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Trade fragmentation and its impact on pre-trade liquidity

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Abstract: The MiFID was introduced in November 2007 to enhance market quality and consumer protection. One dimension of the directive was the abolishment of the former concentration rule, which allowed for the emergence of competition between stock exchanges. As a result, trade flow has fragmented over several trading venues. It is not clear whether fragmentation is beneficial for liquidity. On one hand, exchanges compete for order flow, which reduces liquidity costs. On the other hand, investors might experience difficulties in adjusting their trading behavior to the multimarket environment which increases liquidity costs. In this thesis we describe the current debate and its background. We contribute to the review of MiFID by studying the effects of fragmentation on the constituent stocks of the OMXS30 from November 2010 to April 2011. Our results indicate that fragmentation is beneficial but with a declining marginal effect. We also find that order flows are routed to the venues with the best quotes to a higher extent today than one year ago.

Keywords: Market fragmentation, Market microstructure, MiFID, Liquidity, Bid-Offer Spreads

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Preface

We would like to thank our tutor Francesco Sangiorgi for his guidance. We would also like to thank Thomson Reuters for granting us free access to their newly launched product EMSR, and for providing us with great product support and training. Furthermore, we extend our thanks to Jessica Olsson at Dagens Industri who arranged so that we could attend DI Trading Conference for free, which was a day of many inspiring seminars related to our topic. With this said we hope that you as a reader will take great interest in learning more about the how the European financial landscape has changed over the past few years.

Terms and abbreviations

MiFID= Markets in Financial Instruments Directive

EMSR=Equity Market Share Performance

MTF=Multilateral trading facility

RE=Regulated exchange

SORT=Smart order routing technology

Local BBO=the currently best bid or offer price quote for an individual trading venue

Consolidated BBO= the currently best bid or offer price quote across all trading venues

Trading venue= a regulated exchange or a multilateral trading facility

LBO=Limit order book

OTC=Over the counter

LSE= London Stock Exchange

VWAS= Volume Weighted Average Spread

EWAS= Equally Weighted Average Spread

HHI= Herfindahl-Hirschman Index

1. Introduction

The European trading environment has been largely altered since the European Commission introduced the Markets in Financial Instruments Directive in November 2007. The main objective of MiFID is increased competition, enhanced consumer protection and the creation of a single pan-European financial market. As part of its work to create a more transparent and stable financial system, the European Commission is currently evaluating the implications of MiFID. The official consultation document sent out to investment firms is now closed and under review, but the proposed revision made on the basis of their responses has not yet been publicly presented.

The changes in European financial regulation put an end to the former concentration of equity trading to the regulated exchanges[1] on which the firms are listed, and opened up for the emergence of new trading venues. On one side stand the new entrants arguing that competition leads to gains in improved liquidity and fee reductions sufficient to compensate for the technology costs required by investors. On the other side stand REs claiming that a more fragmented trading landscape has made price discovery more difficult and therefore increases liquidity costs. They argue that as trading becomes more dispersed over a number of trading venues, trade volume for each exchange will be insufficient to the degree that none of the exchanges has capacity to absorb large transactions without causing the investor adverse price impact. Large investors would then be forced to seek other transaction alternatives.

Trading fragmentation's impact on market quality in general and liquidity in particular, has since long interested researchers and regulators. However, over the last years rapid technological process has greatly simplified multi-market access for investors allowing them to monitor several markets simultaneously. This has put multimarket trading in a new light and it is therefore important to not draw conclusions from previous studies but to investigate what the implications are today.

Our thesis adds to the post-MiFID literature by researching the development of the most traded stocks in Sweden over recent years. We provide evidence that consolidated bid-offer spreads improve when the level of fragmentation increases. Second, we provide evidence that investors' ability to discover and allocate their orders to the trading venues with the best quotes has increased over time. More efficient price discovery suggests that the positive impact of fragmentation will continue to improve as monitoring technology and multi-market trading knowledge becomes more widespread.

Based on the findings from our empirical tests, based on OMXS30 data, we note that:

- Higher levels of fragmentation appear to benefit investors in the form of lower liquidity costs.

[1] Henceforth abbreviated as REs

- Investors' ability to allocate their orders to venues providing the best quotes appears to have improved over time.

2. Purpose

Our thesis has two separate purposes; one descriptive and one practical.

Equity investors are affected by the new directive but tend to have limited knowledge about it and its implications for their trading strategies. Our descriptive purpose is therefore to increase investor knowledge of the MiFID.

As trading platform competition is a new phenomenon, the scope of empirical tests on its implications for traders is rather limited. This is particularly the case in the Nordic region. As we have not encountered any previous studies investigating MiFID's implications for investors trading Swedish stocks, we think our results could be a valuable contribution to the Nordic debate and evaluation of the MiFID. Hence, our practical purpose is to provide evidence for the impact of fragmentation on liquidity costs among Swedish stocks.

2.1 Descriptive purpose

As the questions addressed in the debate on MiFID are complex and without any clear-cut answers, we think it is important to provide the reader with a substantial overview of the current debate. We therefore go through the background to and reasons for the regulatory changes that have been made, and present arguments for and against the emergence of competition and fragmentation. We thereafter present previous research on fragmentation's impact on liquidity, as well as other interesting research on trading behavior post-MiFID. After having fulfilled out descriptive purpose the objective is that the reader, assumed to have no prior knowledge of the topic, fully understands the assumptions behind our practical purpose

2.2 Practical purpose

The second purpose of our thesis is to perform empirical tests on how the liquidity of Swedish stocks has been affected by the fragmentation.

Results from previous studies on fragmentation have been quite mixed but tend to conclude that fragmentation is beneficial for traders, both in terms of direct and indirect trading costs (liquidity). If our results are in line with these, we provide evidence that the relationship not only holds in continental Europe, but also in the Nordics. It is likely that post-MiFID fragmentation in Sweden has evolved differently than in other European markets. The long distance to the London-based MTFs and the Nordic-specific example of Burgundy, may affect the competiveness of the pan-European MTFs and their implications for Nordic equity trading.

