after the *Post* period. *Post1* covers the 20 trading days starting one month after the MTU change (February 15 to March 14, 2002); *Post2* covers the 20 trading days starting two months after the MTU change (March 15 to April 16, 2002); *Post3* covers the 20 trading days starting three months after the MTU change (April 15 to May 13, 2002). We compare the cross-sectional average of the daily (obtained as the daily average of intraday observations) bid-ask spread at the five levels of the book before and after the reduction of the MTU. Specifically, individual stocks averages by periods are averaged across all the stocks. The Relative 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. Reported levels of the bid-ask spread are multiplied by 10.

		Pre	**Post1**	**Post1-Pre**	**(Post1-Pre)/Pre**
Level 1	*Quoted spread*	0.202	0.168	−0.035***	−0.121***
Level 1	*Relative spread*	0.024	0.021	−0.003***	−0.123***
Level 2	*Relative spread*	0.059	0.054	−0.005***	−0.082***
Level 3	*Relative spread*	0.093	0.087	−0.006***	−0.069***
Level 4	*Relative spread*	0.128	0.120	−0.008***	−0.061***
Level 5	*Relative spread*	0.163	0.154	−0.009***	−0.055**
		Pre	**Post2**	**Post2-Pre**	**(Post2-Pre)/Pre**
Level 1	*Quoted spread*	0.202	0.159	−0.043***	−0.117***
Level 1	*Relative spread*	0.024	0.020	−0.005***	−0.170***
Level 2	*Relative spread*	0.059	0.052	−0.007***	−0.119***
Level 3	*Relative spread*	0.093	0.084	−0.009***	−0.103***
Level 4	*Relative spread*	0.128	0.116	−0.012***	−0.097***
Level 5	*Relative spread*	0.163	0.149	−0.014***	−0.093***
		Pre	**Post3**	**Post3-Pre**	**(Post3-Pre)/Pre**
Level 1	*Quoted spread*	0.202	0.172	−0.030***	−0.007***
Level 1	*Relative spread*	0.024	0.021	−0.003***	−0.123***
Level 2	*Relative spread*	0.059	0.054	−0.005***	−0.085***
Level 3	*Relative spread*	0.093	0.086	−0.007***	−0.073***
Level 4	*Relative spread*	0.128	0.119	−0.009***	−0.067***
Level 5	*Relative spread*	0.163	0.152	−0.011***	−0.063**

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

2. Cost of Executing a Market Order of Different Sizes

We calculate the cost of executing a market order as the absolute difference between the ask (for buy orders) or the bid price (for sell orders) and the midquote corresponding to the trade. The estimation approach is similar to that used by Griffiths et al. (2000). In computing the cost of a market order that walks up the book, the difference is weighted by the quantities corresponding to the different trades executed.[29] We also consider the cost of market orders as a proportion of

[29] For example, assume that the best bid is equal to €13, the best ask is equal to €15 (with 100 shares offered) and the ask on the second level of the book is equal to €17 (with 200 shares offered). Suppose that one has to compute the cost of a market buy order of 300 shares. The order hits the best ask and gets partial execution, the rest being then executed

Table X. Long-Term Effect of the MTU Change on Liquidity—Multivariate Analysis

This table reports the effect of the minimum trade unit (MTU) change on liquidity. We compare the *Pre* period to three periods after the *Post* period. *Post1* covers the 20 trading days starting one month after the MTU change (February 15−March 14, 2002); *Post2* covers the 20 trading days starting two months after the MTU change (March 15–April 16, 2002); *Post3* covers the 20 trading days starting three months after the MTU change (April 15–May 13, 2002). Panel A reports the results of Model (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 change (from *Pre* to *Post1 or Post2 or Post3*) in the period-average daily level (obtained from intraday observations) of the liquidity measures, *L*, of each stock, *i*, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), *VLM*, the change 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 change 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 Model (8):

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

We regress daily values (*t* refers to the day considered) of the liquidity measures (obtained, as before, from intraday data) on dummy variables for the days in *Post1 or Post2 or Post3* (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 of the 20 Day^k dummy variables is equal to zero. Reported coefficients are multiplied by 10.

			Panel A		*Panel B*	
			β_0	*t*-stat	Median (β_4)	Wilcoxon-*z*
Pre vs. Post1	*Level 1*	*Quoted spread*	−0.038	−4.157***	−0.037	−3.733***
Pre vs. Post1	*Level 1*	*Relative spread*	−0.003	−6.080***	−0.003	−3.882***
Pre vs. Post1	*Level 2*	*Relative spread*	−0.005	−4.310***	−0.004	−3.882***
Pre vs. Post1	*Level 3*	*Relative spread*	−0.006	−3.364***	−0.005	−3.770***
Pre vs. Post1	*Level 4*	*Relative spread*	−0.008	−2.815***	−0.006	−3.621***
Pre vs. Post1	*Level 5*	*Relative spread*	−0.009	−2.437**	−0.007	−3.397***
Pre vs. Post2	*Level 1*	*Quoted spread*	−0.052	−3.706***	−0.054	−3.919***
Pre vs. Post2	*Level 1*	*Relative spread*	−0.004	−5.479***	−0.004	−3.919***
Pre vs. Post2	*Level 2*	*Relative spread*	−0.007	−3.900***	−0.006	−3.770***
Pre vs. Post2	*Level 3*	*Relative spread*	−0.009	−3.243***	−0.007	−3.397***
Pre vs. Post2	*Level 4*	*Relative spread*	−0.012	−2.941***	−0.009	−3.621***
Pre vs. Post2	*Level 5*	*Relative spread*	−0.015	−2.817***	−0.011	−3.733***
Pre vs. Post3	*Level 1*	*Quoted spread*	−0.041	−2.762***	−0.041	−3.882***
Pre vs. Post3	*Level 1*	*Relative spread*	−0.004	−4.929***	−0.003	−3.919***
Pre vs. Post3	*Level 2*	*Relative spread*	−0.005	−3.238***	−0.004	−3.770***
Pre vs. Post3	*Level 3*	*Relative spread*	−0.007	−2.853***	−0.005	−3.621***
Pre vs. Post3	*Level 4*	*Relative spread*	−0.009	−2.371**	−0.005	−3.397***
Pre vs. Post3	*Level 5*	*Relative spread*	−0.011	−2.211**	−0.006	−3.285***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table XI. Market Depth—Multivariate Analysis

