The impact of MiFID on the market quality of Euronext

Hans Degryse,* Frank de Jong,† and Vincent van Kervel‡

June 2010

Abstract

The implementation of the Markets in Financial Instruments Directive, MiFID, in November 2007 aims to create a harmonised regulatory regime for investment services in the EU. The legislation introduces best execution rules, improves transparency and allows for competition between trading venues. This paper investigates the impact on the market quality of Euronext by comparing several periods before and after the implementation of MiFID. While liquidity measures have worsened over time, likely due to the financial crisis, the resiliency seems to have improved. After a liquidity shock, the orderbook reverts quicker to its normal level of liquidity.

*TILEC, Tilburg University

†Tilburg University

‡Corresponding Author. TILEC, Tilburg University. E-mail: v.l.vankervel@uvt.nl Address: Finance Department, Tilburg University, Warandelaan 2, P.O. Box 90153, 5000 LE Tilburg, The Netherlands. Tel.: +31 13 466 4056

1 Introduction

Financial legislation influences the market power of parties involved in the trading process. It also determines the optimal behavior of these participants, allowing social welfare to be maximized. The Markets in Financial Instruments Directive (MiFID) was implemented in November 2007 and aims to create a transparent and efficient integrated European financial market. Competition between providers of financial services is encouraged by allowing different trading venues to enter the market, while best execution rules are implemented to protect the rights of investors. Market efficiency may increase with transparency as information is shared among traders, improving liquidity and lowering trading costs. However, there is also evidence that transparency reduces liquidity, as informed investors are reluctant to make their inside information public by posting limit orders [Harris, 1997]. With respect to trading costs and liquidity also a tradeoff exists between increased competition and market fragmentation.

The natural question that arises is whether MiFID has been successfully implemented, have they achieved their goals? This paper studies the impact of MiFID on market quality by looking at several measures of liquidity. This topic is relevant as it studies the consequences of financial regulation and may provide new policy implications. The implementation of MiFID also provides a natural experiment with changes in trade transparency, best execution rules and the introduction of alternative trading venues, among others.

We compare the market quality of Aex Large Cap constituents between four timeperiods: directly before and after the implementation of MiFID, and nine and fourteen months later. Our main focus lies on resiliency, or the speed of recovery of the order book's liquidity and spread after a large trade. To define large trades, we classify market orders and limit orders to their level of aggressiveness, similar to Biais, Hillion and Spatt (1995) or Degryse, De Jong, Van Ravenswaaij and Wuyts (2005). Next we execute an event study approach, by looking at the evolution of the quoted bid and ask price before and after such a large or aggressive trade. The same methodology is used to construct the evolution of the quoted depth, at both sides of the market. When comparing the four periods, resiliency has improved in period 4, the same time market fragmentation sets in. Despite decreases in quoted and effective spreads, this liquidity measure seems to have improved during the financial crisis.

The remainder of the paper is organized as follows. The second section contains a review of the history and implementation of MiFID, followed by the main consequences. The next subsection discusses theoretical and empirical results, after which the dataset will be described. The methodology is introduced next, along with a description of the results. After the results are interpreted, a conclusion follows.

2 MiFID

This section describes the MiFIDs main objectives and the implementation process. Next to Regulated Markets, MiFID also authorizes Multilateral Trading Facilities and Systematic Internalisers as trading venues, each having specific requirements. The impact of MiFID on market quality goes mainly through two channels, market fragmentation and transparency. Both are reviewed on a theoretical basis, with mixed results. This elicits the need for an empirical investigation, described in the last subsection.

2.1 History and implementation.

MiFID is part of the 1999 Financial Services Action Plan and follows from the 1993 Investment Services Directive. It aims to create a pan - European integrated capital market and was implemented in November 1, 2007 in 25 member states. MiFID is the European counterpart of the U.S. based Regulation National Market System. The demand for a single wholesale market has expanded by improved technology and globalization. By removing regulatory obstacles, such as fiscal barriers and domestic legislation, capital can move freely and should result in a more efficient and liquid market.

The ISD was the first attempt to create a regulatory framework for investment firms to provide services across Europe. This was done by creating a "European Passport", which was granted by one member state and allowed the firm to perform services in another, without requiring local regulatory approval [Aubry and McKee, 2007]. Second, it also defined regulation regarding cross-border trading using electronic access and membership. Lastly, it comprised conduct of business rules for firms dealing in other member states. Compared to the ISD, the size and complexity of MiFID has increased substantially and may have too much detail [Casey and Lannoo, 2006]. Ferrarini and Recine [2006] suggest that the costs of implementing MiFID will be burdensome to investment firms. We refer to the Financial Services Authority (November, 2006).[1] for an

[1] See `www.fsa.gov.uk/pubs/international/mifid_impact.pdf`.

extended cost-benefit analysis.

MiFID has departed from the ISD's principles-based approach to a rules-based approach. In short, these rules contain the following four elements. First, in order to protect retail investors, MiFID requires information from these non - professional clients regarding income, financial education and risk profile. This classifies retail clients as being suitable to acquire complicated financial products, and able to understand the appropriate risks of such products. Other conduct-of-business rules are formulated to serve two other categories in the MiFID regime; professional clients and eligible counterparties, where the latter includes banks, investment institutions and commodity traders [Finney, 2006]. Second, the best execution rule is implemented which, unlike Regulation NMS in the U.S, does not only refer to the best price of an asset, but also to other trade criteria such as speed and probability of execution and transaction costs. This complicates the enforcement of the rule, as the requirements whether best execution is fulfilled becomes less obvious. In a fragmented market, Smart Order Routing Technology (SORT) might be used to automatically find the best prices on the different trading venues [Gomber and Gsell, 2006]. Other relevant trade criteria should be specified by the customer to find the appropriate trading venue. Third, trading venues are required to give more disclosure on trade prices, improving transparency and making SORT feasible. Instead of trading only on regulated markets, investment firms are also allowed to trade shares on their own account, as systematic internalisers. Investment firms are required to publish their prices of the most actively traded stocks real time, improving the price discovery process. Improving transparency also enhances market efficiency and allows clients to monitor their brokers [Davies et al., 2006]. Fourth, MiFID provides "detailed principles" to eliminate market abuse, insider trading and manage conflicts of interest for investment firm's staff [Casey and Lannoo, 2006]. This last term comprises information barriers, independent operation and supervision of employees, as well as sensible compensation policies [Finney, 2006].

MiFID is implemented using the general Lamfalussy approach, named after Alexandre Lamfalussy, the chairman of the EU advisory committee in 2001. The goal is to separate general principles from specific regulatory details, and is composed of four levels or stages of implementation. Level one of MiFID is the guideline that was approved by the Council and Parliament in April 2004 and contains the core principles and basis of the framework. In level two technical aspects are decided upon by sector specific regulators, making the implementation possible. The official publication of Level 2 implementing measures was in September 2006.[2] In the third level specific recommendations and guidelines are made by the Committee of European Securities Regulators (CESR) on how to incorporate the new regulation in the member's current domestic law. Lastly, level four involves the monitors of the European Commissions to enforce the new laws.

2.2 The Consequences of MiFID

Regulated markets are particularly influenced by MiFID. First, they are required to disclose information on offered quotes and executed trades. Second, clients such as investment banks demand lower transaction prices and may create new trading systems on their own account, a consequence of the dismissal of the "concentration rule". This rule followed from the ISD and was adopted by some EU members; it obliges transactions to be executed at regulated markets as opposed to internal settlement. This creates a single and fair market on which all investors post their trades, according to a time and price priority. The repeal of the rule however allows fragmented markets to emerge and increases competition between different trading venues [Ferrarini and Recine, 2006]. Clearly, there is a tradeoff between the advantages of increased competition and the potential loss of market quality.