As there is a large variety of liquidity measures we limit our test to only concern the quoted spread, which is a pre-trade liquidity measure.

2.3 Research questions

We have defined two research questions which we address in our empirical tests:

1. How does fragmentation of trading volume affect pre-trade liquidity for OMXS30 stocks?
2. Are market orders for OMXS30 stocks being routed to the trading venues with the best available price quotes to a higher extent in Q1 2011 than in Q1 2010?

3. Outline

In section 1, Introduction, we briefly introduce our topic and what our main conclusions are from our empirical tests.

In section 2, Purpose, we describe the two purposes that we wish to fulfill with this thesis, and the research questions that we wish to answer.

In section 3, Outline, we provide an overview of the sections of our thesis and their content.

In section 4, Qualitative Description, we focus on our descriptive purpose of providing the reader with background information. We consider this necessary in order for the reader to understand the assumptions that our empirical tests are based on.

In section 5, Previous Research, we give an overview of related research and describe the studies that have inspired us the most in our work. Previous studies are also useful as they provide us with an intuitive feel for what results we expect from our empirical tests.

In section 6, Hypotheses, based on the information in Qualitative Description and Previous Research sections, we transform our two research questions into mathematically expressed hypotheses.

In section 7, Data, we describe how we proceeded to collect the data, and describe the trading venues, stocks and time windows that are included in our empirical tests.

In section 8, Methodology, we specify the regression models and various statistical tests that we employ when testing our two hypotheses.

In section 9, Descriptive Summaries, we present descriptive statistics on some of the variables in our dataset.

In section 10, Results, we report the results from the empirical tests regarding the sizes, signs and statistical significance of the coefficients and constants. We also discuss the meanings of the estimated coefficients and possible reasons for why we observe them.

In section 11, Conclusions, we reach conclusions based on the results from our empirical tests. We are however careful about the extent to which the results can be generalized or used as a contribution in the current revision of MiFID.

In Appendix I: Explanation of variables, we explain the variables that appear in our regressions. For every potential control variable we describe how it might affect liquidity and fragmentation, and discuss our decision whether to include it or not in the regression.

In Appendix II: Trading venues, we provide an overview of the venues in our dataset and their different characteristics.

In Appendix III: Descriptives and Results, we present all our results and other interesting graphs.

4. Qualitative Description

4.1 Basics on stock exchanges and liquidity

On- and off-exchange stock transactions

Stock transactions can be carried out either off or on exchanges. Off-exchange transactions, or over-the-counter-transactions as they are commonly referred to, are based on price negotiations between the two counterparties, whereas stock exchange transactions are based on traders responding to price quotes. The large trade volumes and continuous turnover of shares that we see on today's financial landscape would certainly not be possible without exchanges as they facilitate for interested parties to engage in the trade of stocks, bonds and other securities by matching buyers and sellers. (Bodie, Kane, & Marcus, 2009)

Investors seek OTC-opportunities to mitigate the risk of adverse price impact during the buying or selling process and to avoid exchange fees. However, potential cost savings of OTC are in most circumstances offset by search related costs. As search costs and the potential for OTC cost savings differ between investors depending on transaction size and the firm's ability to find a counterpart, there is room for both exchange- and OTC-trade in the financial landscape. (Pagano, 1989)

From initially requiring physical presence, stock exchanges have taken the next step to become automatic, electronic systems that match orders without the need of the involved parties to ever meet face to face. Electronic markets solve the issue of investors being located remotely from each other. They also reduce the issue regarding asynchronous arrival of buyers and sellers on the marketplace by allowing the primary counterpart to submit and store an order at one point in time for having it executed as soon as a secondary counterpart arrives. Some uncertainty to the primary counterparts nevertheless remains, which is why liquidity costs emerge.

Quote-driven and limit order exchanges

An exchange's structure affects the probability for its participants to find counterparts, and consequently also execution time uncertainty. Traditionally, exchanges have been organized as "quote-driven markets" on which dealers initially post their quotes on the market. Investors then submit market orders to have the transactions executed. Today's electronic trading systems have largely abandoned this old model of designated dealers and instead apply limit order systems. Without dealers, the investors themselves are responsible for providing the quotes, which they do by submitting limit orders. In order to submit a limit order the investor sets an upper (lower) limit to which he is willing to buy (sell) a certain quantity of the security. The time of execution is uncertain, but it is known that the transaction price could never exceed (be less than) the limit. (O'Hara, 1995)

Hybrid exchanges allow public investors to submit limit orders, but contract market makers to augment their order volume. E.g. London Stock Exchange and New York Stock Exchange contract market makers across all stocks, Euronext Paris on selected stocks, whereas Tokyo Stock Exchange and the Australian Stock Exchange do not contract any market makers. (Aitken, Cook, Harris, & McInish)

Usually market makers pay a fee to be registered as market makers. In return, they benefit from lower trading fees. Therefore they have incentives for providing volumes so that the fee reductions compensate for the fixed fee payment. (Riordan, Storkenmaier, & Wagener, 2010) In the past market makers had to be officially registered. This is no longer the case, which makes it much easier to join an exchange as a market maker today. (Andersson & Holmgren, Panel discussion - from a screen based trading infrastructure to the next generation trading tools, 2011)

The limit order system is a continuous auction system. Even though most trade is conducted through continuous auctions, major European equity markets, including Stockholm, use call auctions to open and close the trading days. Investors then have their accumulated orders matched simultaneously, usually at a market clearing price set to maximize trade volume. The main objective is to avoid large jumps between one day's closing price and the next day's opening price. (Stoll, Market Microstructure, 2003)

The choice between market and limit orders

Up to now we have classified orders in quote-driven markets as market orders, and orders in limit markets as limit orders. Although we focus on limit order systems in our thesis, we use both terms for practical reasons. A market order is by our definition a limit order priced for immediate execution, whereas a limit order is nonmarketable at the time of submission. This distinction is common in financial literature, as it creates more clarity about the different roles of primary and secondary counterparts in a transaction even though the order submission process is identical.