Panel A reports the results of Model (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 change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of market depth measures, L, of each stock, i, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), VLM, the change in the period-average daily volatility (measured by the price range, that is, the difference between the highest and the lowest transaction price in a day), VLT, and the change 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 Model (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 market depth measures (obtained, as before, from intraday 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 is equal to zero. Reported coefficients are multiplied by 10.

		Panel A		*Panel B*	
		β_0	**t-stat**	**Median (β_4)**	**Wilcoxon-z**
Level 1	*Total # of shares*	13,280	3.437***	12,996	3.770***
Level 2	*Total # of shares*	20,192	3.575***	16,537	3.770***
Level 3	*Total # of shares*	18,923	3.616***	14,437	3.695***
Level 4	*Total # of shares*	16,686	3.918***	13,756	3.695***
Level 5	*Total # of shares*	15,541	3.730***	12,523	3.509***
Level 1	*Total euro value*	40,671	3.572***	32,262	2.837***
Level 2	*Total euro value*	56,175	3.458***	40,456	2.576***
Level 3	*Total euro value*	51,427	3.528***	34,796	2.426***
Level 4	*Total euro value*	45,536	3.604***	35,509	2.202***
Level 5	*Total euro value*	38,444	3.291***	29,642	1.978***
Cumulative (1–5)	*Total # of shares*	84,622	3.715***	62,066	3.733***
Cumulative (1–5)	*Total euro value*	232,253	3.574***	175,544	2.426***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

the prevailing midquote. We compute the cost of executing market orders considering different sizes: €5,000; €10,000; €20,000; and €30,000/midquote. This measure can be interpreted as the effective spread for different order sizes; because it is adjusted in order to take into account that large orders may walk up the book, this measure reflects both the tightness and the depth of the book. We repeat the univariate and multivariate analysis in Section II.D and report the results in Table A-V (Appendix) and Table XII, respectively. Consistent with the observed decrease in the bid-ask spread, the cost of executing a market order of all different sizes decreases after the reduction of the MTU.

against the second level of the book. The cost of the market order is thus given by [100 ∗ (15–14) + 200 ∗ (17–14)]/300 = €2.333.

Table XII. Cost of Executing a Market Order—Multivariate Analysis

Panel A reports the results of Model (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 change (from *Pre* to *Post*) in the period-average daily level (obtained from intraday observations) of cost of executing a market order measures, L, of each stock, i, on the change in the period-average daily trading volume (the sum of trading volume in euro in a day), VLM, the change in the period-average daily volatility (measured by the price range, that is, the difference between the highest and the lowest transaction price in a day), VLT, and the change 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 Model (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 cost of executing a market order measures (obtained, as before, from intraday data) on dummy variables for the days in *Post* (Day^k is equal to one for day k after the minimum trade unit (MTU) reduction and zero otherwise), on trading volume, on price volatility and on transaction price. The regression involves 2,198 observations. The cost of executing a market order is defined in Section II.7; (*mq*) indicates that the cost of executing a market order is calculated as a proportion of the midquote. 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. Reported coefficients are multiplied by 10.

Order Size (€ Thousand Divided by Midquote)	**Order Direction**	*Panel A*		*Panel B*	
		β_0	***t*-stat**	**Median (β_4)**	**Wilcoxon-z**
5	Buy	−0.009	−2.577**	−0.008	−2.352**
5	Sell	−0.011	−2.364**	−0.008	−2.464**
5	Buy (mq)	−0.002	−4.523***	−0.001	−3.583***
5	Sell (mq)	−0.002	−4.459***	−0.002	−3.733***
10	Buy	−0.011	−2.116**	−0.010	−2.314**
10	Sell	−0.017	−2.936***	−0.012	−2.426**
10	Buy (mq)	−0.002	−4.296***	−0.002	−3.621***
10	Sell (mq)	−0.003	−4.710***	−0.003	−3.733***
20	Buy	−0.029	−4.125***	−0.020	−2.688***
20	Sell	−0.026	−3.365***	−0.023	−2.277**
20	Buy (mq)	−0.004	−4.828***	−0.003	−3.658***
20	Sell (mq)	−0.004	−5.175***	−0.004	−3.770***
30	Buy	−0.043	−4.782***	−0.023	−3.023***
30	Sell	−0.025	−2.150**	−0.018	−1.717*
30	Buy (mq)	−0.005	−5.202***	−0.004	−3.546***
30	Sell (mq)	−0.005	−4.936***	−0.005	−3.845***

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

The decrease in the cost of executing a market order also confirms the first empirical prediction of our model that liquidity increases after the reduction of the MTU.

G. Adverse Selection Costs

According to the model's predictions, the significant improvement in liquidity observed after the reduction of the MTU should be 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. In this section, we investigate the change in adverse selection costs due to the MTU change using three different approaches. First, we follow Hendershott et al. (2011) and we examine the price impact of a trade. Next, we consider two estimates of the adverse selection component of the spread to check the robustness of our results on adverse selection costs: the models of Glosten and Harris (1988) and of Foster and Viswanathan (1993). These models take into account other characteristics of order flow such as trade size and sign in the determination of adverse selection costs.