Besides the regulated markets, MiFID also identifies two other categories of trading services: Multilateral Trading Facilities (MTFs) and Systematic Internalisers. An MTF is similar to a regulated market in the sense that their goal is to accommodate third parties to trade financial instruments. However, an MTF is not subject to the strict rules that apply to a regulated market. Systematic internalization refers to a situation where an investment bank executes retail orders in-house, by executing them against their own position, outside a regulated market or an MTF [Davies et al., 2006]. These trading venues can be distinguished by different market designs; a limit order market, a market maker or a combination of the two. In the former, which is order driven, limit and market orders are posted, allowing investors to trade directly with one another. In case of a market maker the orders are quote driven, or executed against the investment bank's own stock; the hybrid form combines different elements of the two. Another dimension to distinguish these trading venues is to compare traditional regulated markets with Alternative Trading Systems (ATS), which

[2] See `http://ec.europa.eu/internal_market/securities/isd/mifid2_en.htm`

is specific Regulation NMS terminology, applied in the US. Examples of ATSs are Electronic Communication Networks (ECNs) and Crossing Networks. An ECN is a computerized system which matches market order with limit quotes via an order book and usually targets the most liquid stocks. It circumvents the need of a market maker, thus saving the bid-ask spread. There is also no inventory risk and greater operational efficiency, lowering the transaction costs. ECNs have a high speed of execution and investors remain anonymous [Barclay et al., 2003]. Although very similar to a traditional market, ECNs have different regulatory requirements. On a Crossing Network investor's trade at specific points in time, against the then prevailing prices at a regulated market, not contributing to the price discovery process. Highly nontransparent, orders are anonymously placed in a black box and allow large blocks of shares to be traded without impacting public quotes, but with a relatively low probability of execution, see Degryse et al. [2006].

2.3 Theoretical predictions

The new trading platforms can compete on different characteristics to serve heterogeneous clientele. For example, preferences may differ on transaction costs, the speed and likelihood of execution, anonymity, the ability to place hidden orders, transparency, and the size of transactions.[3] In theoretical models traders are often considered informed or uninformed, and related to the speed of execution, patient or impatient. The predictions of such models on market fragmentation and transparency will be discussed next.

Fragmentation has two contradictory effects; there is a tradeoff between competition and market efficiency. A single market improves the quality and price discovery process, while segmented markets allow for competition between trading venues. Competition between liquidity suppliers may result in narrower bid-ask spreads [Biais et al., 2000]. However, fragmentation of the order flow might cause bid-ask spreads to widen and reduce the aggregate markets depth. Thinner markets increase the price impact of trading, resulting in higher price volatility [Harris, 1993]. Pagano (1989A, 1989B) argues that markets that are already liquid tend to attract more trading volume and liquidity suppliers, which is a positive liquidity externality. Each additional trader reduces the stock's liquidity risk for other potential traders, attracting more traders. This

[3]The size influences the trade's price impact, which also depends on factors such as depth and other liquidity measures; as well as transparency.

positive feedback should cause all the trades to be executed at a single market, obtaining the highest degree of liquidity. Also, a single dominant market has economies of scale in order processing costs, lowering the average transaction fees. However, equilibria where trading occurs on multiple markets may arise if markets and traders are heterogeneous. For instance, markets may differ on transaction costs while traders are endowed with varying preferences and trading strategies. Modeling the decisions trading venues face, Foucault and Parlour [2004] find that traditional exchanges compete for listing firms through a listing policy, trading technology and listing fees. Transaction costs have a direct and indirect effect on the trading venues' profit. First, higher transaction costs lead to lower trade activity, reducing direct trading fees. Second, the number of firms that will list on a regulated market depends on the transaction costs, as firms prefer less liquidity risk, encouraging investors to trade.[4] This influences the trading venues' fixed listing fees, and trading fees indirectly. Often, competing exchanges have different policies as to create a heterogeneous market and reduce price competition, allowing for oligopolistic rents. Another consequence of fragmentation might be that new trading venues attract investors with specific characteristics. For instance, Easley et al. [1996] find that regional dealers attract relatively more order flow from uninformed investors, increasing the adverse selection effects on NYSE executed orders. Similarly, by looking at the price impact of trades, Bessembinder and Kaufman [1997A] and Affleck-Graves et al. [1994] find that NYSE transactions convey more information than Nasdaqs. Since different trading venues each have their own characteristics, similar results may follow from MiFIDs implementation.

The theoretical predictions of improved transparency are also ambiguous. First, it is argued that increased transparency improves market efficiency and fairness. For example, Pagano and Röell [1996] show that greater transparency leads to lower trading costs for uninformed traders, following from their improved ability to protect themselves against informed ones. However, the opposite side of the same coin postulates that increased transparency might reduce liquidity since the ability of informed traders to place strategic orders diminishes, as inside information is revealed quicker to parasitic traders [Harris, 1997]. Madhavan et al. [2005] look at the introduction of the rule on the Toronto Stock Exchange requiring limit order books to be publicly displayed in 1990. Their research suggests that this improvement in pre-trade transparency will lead to

[4] Brennan and Subrahmanyam [1996] find that the cost of capital in the stock market increases with transaction costs.

more efficient placement of market orders. This result is driven by the "option element" of a posted limit buy order, where a fast trader can decide to quickly sell his shareholdings in case of bad news, rendering him a long put position. Since trading is a zero sum game, the gains for placing market orders result in losses for the liquidity providers. Consequently, posting limit orders becomes less attractive, flattening the orderbook and increasing the bid-ask spread. Lastly, market orders being more efficient also increases expected profits for informed traders; worsening the adverse selection problem and increasing the bid-ask spread. After these mixed predictions, some empirical results follow.

2.4 Empirical results

The empirical results of market fragmentation and transparency are also mixed. As mentioned earlier, the implementation of MiFID gives rise to alternative trading systems. In the U.S. Weston [2002] finds that the growth of the market share of ECNs lead to increases in liquidity on the Nasdaq of these stocks, and that ECN trades are usually of much smaller size. Barclay et al. [2003] also compare the Nasdaq and ECNs and found that the latter is frequently used when spreads are narrow and stocks have high trading volumes. Similar to the NYSE, trades on ECNs appear to have a larger price impact then Nasdaqs, suggesting that the latter attracts relatively uninformed investors. Despite low transaction costs, large trades do not frequently occur on ECNs due to a lack of depth. Conrad et al. [2003] find that orders sent to traditional brokers have higher execution costs than those executed on alternative trading systems. Notice here that the authors look at the costs of executed transactions, disregarding for example the ex ante probability of execution. Perold [1998] measures the opportunity costs of not transacting. Although it varies with the desired tradesize, it is clearly relevant when choosing a trading venue. Gresse [2006] finds that the liquidity on a dealer market is negatively related to the volume traded on a Crossing Network, suggesting that ill-liquid stocks are traded on the CNs to circumvent the risk of large price impacts of such stocks.

Bessembinder et al. [2006] look at the impact of new regulation in the corporate bond market, where executed transactions become publicly displayed. They find that this increase in transparency leads to a substantial reduction in trade execution costs. Hendershott and Jones [2005] look at an ECN which started to display its limit order book, and also find that increasing transparency leads to faster price discovery and improved market quality. When the ECN stopped publishing the quotes, trading activity fell and the market got fragmented, increasing overall trading costs. Studying market fragmentation, Bennett and Wei [2006] find that the market quality of the consolidated NYSE market is better than the more fragmented Nasdaq; it has lower trading costs and volatility and more liquidity.

Foucault and Menkveld [2008] study the competition induced by the introduction of EuroSETS in the Dutch equity market. EuroSETS is implemented by the London Stock Exchange and competes with the Nouvelle Système de Cotation (NSC), a trading system. They find that the consolidated depth increases due to more competition between liquidity providers, lowering transaction costs. Surprisingly, they also find that the depth on NSC alone has increased, despite the loss of orderflow to EuroSETS. However, this might be due to lowered trading fees on NSC, as a response to the entry of EuroSETS. Their empirical results might differ from ours however, since trading rules in that period did not require best execution and trade-throughs occurred frequently.[5]

[5]A trade-through is a violation of price priority where an order is executed at the traditional market, despite the entrant having better prices.