Stock transactions thus occur when a market order investor buys (sells) to the current market price, which is the lowest (highest) price that is accepted by the limit order investors. Demsetz argued that the two types of orders occur due to temporary imbalances between buyers and sellers. There are two types of investors; those that want immediate execution and those with less need for immediacy. (Demsetz, 1968) A limit order buyer (seller) is prepared to wait for the number of sellers (buyers) to increase so that the price becomes lower (higher). Therefore he stores his order in the LOB. He then faces the risk that the market price will move away from his limit so that his order will not be executed, or that the market price might move past his quote so that the investor has to execute to an unfavorable price. A market order investor does not face these risks since he per definition is guaranteed immediate execution. The market order investor hence pays a premium for immediacy. Later we give a more complete explanation of the risks faced by the primary counterparts, and how he can mitigate the different types of risk. (Liu, 2009)

Incoming limit orders are stored in a limit order book which at any given point in time contains the quantities and prices of the orders that have not yet been executed. Execution priority is usually given to orders with the best price (BBO) and secondary priority to order submission time. (Foucalt & Menkveld, 2008)

Information disclosure in a limit order market

The LOB only displays to investors the orders that have not been hidden. Exchanges apply different rules regarding information disclosure in the LOB. Investors submitting large orders generally wish to submit hidden orders since the revelation of excess supply (demand) on the market place could lead to adverse price effects. It could be very costly for large traders to openly reveal their intentions, and they therefore have strong incentives to search for off-exchange transaction opportunities as the adverse price effect component is large relative to the off-exchange search cost. Hence, in order to remain an attractive alternative for large investors, exchanges often not require full disclosure from them. The permitted amount of hidden orders is subsequently a trade-off for exchanges. Less disclosure demands make an exchange more attractive for large block investors, whereas disclosure increases the LOB's displayed volume and subsequently attract more investors to the market as the possibility to find a counterpart increases. (Moinas, 2010)

Most exchanges handle this trade-off by displaying only a certain fraction of large orders. When execution of the initially displayed fraction has taken place the system automatically refreshes and displays another fraction of the order. This process is repeated until the entire order has been executed. Empirical studies have shown that a significant amount of orders are hidden, implying that the LOB has more volume than real time tick data suggest. (Moinas, 2010)

The importance of liquidity

The need for liquidity not only differs between investors depending on the order size, but also differs dependent on their investment horizons. It is not as important for long-term investors to be able to quickly get in and out of a trading position as it is for short-term traders. Long-term investors are willing to wait longer for secondary counterpart arrivals and therefore have a relatively small aversion for illiquid securities. (Bodie, Kane, & Marcus, 2009) Many investment firms and banks apply strategies based on exploiting small magnitude pricing inefficiencies leading them to exit positions shortly after having entered them. The return from every single position is very small and could become completely eroded by high liquidity premiums. Liquidity costs are therefore crucial for the implementation of their high-frequency trading strategies. Due to differences in structure, disclosure rules and number of traders, exchanges differ in their ability to provide non-expensive immediacy to HFT traders. Since liquidity also differs across stocks, HFT traders choose only to include large, liquid stocks in their trading strategies. (Degryse, Jong, & Kervel, 2011)

4.2 The liquidity premium and its components

The LBO makes immediate execution possible for those traders that are willing to pay a premium for immediacy, revealing to them the best available prices and the quantities supporting those prices at any given point in time.

The ability for a trader to find matching quotes on the exchange when he wishes to buy or sell a certain quantity of a security, without having to pay a large premium[2] to have it immediately executed, is what defines the concept liquidity. Ideally it should be possible also to have large orders immediately executed, without having to buy or sell order fractions at large deviations from BBO, Liquidity is important for exchanges as it is widely recognized as the most important measure for market quality and is a main deciding factor in investors' order allocation decisions. (O'Hara, 1995)

Bid-offer spreads

The most popular method to measure the liquidity premium is in terms of bid-offer spreads, which measure the cost of entering a position to immediately have it exited. Other proxies for liquidity costs also exist, since not only BBOs matter to investors, but also the LBO depth and size. Regardless of the specific spread construction, liquidity premiums are small when the best bid and offer prices are close to each other and supported by sufficiently large quantities so that transactions can actually be executed at those price levels. (Cohen, Maier, Schwarts, & Whitcomb, 1981)

Quoted and effective spreads

Our objective is not to cover the different liquidity measures in depth, but for a better understanding of the liquidity measures that appear in related literature, we point out the difference between the quoted and effective spread:

$$Quoted\ spread = (BBO\_Offer - BBO\_Bid)/(Mid)$$

$$Effective\ spread = D * (Price - Mid)/Mid$$

Both expressions use the midpoint between Bid and Offer as the denominator in order to make spreads comparable between firms with different stock prices. (Riordan, Storkenmaier, & Wagener, 2010) The measures can be adjusted to also take different aspects of LBO depth or breadth into account, depending on what the user considers as the most important liquidity aspects for him.

The quoted spread is calculated using the quotes that appear in the LBO. It is an ex-ante measure which indicates what the expected transaction cost is. The effective spread is the cost actually paid. The variable D in the effective spread calculation is a variable representing the direction of the trade with -1 for sell and +1 for buy.

[2] The price difference in between submitting a market order compared to a limit order

Theoretical works concerning liquidity spread are largely theories about quoted spreads, although we have come across studies on ex-post liquidity. In our analysis we will focus on ex-ante liquidity. (Riordan, Storkenmaier, & Wagener, 2010)

What determines the size of the spread?