1. Price Impact of Trades

Hendershott et al. (2011) measure the adverse selection cost to liquidity demanders by using the price impact of a trade across different time periods. Following their approach, we compute the 1-, 5-, 10-, 15-, 20-, 25-, and 30-minute adverse selection measures for each stock j as follows:

$$as_{jt,d-min} = D_{jt}\left(m_{jt+d-min} - m_{jt}\right)/m_{jt}, \tag{12}$$

where p_{jt} is the trade price, D_{jt} is the sign of the trade (it is equal to +1 for buyer-initiated trades and to –1 for seller initiated trades), m_{jt} is the midquote, and $m_{jt+d-min}$ is the midquote after d minutes.

In panel A of Table XIII, we compare the average adverse selection cost measures in the Pre and Post event windows around the MTU change. The average change in adverse selection costs is negative and significantly different from zero using all our measures. These results broadly support the model's prediction on reduced adverse selection following the reduction of the MTU.

2. Adverse Selection Component of the Spread

We measure the adverse selection component of the spread by relying on the microstructure models of Glosten and Harris (1988) and Foster and Viswanathan (1993).

Glosten and Harris separate 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.

$$C_t = C_0 + C_1 q_t \text{ and } Z_t = Z_0 + Z_1 q_t. \tag{13}$$

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

$$\Delta p_t = C_0 \Delta D_t + C_1 \Delta x_t + Z_0 D_t + Z_1 x_t + U_t, \tag{14}$$

where p_t is the price, D_t is the sign of the trade, and $x_t = q_t\ D_t$ is the signed trade size.[30]

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 $AC/(AC +$

[30] 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 five-second time adjustment, as advised by Bessembinder (2003).

Table XIII. Adverse Selection Cost

This table reports the results of the estimation of adverse selection costs (descriptions of the estimation is reported in Section II.G). The first panel reports the price impact of trades, calculated following Hendershott et al. (2011) $as_{x\min}$, where the subscript refers to x-minutes after the trade the price impact of trades is multiplied by 10,000. Panels B and C report the parameter estimates of the Glosten and Harris (1988) and Foster and Viswanathan (1993) models, respectively. 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 (both are multiplied by 100), respectively; *AC* proportion refers to the adverse selection component as a proportion of the spread.

Panel A. Price impact of trades (Hendershott et al., 2011)				
	Pre	**Post**	**Post-Pre**	***Wilcoxon*-z**
$as_{1\min}$	4.617	4.242	−0.375	−3.535***
$as_{5\min}$	7.396	6.433	−0.963	−5.429***
$as_{10\min}$	7.953	6.843	−1.110	−5.010***
$as_{15\min}$	8.215	6.907	−1.308	−5.236***
$as_{20\min}$	8.323	7.044	−1.279	−4.767***
$as_{25\min}$	8.264	6.962	−1.302	−4.440***
$as_{30\min}$	8.347	7.005	−1.342	−4.197***
Panel B. Glosten and Harris (1988) *model*				
AC	0.045	0.043	−0.002	−4.633***
FC	0.079	0.072	−0.007	−2.103**
AC proportion	0.350	0.324	−0.026	−4.240***
Panel C. Foster and Viswanathan (1993) *model*				
ψ	−0.022	−0.020	0.002	5.513***
λ	0.022	0.013	−0.010	−2.245**

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

FC). We report the estimation results in panel B of Table XIII. In line with the evidence on the spread reduction, both components of the spread significantly decrease after the MTU reduction. More important, in line with the predictions of our model, the proportion of the adverse selection component over the spread decreases.

We also 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:

$$\Delta p_t = \alpha_p + \psi(D_t - D_{t-1}) + \lambda\tau_t + v_t, \tag{15}$$

where τ is the residual from a regression relating trade size, q_t, to previous change in price and to lagged trade size:

$$q_t = \alpha_q + \sum\nolimits_{i=1}^{5} \beta_j \Delta p_{t-j} + \sum\nolimits_{i=1}^{5} \gamma_j q_{t-j} + \tau_t. \tag{16}$$

To avoid tracking the effect of the bid-ask bounce, we estimate the price as the midquote corresponding to the trade, that is, 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 change 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 C of Table XIII. As expected, λ, the measure of adverse selection costs, significantly decreases after the reduction of the MTU, confirming again our second empirical prediction on adverse selection costs.

H. Informational Efficiency

The model's prediction on informational efficiency depends on the parameter values representing the proportion of different types of traders. Under the MTU regime, when the proportion of large uninformed traders is small, market participants learn from observing large orders as they know that the probability that they come from informed traders is high; hence, in this case, moving from the MTU to the NC regime—be it pooling or separating—decreases informational efficiency. When instead the proportion of large uninformed traders is high, insider trading is more concealed. Compared to the NC-separating regime, under the MTU regime informational efficiency is higher as the presence of small trades makes traders' inference on the asset value noisier under the NC-separating regime. However, moving from the MTU regime to the NC-pooling regime, informational efficiency may increase as when insiders play mixed strategies they make not only large trades but also small trades informative. As a consequence, the effect of the regime switch on informational efficiency depends on the proportion of large traders active in the market. Because we do not have direct estimates on this parameter value for our sample of stocks, we have to rely on the data and use standard measures of informational efficiency to assess the overall effect of the change in regime, and to infer approximately the value of the parameter β.

1. Random Walk Tests

As a first approach to studying informational efficiency, we examine the autocorrelation of intraday returns and intraday variance ratios. This approach is widely used; see, for example, Campbell, Lo, MacKinley (1997), Boehmer et al. (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 XIV.