3 Methodology and Results

Our main goal is to investigate the impact of MiFID on market quality, for which we apply several measures. First we describe the dataset, then we classify trades and quotes according to their level of aggressiveness and provide descriptive statistics. Next, we calculate the effective and realized spread for the different time periods. This raises our interest in the most 'aggressive' trades, as the market's reaction is strongest there. In order to analyze these trades in more detail, we proceed with an event study to obtain the evolution of the best bid and ask price around such aggressive events. This will be the main result of the analysis.

3.1 Data

The dataset contains quotes and trades of the 25 AEX Large cap constituents.[6] We have access to the Thompson Reuters Tick History Database and analyze four time periods: September - October 2007, November - December 2007, June - August 2008 and January 2009. The first period is before MiFIDs introduction, the remaining three afterwards. We pick June - August 2008 and January 2009 as the liquidity in those periods matches best with the end of 2007.[7] However, there are still substantial differences due to the financial crisis, making comparisons over time more difficult. As the European market started to become fragmented as of approximately June 2008, we use Thomson Reuters consolidated tape for those periods. Here, the best bid and ask quotes in the market are continuously aggregated into a single time series. Before June 2008, the consolidated tape is almost identical to Euronext Amsterdam.[8]

Euronext Amsterdam is a computerized limit order market, which opens at 9:00 a.m. and runs until 5:30 p.m., liquidity is provided by the public limit order book. Limit orders have time and price priority, while hidden orders only have price priority. A new observation is created when the orderbook changes, e.g. a limit order arrives or gets cancelled or a trade is executed. When a trade occurs, we see the executed price and quantity, directly followed by an update of the

[6]The firms are: Ahold, Aegon, Air France, Akzo Nobel, ASML, Boskalis, Corio, DSM, Elsevier, Fortis, Fugro, Heineken, ING, ISPA, KPN, Philips, Randstad, Royal Dutch Shell, SBM Offshore, TNT, Tomtom, Unilever, USG People, Weshaven and Wolters Kluwers.

[7]We compared quoted, effective and realized spreads on a monthly basis, averaged over the Large cap constituents.

[8]Except for a small market share on Deutsche Boerse, and Virt-X, the market share of Euronext $>$ 99.6% on the entire periods.

Table 1: Descriptive statistics of the sample firms, per period.

The second column is the mean price observed in the sample, equally weighted per day and firm in every period. Next, the average number of trades (in 1000s) and shares traded (in millions of Euros) per trading day. Volatility is the standard deviation of the share price, measured in Euros, based on one quoted midpoint per 15 minutes. The final columns show the medians (over all firms) of the daily averaged (per firm) quoted, effective and realized spread on Euronext, measured in base points.

Period	Mean Price*	Trades	Shares	Volatility	Quoted	Realized half	Effective half
1	58,59	58	3488	0.96	8.64	1.32	4.92
2	53,02	61	3811	1.20	9.99	1.86	6.37
3	31,42	85	5423	1.06	10.08	0.20	4.89
4	22,82	35	2330	0.49	14.86	-0.82	6.59

orderbook. While most trading venues allow for hidden orders, this does not show up in the dataset. Hidden liquidity is only observed when it gets executed, or hit by a trade. Therefore, we have the same information set as traders have: the visible part of the orderbook, continuously observed.

3.2 Descriptive statistics and Methodology

Some descriptive statistics of the sample stocks are presented in table (1). It contains the average stock price, volatility, number of transactions, shares traded and spreads per period. The spreads will be defined in section 3.2.1. The averaged price of the firms decreases per period with 10%, 41% and 27% respectively. The volatility is measured as the standard deviation of the quoted midpoint in Euros, where we use one observation per 15 minutes.[9] This results in 34 observations per trading day. Overall, the average volatility increased at first, but decreases again in period 4. The number of transactions and turnover in euro, averaged per trading day, fluctuates substantially. It should be noted that these statistics are averages, while individual firm can have rather extreme outliers.

Traders must decide on their order submission strategy, where they can

[9] Using all observations overweighs the short term impact of liquidity on trading, that occurs within seconds; we are interested in "long run" volatility, which is not influenced by these temporary effects.

choose market orders (direct execution at the best available price) or limit price orders (which execute if a counterparty is willing to trade). Market orders have immediacy, for which the bid-ask spread is paid while limit orders face execution risk and adverse selection costs, but save the bid-ask spread [Harris and Hasbrouck, 1996]. Similar to Biais et al. [1995] and Degryse et al. [2005] we classify trades and quotes into twelve types, according to their aggressiveness. A trade where the size is smaller than the best offered quantity is considered small, or non aggressive. This is type 3 for a buy order and type 9 for a sell. When the size of the transaction equals the offered best quantity, the best price is worsened and this is considered to be more aggressive.[10] Such a buy order is classified as type 2, a sell order type 8. The last market orders that leads to direct execution are those of which the size of the order is larger than the best offered quantity, and the transaction will walk up or down the order book. Part of the order is executed at the best price; other parts at higher (lower) prices in case of a buy (sell) order. Such an order is considered very aggressive, as the buyer (seller) is willing to acquire shares at increasing (decreasing) prices. Also, the quoted bid-ask spread increases after these trades, where the type is 1 for a buy and 7 for a sell order. We focus mainly on these orders, as the market's reaction is strongest there. The remaining classifications are limit orders, which do not lead to direct execution. These can improve the best available price, which is type 10 for a limit on the ask side and type 4 on the bid side; or be placed at the best price, type 11 for the ask and 5 for the bid side. Lastly, there can be a withdrawal of the limit order, a type 12 on the ask and 6 on the bid side. Limit orders placed below the best price are not classified, as we only have the best quotes available.

The distributions of the trade types are provided in table 2A - 2D. The dataset used in our study contains all the trades and best limit updates in the four periods analysed: September - October 2007, November - December 2007, June - August 2008 and January 2009. The consolidated tape is used, incorporating all visible liquidity on all RMs and MTFs. The bottom row displays the unconditional probability of each type. In analyzing the consequences of MiFID, the dynamics of trading and order submission are important. The table also contains a Markov transition matrix, for each period. It shows the probability that a type occurs, conditional on the previous type. Every row sums to 100%,

[10]Orders know as 'marketable limit orders' qualify for this: part of the order buys all available liquidity at the best price, while the remaining part becomes a limit order (with the same price) at the other side of the orderbook.

the bottom row contains the unconditional probabilities. We can compare each type with its unconditional probability and see how the order submission strategy evolved over time. The tables are very large, but the highest values are in bold.

The tables show several interesting results. The total number of types is very volatile, as the average trading day in period 1 has 230.000 events, which changes to 286.000, 600.000 and 300.000 in the other periods.[11] In accordance with Degryse et al. [2005], the most aggressive orders occur the least frequent and the least aggressive ones most frequent. This can be a result of the presence of small investors; alternatively large investors tend to split up their orders to reduce the price impact of trading, where algorithmic trading might be used. The percentage of limit orders increases from 76% in the first, to 89% in the last period. Similarly, cancellations of limits have increased with 50% over time. This is also in line with algo traders, who are known to place and cancel limit orders frequently [Hasbrouck and Saar, 2009].[12]

Similar to Biais et al. [1995] and Degryse et al. [2005], there is a diagonal effect: the probability that the type of event t is the same as the type at t-1 is larger than the unconditional probability of that event. In general, trades on the same side seem to get clustered; this effect increases over time. Especially small trades are placed quickly one after another. When an order is posted within the best quotes, the probability of an aggressive order following on that side of the book is large. As the best price has improved by only one investor, the depth might be relatively low, making an order more likely to walk up the book. Also, an aggressive trade consumes liquidity and increases the quoted spread; this is often to be followed by quotes that improve both sides of the book. On the opposite however, after such a trade a cancellation at the same side is also more likely to occur, which is in line with large trades containing price information. As expected, this makes a limit order at that side less attractive; the effect becomes stronger over time. Also interesting is the fact that in period 3 and 4, a limit bid improving the best price is often followed by a cancellation at the ask; both prices move in the same direction. This effect is hardly present in period 1 and 2; which might be due to fragmentation. As price discovery takes place at another market (on Dark pools, SIs or OTC; trades that are not

[11] This is aggregated over 25 firms, which boils down to, on average, 20 observations per firm, per minute.