In quote-driven markets the cost of immediacy may partially be an effect of dealers collaborating and engaging in non-competitive pricing, raising their own profits at the expense of market order investors. In limit order markets collaborative behavior between limit order investors is assumed to be impossible. The large number of liquidity providers indicates fierce price competition pushing quotes to the point at which all liquidity provision-related costs are covered but no profits made. (Stoll, Inferring the Components of the Bid-Ask Spread: Theory and Empirical Tests, 1989)

If limit order investors were risk-neutral and incurred equal order handling costs, bid and offer limits would be the same for all competitive limit order investors. Transaction prices would simply bounce between the two levels with equal distance to the market price. However, as it is empirically proven that spreads are non-static, traders must take other factors in account than exogenous order handling costs when choosing between market- or limit orders.

When spreads are wide investors have much to gain from submitting limit orders instead of market orders. The order becomes executed to a much better price than a market order, whereas execution probability remains high. This follows because if the trader's order is at BBO, he is chosen for the transaction as soon as an immediacy-demanding investor arrives. Investors therefore shift from market orders to limit orders. Spreads then become narrow as more liquidity is added to the LBO. But as spreads decrease, traders increasingly prefer certain execution since the gains from a limit order is small relative to the execution risk. They shift back to market orders and the spreads consequently return to their initial size. (Cohen, Maier, Schwarts, & Whitcomb, 1981)

This theory implies that spreads always exist and depend on traders shifting between market orders and limit orders. As a spread approach zero, traders increase their fraction of market orders relative to limit orders, which increases the spread. Short-term changes in liquidity costs thus depend on changes in supply and demand for immediacy. In turn, supply and demand for immediacy depends on the risks involved in submitting limit orders. We now describe these risks:

Inventory risk

The term refers to the opportunity cost of tying up resources. With faster execution an investor could have had sold his stocks earlier to have the money invested elsewhere. Due to the delay he does not obtain the gains that would have resulted from the other investment. Analogously, when buying stocks with delay investors need to carry cash since it is not possible to dispose of another investment for untying cash after the transaction has been agreed on due to the second counterpart's requirement for immediacy. (O'Hara, 1995)

It also refers to the risk of adverse public information arriving after execution. Expected value of new information is zero since it is equally likely to be positive as negative, but as investors are assumed to be risk-averse they require compensation for uncertainty. It is more difficult to predict the market price shortly after execution if time from submission to execution is expanded. (Stoll, Market Microstructure, 2003)

Option effect

The option effect refers to the risk of public information arriving between order submission and execution, changing the market price so that the transaction is favorable for the second counterpart but no longer the first. A limit order thus gives an option to the market to execute when the quote appears attractive but does not impose any obligations to do so. When the transaction is executed unfavorably, the investor becomes picked-off.[3] (Stoll, Market Microstructure, 2003)

Adverse selection risk

Adverse selection risk is similar to option risk in that it refers to market order investors only reacting to quotes that are favorable to them. It however differs in that the new information is not public, but only revealed to some traders which quickly exploit their superior information. Liquidity suppliers lose on transactions with better informed traders and therefore require compensation for this, which is carried on to the uninformed traders. (Bessembinder & Venkataraman, 2009)

Methods to reduce risk

The different forms of inventory and adverse selection risks are highly dependent on the risk for delayed execution and rapid price changes. A non-aggressive order increases execution risk[4] but simultaneously reduces the risk that private or public information changes market prices to the extent that the investor is picked-off. To a certain extent, there is hence a trade-off between execution risk and the risk of being picked-off. (Aitken, Almeida, Harris, & McInish, 2007)

A higher execution risk means that a larger compensation for having placed a limit order is required. But as the limit order investor submits a less aggressive quote ensuring him a larger profit, execution risk increases as the probability of finding an interested counterparty has decreased. It is difficult to know whether the premium is large because of high execution risk or if the high execution risk has occurred due to limit order investors trying to extract large premiums.

Both execution and adverse price risk can be mitigated with better monitoring technology. If news arrive prices move, the quote could be changed to be more aggressive or defensive. Other factors affecting the

[3] A commonly used expression in market microstructure research
[4] Execution risk not only refers to the risk of non-execution, but also the risk of delayed execution

risk components are trade volume, price and volatility. In Appendix I: Explanation of variables we continue the discussion on HFT and other liquidity affecting factors. (Liu, 2009)

4.3 MiFID

The introduction of MiFID

Previously, the concentration rule required all European equity transactions to be carried out on REs. The rule's objective was to create a single and fair market with high levels of disclosure so that all investors would trade on similar conditions. Consequently, the traditional REs enjoyed monopoly positions which enabled them to charge excessively high trading fees from investors and listing fees from companies. A noteworthy indicator of the excessive pricing came when the UK Office of Fair Trading forced LSE to lower listing fees by 25%. (Cherbonnier & Vandelanoite, 2008)

To make equity markets more competitive the MiFID was introduced in November 2007. The directive abolished the concentration rule and authorized exchanges to offer trading on firms without the firm's approval. Multilateral Trading Facilities, e.g. Chi-X, Turquoise and BATS emerged as soon as the content of the directive was known. (Jeffs & Fairless, 2008). MTFs are usually initiated by investment banking groups which were previously restricted from creating their own trading systems. Their objective at launch was to create a market with lower fees and faster computer systems, primarily targeting HFT-based investment firms. Some of them have been successful in gaining market shares, due to their low fees and liquidity enhancing strategies such as asymmetric pricing and market making[5]. They have had great impact on the Res' fee schedules and innovative efforts, making REs feeling obliged to also reduce prices, invest in new technology and apply asymmetric pricing. (Cherbonnier & Vandelanoite, 2008)

Figure 2 shows the market shares on their own listed securities that Stockholm and some other national exchanges have lost to MTFs in recent years. Spain is an exception among European Res, which Pan-European MTFs attribute to extensive administrative post-trading procedures, reducing their competiveness. (Gsell, Gomber, & Lutat, 2011)The rapidly downward market share trend for LSE, Xetra and Stockholm is representative for most European REs.