We compute the autocorrelation of intraday 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), that is, 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 the variance ratios are equal to one, we examine the quantity $|\mathrm{VR} - 1|$. The results indicate that the absolute value of the autocorrelation and the absolute value of the variance ratio deviations from one do not significantly change after the MTU reduction.

Table XIV. Informational Efficiency

The table compares the cross-sectional averages of the informational efficiency measures before and after the reduction of the minimum trade unit (MTU). We measure informational efficiency by the absolute value of daily first order return autocorrelation at different lags; the absolute value of daily variance ratio (*VR*) deviations from 1 at different lags (as described in Section II.H); 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 II.H). 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).

	Pre	Post	Post-Pre	Wilcoxon-z
|*Return Autocorrelation (5 min.)*|	0.129	0.134	0.005	1.265
|*Return Autocorrelation (10 min.)*|	0.150	0.159	0.009	1.508
|*Return Autocorrelation (15 min.)*|	0.181	0.185	0.004	1.038
|*Return Autocorrelation (20 min.)*|	0.200	0.202	0.002	0.050
|*Return Autocorrelation (30 min.)*|	0.245	0.241	−0.004	−0.544
|*VR(30 min.,10 min.)–1*|	0.330	0.326	−0.004	−0.569
|*VR(30 min.,15 min.)–1*|	0.279	0.280	0.001	0.016
|*VR(20 min.,10 min.)–1*|	0.233	0.227	−0.006	−1.072
σ_s/σ_p	0.157	0.149	−0.008	−0.695

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

2. A Structural Model of Prices and Trades

The second approach to measuring informational efficiency follows Hasbrouck (1993). Examples of recent contributions using this approach are Boehmer and Kelley (2009), Hendershott and Moulton (2011), and Boehmer and Wu (2013). It 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 value at risk (VAR) model involving the change 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 D. The results, reported in Table XIV, show that the magnitude of the pricing error decreases after the MTU reduction but the change is not significantly different from zero. The results are therefore similar to those found using random walk tests and confirm that the MTU change 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 change in informational efficiency.

I. Retail Trading Activity

One of the key predictions of our model is that once the MTU constraint is relaxed, we should observe an increased participation of retail traders. In this last section, we test whether retail trading activity increases after the MTU change. To evaluate the change in trading activity after the event, we conduct four different tests. Specifically, we examine the change in the distribution of trade size, in the proportion of online trading, in the proportion of buyer-initiated small trades (Barber et al., 2009), and in the cumulative price impact of orders. All of the four tests suggest that retail trading increases after the MTU change.[31]

1. Trade Size

Examining trade size gives insightful indications on the relative participation of retail traders in the market after the MTU change.

First, Table III shows that the number of trades at a size greater than or equal to the MTU does not significantly change after the MTU reduction whereas, in the *Post* period, the number of trades at a size lower than the MTU becomes a substantial portion of all trades (16.9%). This is consistent with a greater participation of retail traders rather than with large traders deciding to reduce the size of their orders.

Second, we compare the distribution of trades at different sizes in the *Pre* and *Post* periods. We consider the following size thresholds (in euro value of the trade): 2,000; 5,000; 10,000; 20,000; 50,000; and 100,000. The results are reported in Figure 7, which presents the number of trades in the different size brackets before and after the MTU reduction. We use a Kolmogorov-Smirnov test to compare the distributions in the *Pre* and *Post* periods and report the corresponding significance level in the figure.[32] For all size brackets there is an increase in the number of trades, which is consistent with the increase in trading volume documented in Table III. However, when comparing the distribution of trades in the different size brackets, only the distribution of the smallest trades (less than €2,000) is significantly different (at the 5% level) across the *Pre* and *Post* periods. This result indicates that an important driver of the increase in volume is the increase in the number of the smallest trades. Given that the total trading volume increases, the increase in small trades cannot solely come from slicing large orders into small ones, but instead it suggests that there is an increase in small trades which are likely to originate from retail traders. We further elaborate on this conjecture by testing the change in empirical proxies for retail trading.

2. Online Trading

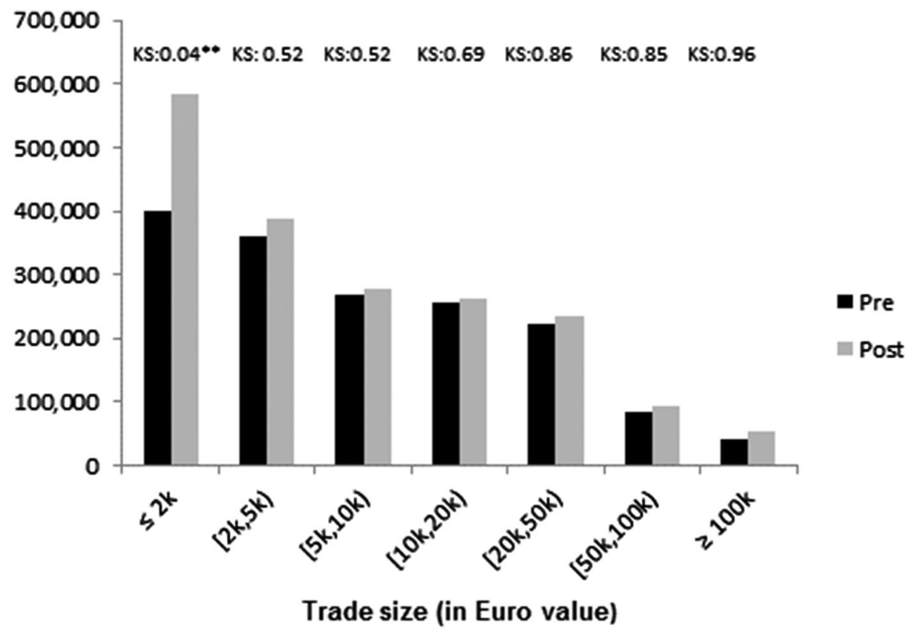
Because in 2002 online trading was an important channel through which the most active retail traders conveyed orders to the market (BIt Notes no. 11, 2004), a key indication of a change in retail trading activity can be traced through online trading activity. BIt does not make available to researchers daily and higher frequency data on online trading and therefore it is not possible to gauge the amount of daily online trading around the event. However, we obtained from BIt proprietary monthly data that allowed us to observe that the total amount of online trading