[12] The optimal size and time to submit orders can be estimated with mathematical models using real time data, see Gsell [2008] for a discussion.

incorporated in the current file), then prices on the consolidated tape also move in that direction. The same holds for a limit improving the ask price, which tends to be followed by a cancellation on the bid side more often in periods 3 and 4.

In general, the distribution of the trades becomes more aggressive: the ratio aggressive trades to total trades increases with 30% from the first to the last period, but this is mainly due to a strong reduction in type 2 and 8, the marketable limit orders.[13] Moreover, especially large and market trades on the same side of the book seem to be more clustered after MiFIDs implementation. Different from Biais et al. [1995], the number of transactions on the bid versus ask side are 47% to 53% instead of 36% to 64% they found. Although they did not specify a clear reason for their result, it might be a consequence of a different time and trading venue.

[13] Defined in footnote 10

Table 2A: Probability Order t, conditional on (t-1), 09-10, 2007

The first column shows the event at time (t-1), the row shows event at time (t). Each row sum up to 100%. The frequencies are first estimated per firm / period, next they are all aggregated. On average, each trading day in this period has 230.000 events, aggregated over all firms in the sample.

t-1 / t	Large Buy	Market Buy	Small Buy	Bid Within	Bid At	Cancel Bid	Large Sell	Market Sell	Small sell	Ask Within	Ask At	Cancel Ask
1 Large Buy	**6.09**	2.6	7.19	**14.16**	14.21	4.89	0.56	3.01	7.22	**16.23**	13.16	10.68
2 Market Buy	0.38	**8.08**	3.88	**8.39**	19.82	6.74	**1.08**	**7.52**	9.15	9.32	12.94	12.71
3 Small Buy	0.84	**6.79**	**35.71**	2.56	15.91	6.32	0.39	1.74	5.74	1.42	14.61	7.97
4 Bid Within	0.58	2.49	5.25	**11.1**	26.4	12.95	**1.5**	5.85	5.07	5.56	12.65	10.58
5 Bid At	0.51	3.1	8.07	5.48	**30.61**	**16.29**	0.29	1.41	7.8	3.01	14.17	9.26
6 Cancel Bid	0.39	2.21	5.71	8.21	25.1	**24.6**	0.33	1.71	4.55	4.74	15.13	7.32
7 Large Sell	0.54	2.9	7.15	**16.69**	13.33	10.77	**6.6**	2.38	6.92	**13.68**	14.29	4.75
8 Market Sell	**1.11**	7.7	9.48	9.5	12.91	12.43	0.42	**7.97**	4.04	8.2	19.32	6.92
9 Small sell	0.39	1.92	6.09	1.57	17.16	8.63	0.95	**7.14**	**28.21**	2.82	17.8	7.32
10 Ask Within	**1.45**	5.71	5	5.42	12.52	10.62	0.63	2.6	5.46	**11.13**	**26.69**	12.77
11 Ask At	0.26	1.4	7.18	3	14.11	8.91	0.54	3.09	8.51	5.58	**30.42**	**17**
12 Cancel Ask	0.27	1.69	4.25	4.59	15.34	7.04	0.4	2.25	6.24	8.15	25.39	**24.39**
Unconditional	0.53	3.11	9.06	5.22	20.02	12.13	0.57	3.11	8.57	5.26	19.98	12.44

Table 2B: Probability Order t, conditional on (t-1) 10-11, 2007

The first column shows the event at time (t-1), the row shows event at time (t). Each row sum up to 100%. The frequencies are first estimated per firm / period, next they are all aggregated. On average, each trading day in this period has 286.000 events, aggregated over all firms in the sample.

t-1 / t	Large Buy	Market Buy	Small Buy	Bid Within	Bid At	Cancel Bid	Large Sell	Market Sell	Small sell	Ask Within	Ask At	Cancel Ask
1 Large Buy	**1.9**	0.98	11.77	**13.25**	10.72	5.67	0.48	0.9	3.6	11.1	8.48	**31.15**
2 Market Buy	0.47	**1.42**	5.17	**17.63**	13.73	7.1	0.36	1.08	4.33	16.23	8.71	23.76
3 Small Buy	**1.1**	**1.58**	**25.98**	4.97	11.54	7.52	0.64	1.34	5.07	2.3	11.48	26.47
4 Bid Within	0.8	**1.81**	10.04	**9.2**	**18.98**	19.32	0.87	3.02	4.45	5	9.2	17.31
5 Bid At	0.52	1.13	9.67	8.61	**23.58**	**20.24**	0.3	0.78	7.31	3.66	10.71	13.47
6 Cancel Bid	0.31	0.68	6.8	10.46	20.4	**22.28**	0.4	1.46	6.88	7.59	15.01	7.74
7 Large Sell	0.49	0.53	4.52	10.47	8.29	**18.1**	**1.79**	1.92	9.75	**26.41**	10.94	6.78
8 Market Sell	0.17	0.29	2.36	7.75	4.44	11.29	0.25	0.97	2.33	**54.37**	12.13	3.65
9 Small sell	0.4	0.63	7.06	2.8	12.92	12.64	**0.93**	**4.17**	**20.78**	10.59	14.39	12.69
10 Ask Within	0.89	**2.19**	8.65	4.93	8.94	18.07	0.73	3.23	6.77	8.76	19.01	17.82
11 Ask At	0.29	0.4	8.44	3.67	10.52	13.15	0.52	2.23	7.8	8.71	**23.92**	**20.37**
12 Cancel Ask	0.38	0.79	8.18	6.6	14.72	7.66	0.4	2.1	6.4	10.08	19.6	**23.1**
Unconditional	0.53	1.01	9.95	6.79	15.33	14.76	0.53	2.02	7.59	8.37	15.92	17.20

Table 2C: Probability Order t, conditional on (t-1) 06-08, 2008

The first column shows the event at time (t-1), the row shows event at time (t). Each row sum up to 100%. The frequencies are first estimated per firm / period, next they are all aggregated. On average, each trading day in this period has 600.000 events, aggregated over all firms in the sample.

t-1 / t	Large Buy	Market Buy	Small Buy	Bid Within	Bid At	Cancel Bid	Large Sell	Market Sell	Small sell	Ask Within	Ask At	Cancel Ask
1 Large Buy	**1.81**	0.97	**11.67**	**11.64**	16.12	7.95	0.45	0.51	2.57	6.76	9.95	**29.59**
2 Market Buy	0.31	**1**	4.18	**15.16**	20.28	10.06	0.2	0.68	3.16	12.28	13.3	19.41
3 Small Buy	**1.2**	**1.66**	**26.69**	5.03	13.24	9.27	**0.82**	1.29	3.83	2.09	10.45	24.43
4 Bid Within	0.5	1.52	6.52	**10.43**	**24.7**	18.56	0.37	**2.14**	2.43	4.36	8.06	20.41
5 Bid At	0.29	0.9	5.35	9.63	**32.07**	21.53	0.12	0.26	2.98	2.44	7.99	16.45
6 Cancel Bid	0.16	0.39	3.91	9.05	20.02	**28.04**	0.27	0.88	5.8	6.58	16.91	7.99
7 Large Sell	0.39	0.32	3.56	7.13	10.23	17.23	**1.92**	1.44	9.52	**23.05**	15.94	9.27
8 Market Sell	0.13	0.25	2.14	8.09	8.58	12.37	0.21	0.82	2.57	**38.74**	19.73	6.36
9 Small sell	0.35	0.53	5.3	2.6	12.23	14.93	**0.92**	**3.18**	**18.03**	10.71	17.34	13.89
10 Ask Within	0.39	**2.15**	6.14	4.17	7.82	19.14	0.52	**2.47**	4.4	10.09	**24.94**	17.79
11 Ask At	0.12	0.17	3.86	2.56	7.95	15.75	0.3	1.41	4.28	9.2	**32.49**	21.92
12 Cancel Ask	0.27	0.6	7.37	5.91	16.26	8.02	0.2	1.09	3.74	8.15	19.98	**28.41**
Unconditional	0.32	0.78	6.75	6.57	17.66	17.27	0.33	1.24	4.69	7.12	18.33	18.95