Best execution, pre- and post trade transparency

To enhance end-investor protection, MiFID also set out a number of obligations for intermediate investment firms in terms of transparency and execution quality. One such principle is that of "best execution", obliging brokers to make reasonable efforts to obtain the best available conditions when trading for their clients, with respect to price, liquidity, transaction costs and speed of execution. It is a broad definition allowing European brokers to define the best-execution benchmarks themselves. Thus,

[5] More on the liquidity enhancing strategies in section 4.5

they can choose to trade on the national exchange only, arguing that the costs of monitoring several venues and splitting orders between them would outweigh potential gains from multi-market trading. This principle differs from its US equivalent, which obliges brokers to always execute clients' trades on the venue at consolidated BBO. In the US, new entrants are therefore guaranteed to attract order flow when being at BBO, which is not the case in Europe. Nevertheless, the European venues do compete on their ability to display the best prices, and do gain market shares on the basis of their BBO performance. (Degryse, Jong, & Kervel, 2011)

MiFID also contained new regulations requiring pre-trade and post-trade transparency. Pre-trade transparency requires regulated markets and MTFs to publish listed security quotes on a continuous basis, whereas post-trade transparency requires them to publish transaction information after the trades have been executed. (Cherbonnier & Vandelanoite, 2008)

Smart order routing technology

The competition between trading venues is not only a consequence of regulatory changes but also of improvements in technology. Human traders are increasingly becoming replaced by smart order routing technology (hereafter referred to as SORT), which identify the best destinations and slice up investors' orders. In the next step the suborders are routed to different venues to optimize execution. (Gsell, Gomber, & Lutat, 2011)

Due to the ambiguous definition of best execution and investor preferences assumed to be heterogeneous, different types of SORT have accordingly been created too. Investors that prioritize price would ideally opt for SORT solutions accessing a certain price level at multiple venues at once, whereas investors with preference for speed would choose to access multiple trading venues at multiple price levels at once. (Foucalt & Menkveld, 2008)

Some of the MTFs, such as BATS and Turquoise, offer smart order routers to their participants, not very surprising considering that they are dependent on widespread smart order routing usage to have their prices discovered by investors. Regulated exchanges, such as Stockholm, are now responding by starting their own SORT offerings, also offering access to all competing trading venues. (Sibbern, 2011)SORT with ability to discover hidden orders in the LOB have also been developed, but are not yet nearly as widely used as the lit counterparts. (Salmon, 2010)

SORT requires substantial investments in technology and know-how. Not all brokers are willing to bear these costs, which is why far from all European brokers take advantage of algorithmic trading opportunities despite the potential for future reductions in transaction costs. There is a concern that end-customers to the investment funds that choose not to make use of SOR will be damaged. Therefore there are ongoing discussions whether the European definition of Best Execution should be dropped in favor for the US equivalent, which obliges brokers to invest in SORT. (Degryse, Jong, & Kervel, 2011)

However, there is disagreement what investments are required. In a recent panel debate, Peter Holmgren, ULLINK (SOR-provider), stated that multimarket connectivity development requires a large workforce of highly-skilled engineers, and therefore is very expensive. Continuous technology improvements force brokers to incrementally invest more to be in line with competition in getting first to the best prices. Martin Andersson, Nordnet Bank confirmed this by saying that his company has taken large SORT investments as a response to MiFID. (Andersson & Holmgren, 2011) Of another opinion was Claes Cramer, Montgomery Capital, arguing that SORT prices have come down substantially due to more aggressive competition between SORT providers, and that more basic versions of SORT are today so cheap so that the cost argument is no longer a valid excuse for investment firms not to invest. (Cramer, 2011)

4.4 Market consolidation

In February 2011, London Stock exchange acquired Toronto Stock Exchange, NYSE Euronext and Deutsche Boerse announced their intent to merge, and Nasdaq Group made official its desire to acquire NYSE Euronext (Bunge, 2011). Not only regulated markets are merging their operations in order to compete with MTFs but BATS simultaneously announced the takover of Chi-X Europe and their plans to diversify into derivatives trading and a listing business[6]. (Jeffs & Spicer, BATS buying Chi-X Europe, challenge national rivals, 2011) Wenow describe the background to the lively M&A activity, and provide arguments for why consolidation improves liquidity.

Cost structure of exchanges

Operating an exchange is costly. Setting up the trading platform requires large upfront investments, and then there are substantial expenses related to monitoring, listing, clearing and settlement, storage and presentation of financial data. Many of the required costs are largely fixed, indicating that an exchange is able to significantly lower their cost per trade if they operate on a larger scale. Lower costs could then be used to lower prices. Since most exchanges are for-profit organizations however, it is likely that lower costs only lead to improved margins.

Positive network externalities

Another commonly cited argument for large, consolidated exchanges is that of positive network externalities for traders, which occur when more traders allocate their orders to the same venue. The more buyers and sellers there are in a market, the higher is the market's ability to match buyers and sellers. The LOB expands as a natural consequence of an increasing number of limit orders and the quotes become more aggressive as investors try to reduce execution risk by providing better quotes than other limit order investors do. Price competition between limit order investors lead to lower indirect transaction costs, and hence improved market quality.

[6] The transaction is expected to close in the second quarter 2011, and has therefore not had any implications for our analysis, in which they are two separate venues over the full time-period.

Concentration and its impact on liquidity

Due to positive network externalities, concentration of exchanges has been assumed to compensate for the lack of downward fee pressure and limited technological innovativeness incurred by the monopolistic market. The centralized national exchanges have widely been regarded as the best possible solution in order to ensure liquidity to investors. (O'Hara & Ye, 2009) Early theoretical work has argued that equilibrium with trading in more than one market could never remain stable. As soon as a venue displays greater liquidity than the others, all orders would automatically flow to that market (Pagano, 1989). The argument however assumes trading venues and investor strategies to be homogenous, and will be discussed more in the section on fragmentation. Nevertheless, even if equilibrium with a more fragmented financial landscape can remain stable, it might not be in traders' best interest. The probability of finding a counterparty is reduced when investors become more scattered which consequently lowers execution probabilities. (Degryse, Jong, & Kervel, 2011) Traders have to invest in SORT to overcome the problem of scattered order flows.