[31] We also estimate the parameters of the model of Easley et al. (1996). The results are reported in Appendix E. We find that the rate of arrival of uninformed traders significantly increases after the MTU change whereas the rate of arrival of informed traders does not change significantly. Because retail traders are likely to be uninformed, this result is consistent with a greater participation of retail traders after the microstructure change. We note that the results of the estimation 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 is originated from retail vs. institutional traders.

[32] To implement the Kolmogorov-Smirnov test, we use, for each stock and size bracket, the total number of trades at the relevant size in a period.

Figure 7. Trade Size Distribution around the MTU Change

This figure compares the distribution of trade size in the *Pre* and *Post* periods. We consider the following size thresholds (in euro value of the trade): 2,000, 5,000, 10,000, 20,000, 50,000, and 100,000. The figure reports the number of trades for each size bracket. We also report the *p*-value of a Kolmogorov-Smirnov test (denoted by KS) for the null hypothesis that the distribution of trade size is the same in the *Pre* and *Post* periods.



relative to total trading increases by approximately 16% in a period of one month around the event (excluding the event month); as Figure 8 shows the increase in online trading is more pronounced if we take longer event windows. We interpret this result as a further piece of evidence that retail trading increases following the reduction of the MTU and this increase is not limited to a temporary period, suggesting a structural change in online trading due to the MTU reduction.

3. Proportion of Buyer-Initiated Small Trades

Following Barber et al. (2009), we measure the proportion of retail trading by the number of buyer-initiated small trades as a proportion of total small trades. The results are reported in Table XV. Small trades are defined using three different percentiles of the trade size distribution and the firms are classified based on the severity of the MTU constraint. The first panel shows the change in retail trading activity for the Italian firms in a window of 20 days around the MTU reduction. We find a significant increase in retail activity after the MTU reduction regardless of the small trade definition (which amounts to up to 9% change, that is, (*Post-Pre*)/*Pre*, when concentrating on the smallest decile of trades), which is in line with the predictions of the theoretical model. More important, the increase in retail trading mainly comes from the stocks

Table XV. Retail Trading

This table reports the changes in retail trading. All trades per stock are divided into terciles, quintiles, and deciles in the *Pre* and *Post* period based on euro value and the table reports the trades in the first (i.e., smallest) tercile, quintile, and decile. Firms are grouped based on the severity of the minimum trade unit (MTU) constraint, that is, low, medium, and high; the MTU constraint is measured as the average number of trades at the MTU over the average number of trades in the *Pre* period. Panel B reports the results of a difference-in-differences test using a matched sample of French firms that trade on Euronext Paris. One-to-one matching is based on market capitalization and stock price as of November 2001. Following Barber et al. (2009), retail trading is measured by the proportion of small trades that are buyer initiated. Cross-sectional averages of daily (obtained as the daily average of intraday observations) results are reported; specifically, individual stocks averages by periods are (equally weighted) averaged across all the stocks The table reports the results for all stocks ($n = 55$) in the sample and for subgroups based on the exposure to MTU constraint. The significance level corresponding to a Wilcoxon signed rank test is reported.

Panel A

	Small Trades (1st Tercile)			Small Trades (1st Quintile)			Small Trades (1st Decile)		
	Pre	**Post**	**Post-Pre**	**Pre**	**Post**	**Post-Pre**	**Pre**	**Post**	**Post-Pre**
All stocks, $n = 55$	0.472	0.479	0.007	0.469	0.488	0.019**	0.456	0.497	0.041***
MTU constraint, low	0.479	0.483	0.004	0.478	0.498	0.020*	0.479	0.509	0.030*
MTU constraint, medium	0.485	0.474	−0.011*	0.480	0.471	−0.009	0.478	0.475	−0.003
MTU constraint, high	0.452	0.479	0.027**	0.447	0.495	0.048***	0.410	0.509	0.099***

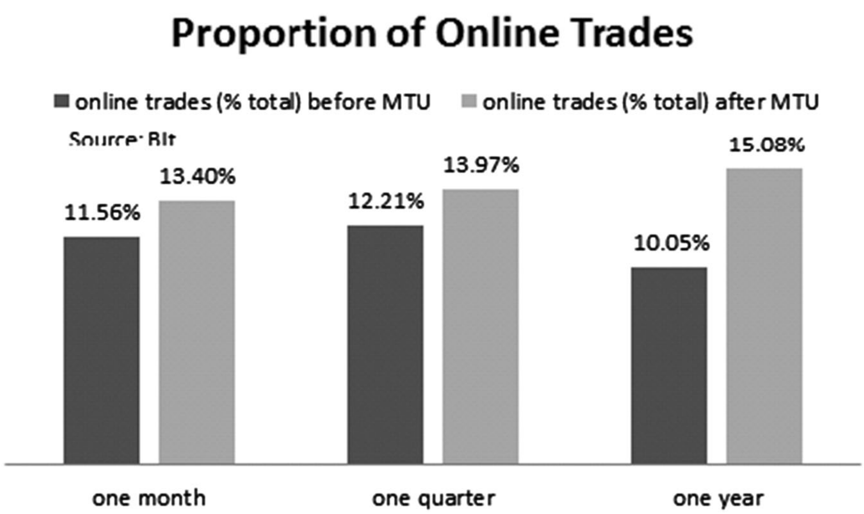
Panel B

	France	Italy	Diff-in-Diff	France	Italy	Diff-in-Diff	France	Italy	Diff-in-Diff
All stocks, $n = 55$	0.012*	0.007	−0.005	0.004	0.019**	0.015	0.015*	0.041***	0.026
MTU constraint, low	0.032*	0.004	−0.028	0.000	0.019*	0.019	0.016	0.030*	0.014
MTU constraint, medium	0.005*	−0.011*	−0.016	0.004*	−0.007	−0.011	0.013	−0.003	−0.016
MTU constraint, high	0.000	0.027**	0.027*	0.003	0.048***	0.045**	0.014	0.100***	0.086**