Table 2D: Probability Order t, conditional on (t-1) 01, 2009

The first column shows the event at time (t-1), the row shows event at time (t). Each row sum up to 100%. The frequencies are first estimated per firm / period, next they are all aggregated. On average, each trading day in this period has 300.000 events, aggregated over all firms in the sample.

t-1 / t	Large Buy	Market Buy	Small Buy	Bid Within	Bid At	Cancel Bid	Large Sell	Market Sell	Small sell	Ask Within	Ask At	Cancel Ask
1 Large Buy	**2.64**	0.9	**14.21**	**12.34**	15.3	9.61	0.68	0.45	2.76	4.47	6.61	**30.02**
2 Market Buy	0.43	**0.83**	4.92	**15.88**	**22.43**	10.99	0.26	0.66	2.92	9.37	11.07	20.24
3 Small Buy	**1.69**	**1.54**	**25.55**	6.62	12.38	10.81	**1.09**	1.05	3.46	2.39	8.92	24.52
4 Bid Within	0.5	0.92	5.81	**10.46**	21.04	16.24	0.31	1.4	1.98	4.2	8.17	**28.96**
5 Bid At	0.26	0.54	3.85	9.49	**26.57**	**23.16**	0.1	0.16	2.15	2.53	10.21	20.99
6 Cancel Bid	0.19	0.3	3.1	8.43	20.09	**23.03**	0.33	0.55	4.58	8.83	20.03	10.54
7 Large Sell	0.57	0.17	4.03	4.83	6.95	**22.26**	**2.56**	**1.28**	**11.24**	**21.11**	14.81	10.21
8 Market Sell	0.15	0.23	2.29	6.84	8.04	18.48	0.36	0.76	3.35	**33.68**	19.47	6.36
9 Small sell	0.62	0.42	4.7	2.85	9.88	17.98	**1.45**	**2.65**	**19.81**	11.85	15.09	12.7
10 Ask Within	0.41	**1.21**	5.56	4.33	7.92	**22.8**	0.71	1.93	5.15	**10.64**	**22.58**	16.77
11 Ask At	0.12	0.1	2.78	2.92	10.53	16.04	0.32	0.89	3.43	8.43	**30.85**	23.59
12 Cancel Ask	0.44	0.45	6.32	6.41	15.58	11.76	0.24	0.66	3.12	6.84	20.52	**27.64**
Unconditional	0.39	0.52	5.56	6.68	16.59	17.85	0.40	0.85	4.08	7.12	19.01	20.97

3.2.1 Measuring Liquidity

We use the following formula to estimate the normalized quoted spread, per best limit observation:

$$Normalised\,Quoted\,Spread = \frac{Ask\,Price - Bid\,Price}{MQ_o} * 100.$$

Where $MQ_o = 0,5 * [Ask\,Price + Bid\,Price]$. Next we take a timeweighted average per period, and an equally weighted average over all firms, the results are displayed in Table 1. The quoted spread is calculated at every quote, showing the available trading opportunities. However, traders can time their trades and place them when it is cheap to do so, e.g. when liquidity is high. The realized and effective spreads are calculated around trades, and look at actually incurred trading costs. The effective spread measures direct execution costs while the realized spread takes the order's price impact into account. Denote MQ_o as the quoted midpoint before an order takes place and D = [1,-1] for a buy and a sell order respectively.

$$Effective\,half\,spread = \frac{Price - MQ_o}{MQ_o} * D * 100 \tag{1}$$

The effective spread overestimates the actual costs of trading, since the transaction itself reveals the traders' private information about the share price. A buy suggests positive information and will improve the share price, which benefits the investor placing the market order. The realized spread takes the price impact into account, and can be considered as the gains for the party placing the limit order. The price impact is evaluated against the midpoint in five minutes, MQ_{o+5}.

$$Realized\,half\,spread = \frac{Price - MQ_{o+5}}{MQ_{o+5}} * D * 100 \tag{2}$$

The effective half spread is weighted by traded volume and equally weighted over all firms, per period. For the periods after November, 2007 we use the consolidated tape to analyze the spreads; where the liquidity is aggregated over the entire market and the best prices and quantities are displayed.[14] This is the inside spread and may become even negative, when for instance the best ask on Chi-X is lower than the best bid price on Euronext Chlistalla and Lutat [2009].

[14] Only the visible liquidity is aggregated, available at Euronext, Deutsche Boerse and MTFs where the stock is traded.

While technically this is a price violation, it can be explained by the presence of transaction costs or make/take fees which make it too expensive to exploit this arbitrage opportunity.

As displayed in table 1, the quoted increased from 8,6 to 14,9 basepoints and the effective spread from 4.9 to 6.6 from period 1 to 4. The effective spread is roughly one half of the quoted spread, a quite general result that follows from the fact that trading mostly occurs when spreads are low, or involve stocks with low spreads. The realized spread was 1.3 basepoint, and turned to -0.8, it has become even negative in January, 2009. A low realized spread means that the price impact of a trade is high, trades are informative. Notice that this is the realized spread on Euronext, while the market is fragmented in that period. Part of the price discovery takes place at other trading venues and this suggests Euronext might attract more informed traders. An alternative explanation might be that large trades are split up into many smaller ones more often in January 2009. If all these trades take place on the same side of the orderbook, the MQ_{o+5} incorporates every individual trades price impact. The percentage of small trades to total trades has increased from 70% to 81% from period 1 to 4.[15] While the spreads are quite different already, we picked the dates of period 3 and 4 to match 1 and 2 as closely as possible; the spreads in the other months are higher.

In the following section we extend our analysis to the aggressive trades, the reason being that such trades have the strongest impact on liquidity. By looking at these trades, we can create the evolution of the spread, bid and ask price and the number of shares available. It also allows us to measure resiliency, which is defined as the amount of time the limit book requires to recover from a large trade, regarding price impact and depth.

3.3 Aggressive Trades

In this section we look at the evolution of the bid and ask price around an aggressive trade. This shows a temporary impact, right after the trade and a permanent impact, which can be considered as new information which is captured in the stock price. The graphs implicitly show the quoted spread around such trades as well; which allows for comparisons over time. Although our analysis is very similar to Degryse et al. [2006], we look at a time window

[15] We divide the unconditional probability of type = 3 or 9 to the probability of type=1,2,3,7,8 or 9, for every period.

after an aggressive trade, as opposed to a fixed number of quotes. As the time window is fixed per event, the number of quotes can fluctuate heavily.

3.3.1 Evolution of the bid and ask

Our goal is to consider the impact of MiFID on the evolution of the best bid and ask prices, by comparing periods before and after the implementation. We proceed by executing an event study approach, where an aggressive order, type 1 or 7, is considered the event. Our time window t = {-60,...,300} or one minute before until five minutes after the event. Our interest lies in the evolution of the best bid and ask prices, relative to the final transaction price of the aggressive order.[16] We create a separate time window for each event and divide the associated best bid and ask prices by the event price, for all t on {-60,...,300}, or $Normalized\,Ask = \frac{Best\,Ask}{Event\,Price} * 100$. The difference between the $Normalized\,Ask$ and $Normalized\,Bid$, the absolute spread, increases with the firm's share price. Dividing by the event price accounts for this and allows us to compare different stocks in different periods. Next we stack all the event windows in one file and average the normalized bid and ask prices, resulting in 361 observations per firm, per period. Finally, we average the 361 values over the firms in our sample, weighted by the number of events.