Summary of arguments why consolidation lowers transaction costs

Economies of scale → *lower cost per trade* → *lower direct prices charged by the exchanges*

More market participants at the same venue → *reduced execution uncertainty* → *smaller required liquidity premium*

4.5 Market fragmentation

The model that two market venues could never co-exist without all trade flow gravitating towards the most liquid market is based on the assumption of homogenous markets and investors.Investor strategies however are not considered homogeneous. They for example differ in how active or passive they are. For active high frequency traders every millisecond as valuable and they therefore see high-speed technology as a key criterion when allocating their orders, whereas more passive investors do not attach the same importance to speed but attach larger value to specific pre- or post- trade services. They also differ depending on transaction size, which creates heterogeneous preferences, highlighted in the following commonly applied theoretical model:

In the model there are two markets that differ in depth, with the deeper market having higher direct trading costs. Only large traders are willing to pay higher direct transaction costs to enjoy a larger LBO and thus cluster on the deeper market, whereas small traders attach more importance to the BBO levels and thus cluster on the shallow market. This means that two exchanges which are differentiated from each other and have benefits that are valued differently by traders both can exist in equilibrium. (Pagano, 1989)

The theoretical model of different types of investors clustering at separate markets is consistent with the fact that Burgundy has captured up to 90% of volume in certain small- and microcap securities. It is proven that institutional investor with large average transaction sizes mostly focus on mid- and large cap securities, whereas retail investors are more prone to invest in small- and microcap stocks. Since institutional investors are more concerned about LBO depth and the risk of adverse price impact they tend to keep much of their trading at Stockholm despite higher direct transaction costs. For retail investors BBOs are of relatively higher importance than depth, and they therefore cluster at Burgundy with their small- and microcap security holdings. (Aronsson, 2011)

New entrants' strategies to attract order flow and their impact on liquidity

The MTFs launched their platforms in Europe accompanied by the introduction of asymmetric pricing. Asymmetric pricing models mean that market order investors are charged extra for removing liquidity, while limit order submitters receive a rebate for their liquidity provision. It has been proven to help MTFs to quickly gain market share. For example, when BATS announced a fee schedule by which passive liquidity providers were rebated 0.4 bps and liquidity takers were charged 0.2 bps, its UK market share was doubled in the course of one month. (News) REs now also employ asymmetric fee regimes but are not as aggressive in their fee asymmetry as the MTFs are.

Most of the MTFs also contract market makers, typically the owners of the MTFs. Market makers commit for a certain size and spread, and thus guarantee liquidity that is meant to attract further volume to the LBO. This is done in order for the market to reach a critical mass of liquidity on which further liquidity is generated by the already displayed liquidity. When that critical point is reached market makers are no longer needed. Market makers are able to provide aggressive price quotes due to their rebates, and in doing so they ought to improve BBOs. In a study on Euronext Paris it was concluded that the presence of a market maker decreased quoted spreads by 22%. (Aitken, Cook, Harris, & McInish, 2007)

Optimized multi-market trading (queue jumping)

It is also predicted that consolidated volume at different prices should increase with fragmentation due to the absence of time priority across markets. First priority is usually given according to price, and second priority to time of order submission. If there was only one market, a limit order investor would have to provide his quote one tick size (price step) better than BBO to obtain first priority. If there is another market with same BBO but with less quantity supporting it, he can queue-jump by submitting a quote that equals BBO and have it executed before some of the BBO submitters in the first market. The possibility to queue jump leads liquidity suppliers to provide quotes on more than one market to increase the likelihood of rapid execution which leads to a higher aggregated volume. (Foucalt & Menkveld, 2008)

Summary of arguments why fragmentation lowers transaction costs

Aggressive pricing by market makers trying to attract order flow → improved BBOs → smaller spreads

Absence of time priority across markets → queue-jumping and multimarket limit order submission → increased consolidated volume at certain price levels

4.6 Concentration or fragmentation?

The discussion whether market fragmentation is better than market concentration for total transaction costs[7] generally revolves around the trade-off between the welfare losses incurred by monopolies (such as lack of price-competition and quality-improving efforts) and the network externalities that are lost in a more fragmented market. We only focus on liquidity costs which is why we do not take into account the potential for fee cuts and innovative efforts that the abolishment of monopoly implies. Instead we address whether the benefits of competition offsets the benefits of concentration. The key to this discussion concerns whether SORT is sufficiently widespread and well-developed to allow a sufficiently large number of investors to trade as if they acted on a single, centralized market. If this is the case, then competition, and the fragmentation that comes with competition, leads to a reduction of liquidity costs. If not, then centralization is preferable, in particular for those traders that do not have the resources to employ SORT.

Clara Furse, chief executive of the London Stock Exchange, summarizes the issue by putting it this way: -"The test for MiFID will be whether competition will increase liquidity and efficiency. The risk is that the benefits of competition for investors will be lost to the increase in fragmentation. Wider spreads and an increase in the cost of trading and the cost of market data would undermine the whole aim of MiFID." (Jeffs & Spicer)

5. Previous Research

In the field of market microstructure; the study of financial market frictions at a micro level, numerous studies have been undertaken aiming to answer questions about liquidity. Research questions have typically studied the implications for liquidity for different listing locations, quote-driven vs. limit order systems and different news announcements at the macro- and corporate level. Although there unarguably is a great scope of research available that covers asset liquidity, the amount of previous research on the impact of fragmentation on consolidated stock liquidity is scarce due to the novelty of fragmented trading.