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Figure 8. Online Trading

This figure shows the proportion of online trading to total trading volume (in shares) around the minimum trade unit (MTU) change. The percentage of online trading is measured one month, one quarter, and one year around the MTU change excluding the month of the event, that is, January 2001. The proprietary monthly data are provided by Borsa Italiana.



that were subject to the most binding MTU (within the smallest decile of trade value, the increase is equal to 24.4% for the stocks with the most binding MTU).

One could argue that the increase in retail trade activity we document is part of a trend observed in other markets instead of being the result of the MTU reduction. To test this conjecture, we conduct a difference-in-differences analysis using a matched sample of French firms traded on Euronext Paris. Following Davies and Kim (2009), we match each Italian stock one-to-one with a stock from Euronext Paris based on market capitalization and share price (end of November 2001) and focus on the differences in retail trading activity around the MTU reduction:

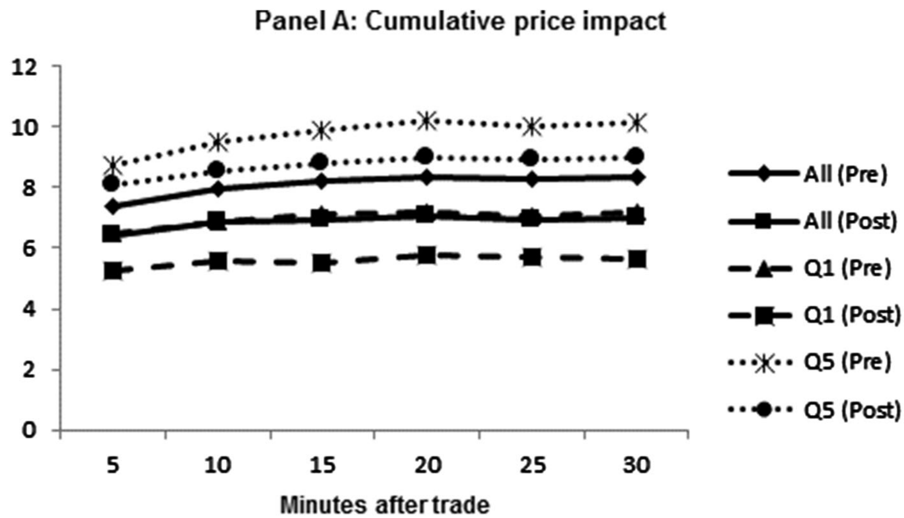
$$dif = (retail_{BIt}^{Post} - retail_{BIt}^{Pre}) - (retail_{Euronext\ Paris}^{Post} - retail_{Euronext\ Paris}^{Pre}), \tag{17}$$

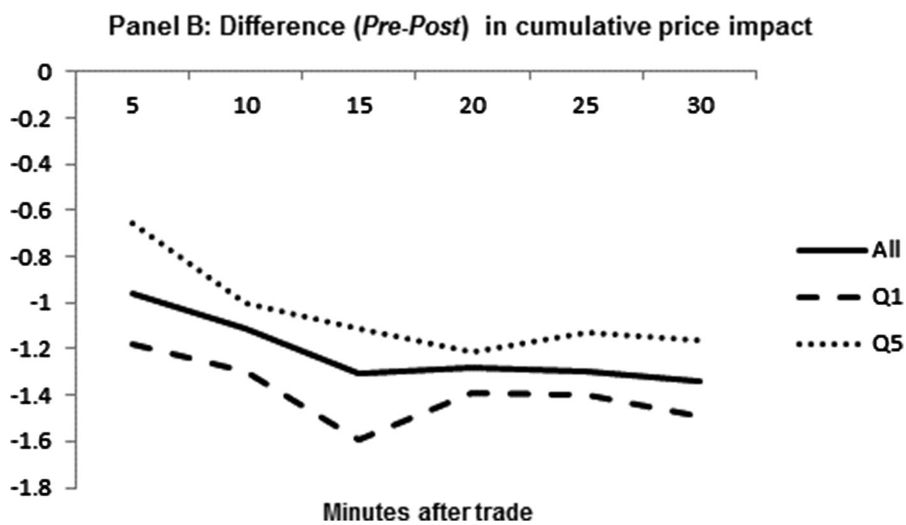
where the subscripts indicate the trading venue—Borsa Italiana (BIt) and Euronext Paris—and the superscripts *Pre* and *Post* refer to observations before and after the MTU reduction.[33] We compute a signed-rank Wilcoxon test for the null hypothesis that the median of this difference is equal to zero. Panel B of Table XV shows that even though there is on average a slight increase in retail activity for the control sample of French firms, we observe a significant difference in the change of retail activity for the firms with the most binding MTU constraint between the French and the Italian sample, providing strong evidence for the MTU change causing the increase in retail trading.

[33] The intraday trading data of French firms are kindly provided by DRM Finance, the finance research group of Université Paris-Dauphine.