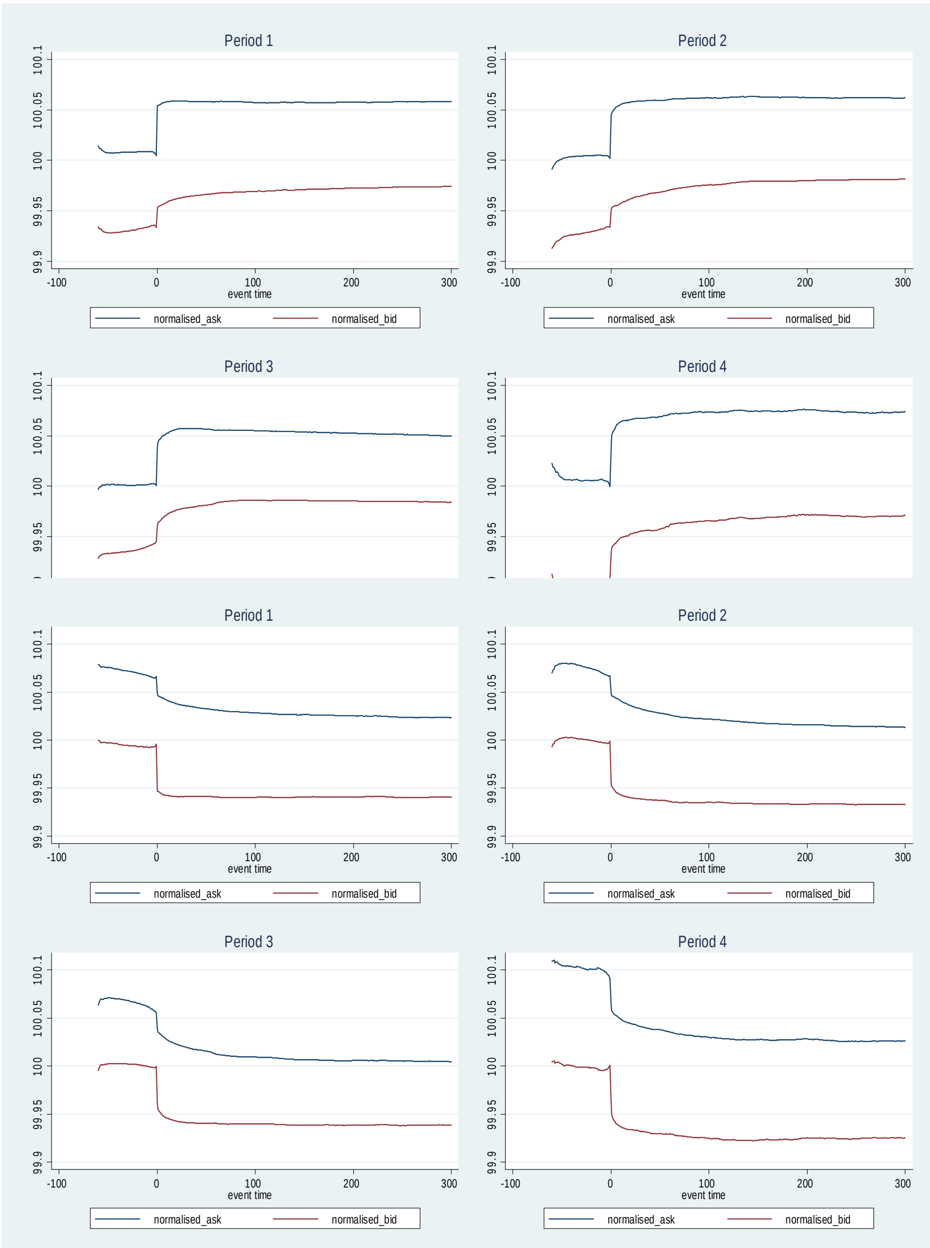
The results are presented in figures 1 and 2; four periods for type 1 and 7 respectively.[17] Figure 1 contains type 1, the horizontal axis represents the seconds before and after the event. This aggressive buy takes place on the ask side, hence the sharper peak there.

The bid side quickly adjusts, after 1 second. However, it does take the bid price longer to adjust, the reaction is smaller at $t = 0$, but after approximately 1 minute the bid side reaches a stable level. Figure 2 shows the same results, but for the opposite sides. Notice that the askside in figure 1 exceeds 100 on the whole domain, which seems odd at first sight since one would expect the line to be exactly 100 at $t = 0$. Notice however that the price of the last transaction of the aggressive order is considered the event price. After the event, within the

[16] For every limit order that gets hit by a market order a new observation is generated, so one market order can lead to several observations. We consider the transaction price of the last limit that gets hit to be the event price; this is the highest price for a buy, and lowest for a sell market order.

[17] First, we created the figures per firm, for each period. As they turned out very similar, we decided to average them, obtaining figures 1 - 2.

Figure 1: Type 1 and 7, for 4 periods. Average evolution of the best bid and best ask price.



same second, new quotes can emerge at different prices; which usually worsen the price. Also, the ask price exceeds 100 before the aggressive trade. This might be due to undercutting investors, who improves the best price with a relatively small amount. A buyer obtaining more shares then offered by this investor automatically becomes an aggressive trader in our classification. Therefore, we end up dividing the best ask by the low price of the undercutting investor, such that the normalized best ask is greater than 100. In case of an aggressive sell, the bid price on the whole domain is divided by the high bid price of the improving investor. As such, the bid sides in figure 2 are lower than 100 before the trade. Consistent with earlier evidence, the quoted midpoint increases (decreases) after an aggressive buy (sell) order.[18] In line with the decrease in realized spread for period 4 (see table 1), the price impact of an aggressive order is larger there, around 2 basepoints for both buys and sells. This suggests that resiliency has improved in period 4: while the price impact is larger, the orderbook adjusts for this just as quickly as in other periods.

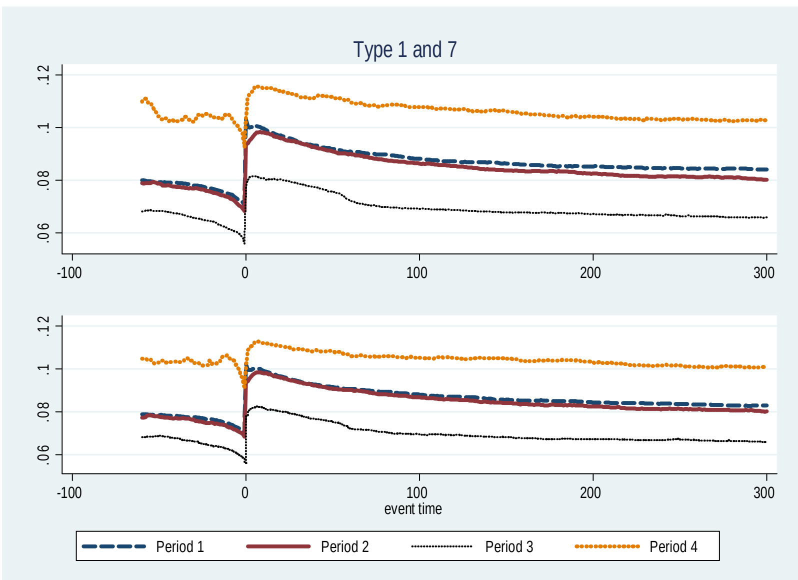
Besides the larger price impact, the shape of the evolutions of the best bid and ask prices before and after implementation are highly similar, there does not seem to be an impact of MiFID or market fragmentation. However, not obvious from the graphs right away, the quoted bid-ask spread has changed. This becomes clearer in figure 3, where the quoted spread for each period is presented, for type 1 and 7 respectively. Figure 3 depicts the difference between the variables in the previous figures. Summarizing, first the average best bid and ask per second, for each t on {-60,...,300}, per event is calculated, normalized to the transaction price. Next we average all events per firm and take the difference between the bid and ask to obtain the averaged quoted spread. Period 1 and 2 are similar, but the spread in period 3 is 2 basepoints lower on the entire domain. The spread of period 4 is about two basepoints higher than period 1. Interestingly, while the price impact in period 4 is high, the quoted spread does not increase that much: markets seem to have become quicker in adjusting prices to new events. Moreover, in the first three periods the spread starts to decrease at about 30 seconds before the trade takes place, in period 4 this has reduced to 10 seconds. Traders seem to act faster on high levels of liquidity by placing large orders, and after such a liquidity shock they are quicker in

[18]The time window might be too short to separate a permanent and temporary impact, resulting from adverse selection and inventory costs respectively. However, Huang and Stoll [1994] use 5 and 30 minute time horizons to proxy the post-trade economic value; Bessembinder and Kaufman [1997B] use 30 minutes and one day.

providing liquidity. The patterns for type 1 and 7 are almost identical, the increase in spread after the aggressive order reverses back to their normal level after about 200 seconds.[19] Degryse et al. [2005] found this reversion to be around 20 best limit updates.