5.1 General research overview

For our analysis we have mostly been interested in post-MiFID research, particularly European. US research has proven quite interesting as well as US stock trading is highly fragmented. However, the US version of best execution is different from its European equivalent, in that it obliges investment funds to trade on the venue currently offering BBO. This makes it more difficult to compare US effects to European post-MiFID effects since fragmentation in US is taking place in a different regulative environment. On the other hand, US best execution has lead to US investment funds/brokers being at

[7] Includes direct fees charged by the exchanges and the liquidity costs extracted by limit order submitters

the forefront of multimarket trading. It might therefore be easier to see and verify the results of fragmented trading in the US, which would give European legislators an idea of the implications when routing technology becomes more widely spread.

Market microstructure studies that we have looked at have u*sed either matched sample estimation or panel data regressions. The matched sample approa*ch usually matches stocks according to similarities in certain firm characteristics, such as market cap, but that differ in some crucial aspect that might have an impact on liquidity. After having constructed the matched samples a statistical test of the observed differences in bid-offer spreads between the matched pair components is calculated in order to interfere whether the differential factor has had an impact on the spread or not. (Davies & Kim, 2009)

Following list displays the matching characteristics from 16 different matched samples studies. These factors have been employed as they are believed to imply similar liquidity costs.

Matching characteristics:	Nr of studies:
Market capitalization	15
Share price	12
Trade volume	11
Volatility	9
Tick size	1
Book value and debt level	1

These characteristics are all potentially important to control for in our test. There seems to be consensus regarding control variables, but as some of the studies are rather old the technological development has introduced new potentially important factors that do not appear in the list.

5.2 Specific research

In this section we will cover four of the research articles that we have read in greater detail. We have of course read other related research as well in order to understand the liquidity concept, but these have proven more helpful for us when we try to find answers to our research questions. The first two articles described below have been helpful for the main research question, whereas the other articles have been helpful for our second research question.

Fragmented trading in the Netherlands and its impact on liquidity

The article that we have been mostly influenced by is from January 2011, in which Hans Degryse, Frank de Jong and Vincent van Kervel evaluates the impact of fragmentation on liquidity on Dutch equities, both for traders with access to all markets through SORT and for traders with access only to the traditional market. The study is conducted using panel data with 52 stocks from 2006 to 2009. The time dimension is set to include time before the MiFID, in order to observe greater variation in fragmentation.

To estimate how fragmentation can predict liquidity they have specified their regression as $\boldsymbol{Liquidity_{it} = Firm_i + Fragmentation_{it} + Fragmentation_{it}^2 + Ln(volatility)_{it} + Dark_{it} + Ln(Price)_{it} + Ln(Size)_{it} + Ln(Volume)_{it} + Algo_{it} + \varepsilon_{it}}$

In the base specification, they also control for time fixed effects by including quarter dummies.

The positive sign of the coefficients for Fragmentation and the negative sign of that for Fragmentation^2 indicate that predicted liquidity first strongly increases with fragmentation and then starts to decrease after having reached a critical point, i.e. when the negative effect of the quadratic Fragmentation term becomes larger than the positive effect of the linear Fragmentation term. They therefore conclude that additional fragmentation is good for rather concentrated firms, but harmful for already fragmented firms.

Fragmented trading in Europe and its impact on liquidity

Post-MiFID Spanish stocks are special as they have almost not experienced any fragmentation at all. This difference is used by Markus Gsell, Peter Gomber and Marco Lutat (2011) in their study of fragmentation's impact on liquidity. In their sample of stocks they include stocks with high levels of fragmentation (stocks listed on Xetra or LSE) and stocks with low levels of fragmentation (Spanish stocks), but otherwise comparable in terms of market capitalization. For this they select a total of 48 stocks and extract order book snapshots from Tick History, using two different time windows; 60 pre-MiFID trading days, and 60 post-MiFID trading days. The panel regressions are specified as:

$$\boldsymbol{Liq\_measure = Stockspec\_mean + \delta PostMiFIDdummy + \beta controlvar + \varepsilon}$$

As liquidity measures they employ the quoted spread, XML[8] and quoted value[9]. Control variables are traded volume, price, volatility and minimum tick size.

For Spanish stocks, they find that liquidity has slightly decreased in the post-MiFID window, whereas it has greatly increased in the post-MiFID window for non-Spanish stocks. In their concluding discussion they attribute the positive impact to the competition between trading venues, arguing that traders submit more aggressive quotes in order to attract order flow if they operate in a more competitive environment.

[8] The execution cost of immediately entering and exiting a position; a post-trade measure

[9] The total value of volumes at BBO

Fragmented trading in USA and its impact on liquidity

An article that uses the matched sample approach[10] is Maureen O'Hara and Mao Ye's study from May 2009 on the impact of fragmented trading on trading quality in U.S. markets. The matched samples are used to compare the execution quality of stocks with more fragmented trading to that of stocks with more consolidated trading. Execution quality refers to metrics such as transaction costs, execution speed, short-term volatility and price efficiency.

Their sample consists of 2574 equities. They use January-March 2008 data to measure each stock's volume by trading venue, and then they use April- June 2008 data to investigate how market quality measures differ between firms with fragmented trading and firms with concentrated trading.

They construct a matching variable which compares the firms' market cap and stock price, and matches together those firms with smallest discrepancies.[11] Furthermore, they divide the matched pairs in categories based on market cap to see how the impact of fragmentation on liquidity differs depending on firm size.

The overall conclusion is that fragmentation does not appear to harm market quality. Market fragmentation tends to be good for liquidity costs, execution speed and price efficiency[12], however short-term volatility increases slightly. Among the three subsamples, the results show that fragmentation benefits large and small stocks, whereas medium stocks remain unaffected.

Market competition in the UK and its impact on order flow

Another analysis of the European post-MiFID landscape was published by Ryan Riordan, Andreas Storkenmaier and Martin Wagener in June 2010. In their paper they study the competition between LSE and the MTFs Chi-X, Turquoise and BATS during April-May 2009, which is regarded as a period with a stable market structure not disturbed by any major macro shocks or changes to the markets' microstructures, fees, or trading systems.