Figure 9. Cumulative Price Impact of Orders

This figure reports the results of cumulative price impact of orders. The cumulative price impact is the cumulative price change over the specified interval, signed by the direction of the trade; price change is measured using quote midpoints and is positive if price is moving up around a buy or down around a sell. The results are reported in basis points. The *x*-axis reports the lag (number of minutes after the trade). Panel A reports the level and Panel B reports differences (*Pre-Post*). We rank trades in five quintiles based on their size. Q1 refers to the lowest and Q5 refers to the highest quintile.





4. Cumulative Price Impact of Orders

Prior literature (e.g., Kraus and Stoll, 1972; Chan and Lakonishok, 1993; Jones and Lipson, 2005) indicates that orders submitted by informed traders have a higher permanent price impact than uninformed orders, in particular retail orders. If after the MTU change more retail traders access the market, we expect to observe a decrease in the permanent price impact of orders. The adverse selection measure developed by Hendershott et al. (2011) that we describe in Section II.G can be interpreted as a measure of price impact of orders; therefore, panel A of Table XIII, which reports a decrease in the Hendershott et al. (2011) measure after the MTU decrease, gives a first indication of a decrease in the long-term price impact of orders. Following Jones and Lipson (2005), we also calculate the cumulative price impact, which is the cumulative price change over the specified interval, signed by the direction of the trade; the price change is measured using quote midpoints and is positive if the price is moving up around a buy or down around a sell. We plot the cumulative price impact before and after the reduction of the MTU in Figure 9. The results (panel A) indicate that the cumulative price impact decreases for all lags after the MTU reduction.[34] The decrease in the cumulative price impact at all lags is in line with an increase in the participation of retail traders in the market. Furthermore we find that the decrease in the cumulative price impact is higher for the smallest orders (panel B), which are more likely to originate from retail traders.[35]

III. Conclusions

In this paper we investigate how the MTU constraint imposed on traders' order submission strategies affects liquidity, adverse selection costs, and informational efficiency. We address this question by considering a natural experiment that took place in 2002 when BIt reduced the MTU to one share for all listed stocks.

We find a marked improvement in liquidity after the MTU reduction, measured by a decrease in the bid-ask spread at the first five levels of the book; this result is confirmed by an increase in market depth and a reduction in the cost of executing a market order of different sizes. We also observe a substantial reduction in adverse selection costs, measured by the price impact of orders of different sizes, as well as by the adverse selection component of the spread. This improvement in liquidity results in a decrease in transaction costs both for small orders and for larger orders walking up the book.

We show that our results are not driven by any local or global liquidity trend. We also show that the cross-sectional variation in the size of the MTU constraint—which we measure as the proportion of trades executed at the MTU in the *Pre* period—has a significant impact on liquidity. Firms that were subject to a more binding constraint before the removal of the MTU benefit from a greater improvement in liquidity after the change in the market design.

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 and offers empirical predictions for the effects of a removal of the MTU constraint on liquidity, adverse selection costs and informational efficiency. With the reduction of the MTU, more traders have access to the market;

[34] All the median changes are significantly different from zero using a signed-rank Wilcoxon text.

[35] We also calculate the relative change, defined as *(Post-Pre)/Pre*. Q1 has a significantly higher decrease than Q5 at the 1% level for lags 5, 10, 15, and 20, and at the 10% level for lag 25. Q1 has an insignificantly higher decrease than Q5 at lag 30.

hence the proportion of uninformed traders increases, adverse selection costs decrease, and liquidity improves. Finally, we do not find any evidence that informational efficiency changes after the MTU removal; therefore, the improvement in liquidity we observe comes at no cost to informational efficiency.

References

Amihud, Y., 2002, "Illiquidity and Stock Returns: Cross-Sectional and Time-Series Effects," *Journal of Financial Markets* 5, 31–56.

Amihud Y. and H. Mendelson, 1986, "Asset Pricing and the Bid-Ask Spread," *Journal of Financial Economics* 17, 223–249.

Amihud, Y., H. Mendelson, and J. Uno, 1999, "Number of Shareholders and Stock Prices: Evidence from Japan," *Journal of Finance* 54, 1169–1184.

Andersen, T., T. Bollerslev, F.X. Diebold, and P. Labys, 2003, "Modeling and Forecasting Realized Volatility," *Econometrica* 71, 529–626.

Angel, J.J., L. Harris, and C. Spatt, 2013, "Equity Trading in the 21st Century: An Update," Carnegie Mellon University Working Paper.

Barber, B., T. Odean, and N. Zhu, 2009, "Do Retail Trades Move Markets?" *Review of Financial Studies* 22, 151–186.

Bessembinder, H., 2003, "Issues in Assessing Trade Execution Costs," *Journal of Financial Markets* 6, 233–257.

Boehmer, E. and E. Kelley, 2009, "Institutional Investors and the Informational Efficiency of Prices," *Review of Financial Studies* 22, 3563–3594.

Boehmer, E., G. Saar, and L. Yu, 2005, "Lifting the Veil: An Analysis of Pre-Trade Transparency at the NYSE," *Journal of Finance* 60, 783–815.

Boehmer, E. and J. Wu, 2013, "Short Selling and the Price Discovery Process," *Review of Financial Studies* 26, 287–322.

Borsa Italiana, *BIt Notes* no. 2 (2001a), no. 3 (2001b), no. 11 (2004).

Borsa Italiana, *Facts and Figures* (2001) (2002).

Brennan, M.J. and A. Subrahmanyam, 1996, "Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns," *Journal of Financial Economics* 41, 441–464.

Campbell, J.Y., A.W. Lo, and A.C. MacKinley, 1997, *The Econometrics of Financial Markets*, Princeton, NJ, Princeton University Press.

Chan, L.K.C. and J. Lakonishok, 1993, "Institutional Trades and Intraday Stock Price Behavior," *Journal of Financial Economics* 33, 173–199.