The spread before the trade is roughly 1.5 basepoint lower then the average spread, displayed in table 1. After roughly 200 seconds the spread converges to a new level, which is approximately 1 basepoint higher than the pre-trade level, and more closer to the average level. This is in line with results of Gomber et al. [2004], it suggests that large trades are timed in periods of high liquidity. Liquidity does revert back, although not to its pre-event level, but rather to its "normal" level. Because of the timing of trades, the pre-event spread is not a good proxy for the average quoted spread.

Figure 3: Quoted Spread, type 1 and 7.



The increase in quoted spread after MiFIDs implementation might be due to changes in depth. When placing limit orders, an investor can choose to 'wait in line' by offering the best price, or to gain time priority by improving the price. When depth is relatively high, the queue is long and it becomes more attractive to improve the price. Therefore, quoted spreads decrease with depth.

[19] When the analysis was executed for five extremely liquid firms, the orderbook required 40 seconds to revert back to its original level.

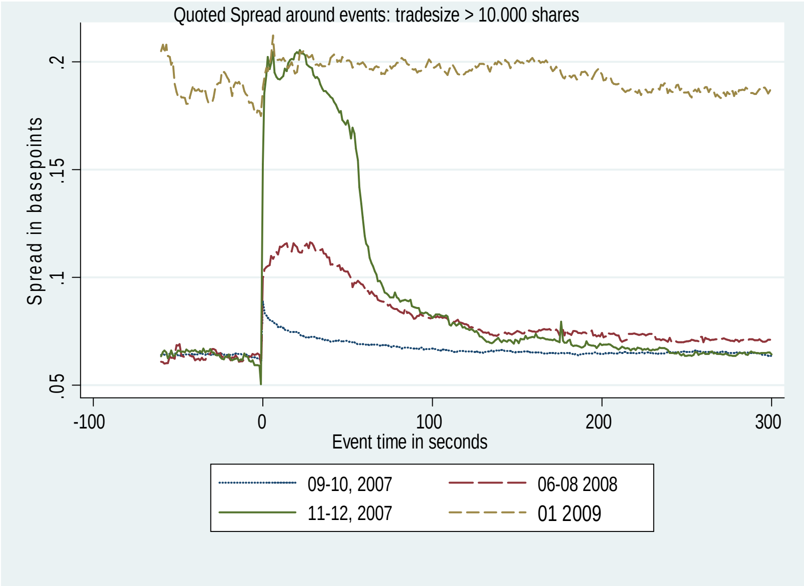
Also, MiFID improves pre trade transparency, increasing the value of the put option element of posted limit orders [Madhavan et al., 2005], putting downward pressure on depth. When the depth at the best price reduces, a trade will walk up or down the orderbook more often and will be classified accordingly. As a robustness check, the analysis in section 3.3.1 is executed where we select large trades, e.g. when the number of shares exceeds 10.000. This controls for the state of the orderbook, as small trades which are only classified as aggressive because of a thin orderbook are discarded. The graphs are presented in figure 4A and 4B, for both types and shows the evolution of the quoted spread around trades, similar to figure 3.

There are several interesting results, first the quoted spreads are much higher. As the transaction size is larger, more liquidity gets taken away, increasing spreads. Moreover, larger trades might convey more information, which has the same effect. Several differences emerge between the four periods. Compared to period 1, spreads in period 2 and 3 before the trade are very similar, but after the trade increase much steeper, especially for period 2. Looking at figure 4B, this effect is more present for aggressive sells, where the spread increases with 20 basepoint in period 2 after the trade. As for period 4, the evolution is much different, where the impact at the time of the trade is less pronounced, but the overall spread is 14 basepoints higher. This is in line with traders acting faster on new events, liquidity gets supplied quicker after a negative shock.

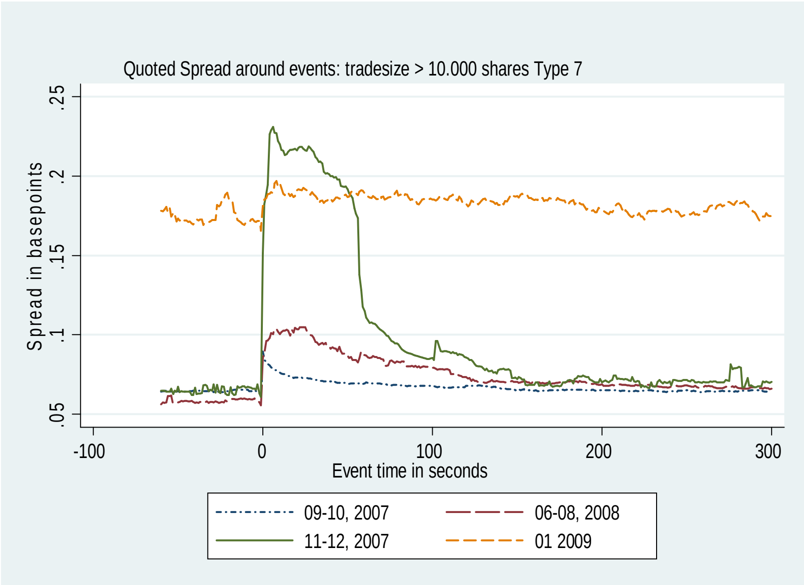
The observed change in quoted spread between periods does not seem to be due to differences in the order book prior to the transaction. The graphs are more volatile however, as we use only 10% of the initial observations.

Figure 4

(a) Quoted Spread, type 1.



(b) Quoted Spread, type 7.



4 Results

After the implementation of MiFID, we find that quoted spreads have increased in both the short and long run. Fragmentation did not increase in the short run, so the observed changes in liquidity in period 2 are likely due to the financial crisis, making a comparison over time more difficult. Related, the total number of orders fluctuates substantially. Compared to the first period, the daily average between the remaining three changed with +20%, +110% and -100%. Again, this is likely due to the financial crisis; as can also be seen by the reduction in average share price of 60%, and the increases in volatility and spreads. Concluding from the order submission, several facts emerge. Looking at trades only, small trades have become more common over time, at the expense of marketable limit orders. Also, cancellations at the bid and ask have gradually increased with 50% over time. Both results are in line with algorithmic trading, where orders are split up to reduce price impact, and limit orders are frequently placed and cancelled.

In period 4 the market has become relatively fragmented, and the event study shows it became more resilient. Although spreads are higher on the entire domain, the initial price impact of the trades are 20% larger, while the spreads converge just as fast to their normal level. This is especially due to the other side of the orderbook, which quickly adepts to the shock. Information might be incorporated quicker, which is confirmed by the increase in total amount of limit orders (table 2). There can be several causes for the observed change in resiliency. First, the competition introduced by trading venues might make active trading more attractive. An active trader can combine liquidity via Smart Order Routing technology, for example, and the algorithmic trading as mentioned earlier. Also, as trading can shift from one venue to the next, time priority can be violated.[20] In this case, actively following the market can increase the probability of execution.

We control for the trades aggressiveness and also specifically focus on very large trades. In period 2, after extremely large shocks, where the quoted spread on average increases from 8 to 23 basepoints, the market is still very resilient: after 200 seconds the spread has almost completely recovered. While larger trade sizes increase the price impact at the time of the transaction in periods 1 to 3, it does not do so for period 4.

[20] e.g. two limit orders with the same price are placed on two markets, but the order placed last gets executed first.

In this analysis we average over all firms in the sample, but in a previous version we executed the event study per firm and this showed similar results regarding the evolution of the bid and ask and the changes in quoted spreads, for period 1 and 2.[21] Per firm, the level of the quoted spread differs, but this is rather equal on the entire domain in the event window. Therefore, specific firm effects do not seem to account for the change in resiliency. Separating the analysis per firm can thus be considered as an additional robustness check, next to controlling for the size and aggressiveness of the trade.

There is a lot of room for improveming the current results. Our results support the notion that market fragmentation is correlated with improved resiliency; but an exogenous event is necessary to disentangle whether the observed effect is actually due to fragmentation, or simply a time effect; such as increased usage of SORT and algorithmic trading. In order to circumvent the impact of the financial crisis, a time effect, we could analyze the role of variation in fragmentation between firms, in the cross section. This variation in fragmentation can be linked to resiliency. Another caveat is that we analyze aggressive orders which are endogenous to the extend that they both affect, and are affected by the orderbook we are analyzing. Also, in future work we will try to control for the depth in the orderbook, which directly influences our definition of aggressive trades. Finally, we can focus on the resiliency at different trading venues, instead of the aggregated market. It would also be interesting to analyze firm characteristics that influence resiliency and market fragmentation.

References

J. Affleck-Graves, S.P. Hedge, and R.E. Miller. Trading mechanisms and the components of the bid-ask spread. *Journal of Finance*, 49(4):1471–1488, Sep 1994.

N. Aubry and M. McKee. MiFID: Where did it come from, where is it taking us? *Journal of International Banking Law and Regulation*, 4:177–186, 2007.

M. Barclay, T. Hendershott, and D.T. McCormick. Competition among trading venues: Information and trading on electronic communications networks. *Journal of Finance*, 58:2637 – 2666, 2003.

[21] These firms are Aegon, Ahold, Philips, Royal Dutch Shell and Unilever.

Paul Bennett and Li Wei. Market structure, fragmentation, and market quality. *Journal of Financial Markets*, 9(1):49 – 78, 2006. ISSN 1386-4181.

H. Bessembinder and H. Kaufman. A cross-exchange comparison of execution costs and information flow for NYSE-listed stocks. *Journal of Financial Economics*, (46):293–319, 1997A.

H. Bessembinder and H. Kaufman. A comparison of trade execution costs for NYSE and NASDAQ-listed stocks. *The Journal of Financial and Quantitative Analysis*, 32:287–310, Sep. 1997B.

H. Bessembinder, W Maxwell, and K. Venkataraman. Market transparency, liquidity externalities, and institutional trading costs in corporate bonds. *Journal of Financial Economics*, 82(82):251–288h, 2006.

B. Biais, P. Hillion, and C. Spatt. An empirical analysis of the limit order book and the order flow in the paris bourse. *Journal of Finance*, 50(5):1655–1689, December 1995.

B. Biais, D. Martimort, and J.C. Rochet. Competing mechanisms in a common value environment. *Econometrica*, 68(4):799–837, July 2000.

M. Brennan and A. Subrahmanyam. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41:441–464, 1996.

J.P. Casey and K. Lannoo. The MiFID implementing measures: Excessive detail or level playing field? *European Capital Markets Institute Policy Brief*, 1:1–8, May 2006.

M. Chlistalla and M. Lutat. The impact of new execution venues on european equity markets liquidity: The case of Chi-X. *Proceedings of the Fifteenth Americas Conference on Information Systems (AMCIS), San Francisco*, 2009.

J. Conrad, K. Johnson, and S. Wahal. Institutional trading and alternative trading systems. *Journal of Financial Economics*, 70:99–134, 2003.

R. Davies, A. Dufour, and B. Scott-Quinn. The MiFID: Competition in a new european equity market regulatory structure. *Oxford Scholarship Online Monographs*, pages 163–199, October 2006.

H. Degryse, F. De Jong, M. Van Ravenswaaij, and G. Wuyts. Aggressive orders and the resiliency of a limit order market. *Review of Finance*, Vol. 9:pp. 201–242, 2005.

H. Degryse, M. Van Achter, and G. Wuyts. Crossing networks: Competition and design. *Competition and Regulation in Network Industries*, 1:453–469, 2006.

D. Easley, N. Kiefer, and M. O'Hara. Cream-skimming or profit-sharing? the curious role of purchased order flow. *The Journal of Finance*, 51:811–833, July 1996.

G. A. Ferrarini and F. Recine. *Investor Protection In Europe: Corporate Law Making, the MiFID and Beyond*. Oxford University Press, 2006.

R. Finney. MiFIDs impact on market centers. *Futures Industry*, may/june: 36–39, May/June 2006.

T. Foucault and A. Menkveld. Competition for order flow and smart order routing systems. *Journal of Finance*, 63(1):119–158, feb 2008. URL `http://ideas.repec.org/p/ebg/heccah/0831.html`.

T. Foucault and C. A. Parlour. Competition for listings. *RAND Journal of Economics*, 35:329–355, 2004.

P. Gomber and M. Gsell. Catching up with technology - the impact of regulatory changes on ECNs/MTFs and the trading venue landscape in europe. *Competition and Regulation in Network Industries,*, 1(4):535–557, December 2006.

P. Gomber, U. Schweickert, and E. Theissen. Zooming in on liquidity. *Working Paper Series*, 2004.

C. Gresse. The effect of crossing-network trading on dealer market's bid-ask spreadsh. *European Financial Management*, 12(2):143–160, 2006.

M. Gsell. Assessing the impact of algorithmic trading on markets: A simulation approach. *Working Paper Series*, 2008.

L. Harris. Consolidation, fragmentation, segmentation and regulation. *Financial Markets, Institutions & Instruments*, 5:1–28, 1993.

L. Harris. Order exposure and parasitic traders. *Working Paper Marshall School of Business*, 1:1–22, 1997.

L. Harris and J. Hasbrouck. Market vs. limit orders: SuperDOT evidence on order submission strategy. *Journal of Financial and Quantitative Analysis*, 31(2):213–231, 1996.

J. Hasbrouck and G. Saar. Technology and liquidity provision: The blurring of traditional definitions. *Journal of Financial Markets*, 2009.

T. Hendershott and C.M. Jones. Island goes dark: Transparency, fragmentation, and regulation. *Review Financial Studies*, 18(3):743–793, 2005.

R.D. Huang and H.R. Stoll. Market microstructure and stock return predictions. *Review Financial Studies*, 7(1):179–213, 1994. doi: 10.1093/rfs/7.1.179.

A Madhavan, D. Porter, and D. Weaver. Should securities markets be transparent? *Journal of Financial Markets*, 8:266–288, 2005.

M. Pagano. Endogenous market thinness and stock price volatility. *The Review of Economic Studies*, 56:269–287, Apr. 1989A.

M. Pagano. Trading volume and asset liquidity. *Quarterly Journal of Economics*, 104:25–74, 1989B.

M. Pagano and A. Röell. Transparency and liquidity: A comparison of auction and dealer markets with informed trading. *Journal of Finance*, 51(2):579–612, June 1996.

A.F. Perold. *Streetwise: The Best of The Journal of Portfolio Management*, chapter The implementation shortfall: paper versus reality, pages 106–112. Journal of Portfolio Management, 1998.

J. Weston. Electronic communication networks and liquidity on the nasdaq. *Journal of Financial Services Research*, 22:125–139, 2002.