Chordia, T., R. Roll, and A. Subrahmanyam, 2005, "Evidence on the Speed of Convergence to Market Efficiency," *Journal of Financial Economics* 76, 271–292.

Corwin, S. and P. Schultz, 2012, "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices," *Journal of Finance* 67, 719–759.

Davies, R.J. and S.S. Kim, 2009, "Using Matched Sample to Test for Differences in Trade Execution Costs," *Journal of Financial Markets* 12, 173–202.

deJong, F. and B. Rindi, 2009, *The Microstructure of Financial Markets*, Cambridge, UK, Cambridge University Press.

Deutsche Boerse Press Release, August 1, 2002, available at: deutsche-boerse.com/dbg/dispatch/de/notescontent/dbg_nav/press/10_Latest_Press_Releases/20_Deutsche_Boerse/INTEGRATE/mr_pressreleases?notesDoc=7413694469C27B8FC12573D5004E4549&newstitle=deutscheboerse:allewerteaufxet&location=press.

Easley, D., N.M. Kiefer, M. O'Hara, and J.B. Paperman, 1996, "Liquidity, Information and Infrequently Traded Stocks," *Journal of Finance* 51, 1406–1436.

Easley, D. and M.O'. Hara, 1987, "Price, Trade Size and Information in Securities Markets," *Journal of Financial Economics* 19, 69–90.

Fama, E. and J. MacBeth, 1973, "Risk, Return, and Equilibrium: Empirical Tests," *Journal of Political Economy* 81, 607–636.

Foster, F. and S. Viswanathan, 1993, "The Effect of Public Information and Competition on Trading Volume and Price Volatility," *Review of Financial Studies* 6, 23–56.

Foucault, T., O. Kadan, and E. Kandel, 2005, "Limit Order Book as a Market for Liquidity," *Review of Financial Studies* 18, 1171–1217.

Glosten, L. and L. Harris, 1988, "Estimating the Components of the Bid-Ask Spread," *Journal of Financial Economics* 21, 123–142.

Glosten, L. and P. Milgrom, 1985, "Bid-Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics* 14, 71–100.

Griffiths, M., B. Smith, A. Turnbull, and R. White, 2000, "The Costs and Determinants of Order Aggressiveness," *Journal of Financial Economics* 56, 65–88.

Harris, L., 2003, *Trading & Exchanges: Market Microstructure for Practitioners*, Oxford, Oxford University Press.

Hasbrouck, J., 1993, "Assessing the Quality of a Security Market: A New Approach to Transaction-Cost Measurement," *Review of Financial Studies* 6, 191–212.

Hauser, S. and B. Lauterbach, 2003, "The Impact of Minimum Trading Units on Stock Value and Price Volatility," *Journal of Financial and Quantitative Analysis* 38, 575–589.

Hendershott, T., C.M. Jones, and A. Menkveld, 2011, "Does Algorithmic Trading Improve Liquidity?" *Journal of Finance* 66, 1–33.

Hendershott, T. and P. Moulton, 2011, "Automation, Speed, and Stock Market Quality: The NYSE's Hybrid," *Journal of Financial Markets* 14, 568–604.

Huberman, G. and W. Stanzl, 2005, "Optimal Liquidity Trading," *Review of Finance* 9, 165–200.

Jones, C. and M. Lipson, 2005, "Are Retail Orders Different?" Columbia University Working Paper.

Kandel, E., B. Rindi, and L. Bosetti, 2012, "The Effect of a Closing Call Auction on Market Quality and Trading Strategies," *Journal of Financial Intermediation* 21, 23–49.

Kraus, A. and H. Stoll, 1972, "Price Impacts of Block Trading on the New York Stock Exchange," *Journal of Finance* 27, 569–588.

Kyle, A., 1985, "Continuous Auctions and Insider Trading," *Econometrica* 53, 1315–1335.

Lee, C. and M. Ready, 1991, "Inferring Trade Direction from Intraday Data," *Journal of Finance* 46, 733–746.

Lipson, M., 2001, “Stock Splits, Liquidity, and Limit Orders,” University of Virginia Working Paper.

Obizhaeva, A. and J. Wang, 2013, “Optimal Trading Strategy and Supply/Demand Dynamics,” *Journal of Financial Markets* 16, 1–32.

O’Hara, M., C. Yao, and M. Ye, 2014, “What’s Not There: The Odd-Lot Bias in TAQ Data,” *Journal of Finance* 69, 2199–2236.

O’Hara, M. and M. Ye, 2011, “Is Fragmentation Harming Market Quality?” *Journal of Financial Economics* 100, 459–474.

Pagnotta, E., 2013, “Information and Liquidity Trading at Optimal Frequencies,” New York University Working Paper.

Parlour, C., 1998, “Price Dynamics in Limit Order Markets,” *Review of Financial Studies* 11, 789–816.

Rosu, I., 2009, “A Dynamic Model of the Limit Order Book,” *Review of Financial Studies* 22, 4601–4641.

Schultz, P., 2000, “Stock Splits, Tick Size, and Sponsorship,” *Journal of Finance* 55, 429–450.

SEC Research Highlights, 2014, available at: http://www.sec.gov/marketstructure/research/sec_data_highlight_2014-01.pdf.

US Securities and Exchange Commission (SEC), 2010, Concept Release on Equity Market Structure No. 34–61358.

Werner, I.M., Y. Wen, B. Rindi, F. Consonni, and S. Buti, 2015, “Tick Size: Theory and Evidence,” SSRN collection Working Paper.

Yao, C. and M. Ye, 2015, “Tick Size Constraints, High-Frequency Trading, and Liquidity,” University of Illinois at Urbana-Champaign Working Paper.