The authors take an opposite approach to ours. Rather than investigating fragmentation's impact on liquidity they investigate to what extent traders take into account different market quality measures when allocating their traders, such as BBOs, smaller spreads or increased depth. Put differently, they treat fragmentation as endogenous and liquidity as exogenous.

Their results support the theory that investors are more prone to allocate their trades to an MTF when its bid-ask spread decrease and depth increases. They also provide evidence that when an MTF is at consolidated BBO, the likelihood of attracting an order increases. The authors state that the results may

[10] Not included in the list on matched sample characteristics

[11] $D_{ij} = \left|\frac{MCAP_i}{MCAP_j} - 1\right| + \left|\frac{PRICE_i}{PRICE_j} - 1\right|$

[12] Prices are considered efficient when they follow a random walk

not be very surprising but nevertheless important since they provide clear evidence on how investors base their allocation decisions on the liquidity measures that the exchanges present.

The venues do not display equal correlations between being at BBO and the probability of attracting a trade. When LSE presents the best price it attracts 96% of order flow, whereas Chi-X similarly attracts 84%. BATS and Turquoise also increase their likelihood dramatically when they are at BBO but still have lower probabilities of attracting order flow than LSE and Chi-X have, even though the prices that they offer are better.

They also find that LSE leads the price formation process[13], due to a higher presence of informed traders. By possessing private information the trades of informed traders lead to permanent price changes. The authors find evidence for and argue that informed traders attach less importance to price and more importance the execution speed and reduced market impact. LSE is the most liquid market for FTSE100 equities, which causes it to attract more informed traders and lead price formation.

Market competition in the Netherlands and its impact on order flow

An influential article by Thierry Foucalt and Albert Menkveld studies the introduction of the MTF EuroSETS in the Dutch equity market. They find that consolidated LOB depth increases after its entry, due to increased competition among limit order investors. The regulated Dutch market NSC also displayed better liquidity after EuroSETS entry, which might be surprising but explained by a reduction in direct trading fees that were introduced as a response to the new competitor. Lower trading fees imply a higher trade volume and improved liquidity.

They also find that NSC is more likely than EuroSETS to attract order flow when it is not at BBO. They argue that this is due to lack of SOR. Of course, there was no need for SOR when trading was centralized in NSC. After its entry however, there is still not much benefit of investing in SOR because the limit orders at EuroSETS are not aggressively priced enough, which they say is due to the low probability for EuroSETS to attract order flow despite being at BBO. Hence, there is a severe chicken-or-egg-problem in the Dutch market, which is likely to be as severe in all markets where there is no installed base of smart order routers.

[13] Price change due to changing supply/demand for a security instead of imbalances in limit/market orders

6. Hypotheses

Hypothesis 1: Fragmentation has no impact on liquidity

The first research question concerns trading volume fragmentation's impact on pre-trade liquidity for Swedish large cap stocks. We aim to answer the question by running a panel-data regression from which we can see the fragmentation level's estimated impact on the consolidated quoted spread. Hence, if β_1 is the coefficient on the fragmentation variable, we define the null-hypothesis as:

$$H_0: \beta_1 = 0$$

Against

$$H_1: \beta_1 \neq 0$$

The alternative hypothesis is two-sided. This follows from the arguments in section 3.3 which indicated that trading venue competition and fragmentation theoretically could lead both to improved or reduced liquidity. Given that the size of the coefficient is statistically significant we therefore accept both signs in order to reject the null-hypothesis.

Hypothesis 2: The causal relationship between a trading venue's competitive performance and market share has not increased over time

The second research question concerns if a trading venue's ability to attract order flow through offering investors the best prices has increased over time. We aim to answer this question by first running stock-level regressions which provide us with a venue's BBO performance' impact on its market share. We then test if the causal effect is stronger in our second time period than it is in the first time period.

$$H_0: \mu\beta_{Period2} = \mu\beta_{Period1}$$

$$H_1: \mu\beta_{Period2} > \mu\beta_{Period1}$$

The alternative hypothesis is one-sided. This is because all theory and empiric research has pointed towards more widespread adoption of SORT. As European investors can freely choose whether to invest or not in SORT, and might not be using it in order to always trade at consolidated BBO, it is not evident that we will observe a significantly higher coefficient in the later time period. However, no theory supports that we would observe a decrease, hence we employ a one-sided hypothesis test.

7. Data

Databases

Most previous studies have been made using Thomson Reuter's Tick History, which provides millisecond tick data from all market venues going back over eleven years in time. Practitioners use the product to back-test their algorithmic trading strategies and determine evaluate compliance with best execution. Degryse et al. (2011),Chlistalla and Lutat (2009), and Foucault and Menkveld (2008), all use it to extract snapshots of the venues' LBOs. A snapshot captures the ten best bid and offer prices and their associated quantities and is typically taken every one to five minutes.

Unfortunately, the database was very expensive. We therefore tried to collect the data from the exchanges. At Burgundy they had to extract the snapshots manually, which would have required too much of their resources. At Stockholm they had changed their computer systems, limiting their data access.

Thomson Reuter agreed to set us up for a free trial account of their product Equity Market Share Reporter[14]. EMSR is a new product, used by practitioners to identify differences in liquidity across trading venues. EMSR does not reveal the tick data to clients but uses it to construct its own liquidity measures which are displayed. We have therefore not been able to construct our own consolidated LBOs but have instead used the measures provided by EMSR.

As EMSR is a brand-new product, it has continuously been developed during the time that we have worked on our thesis. Post-trade data can be downloaded but the corresponding function for pre-trade data is not yet available. Therefore we have spent considerable time adding data points in Excel. Although this has been time-consuming, the novelty of the product at least guarantees that we possess a data set not readily available for most others.

The usage of an independent database ensures that the data is objective. Collecting data from the venues could have led to them providing us with incompatible data points and different definitions of key measures[15]. We have extracted price and size data from Factset.

Stocks

Data has been extracted for OMXS30[16]. The underlying logic for choosing this particular sample is that the stocks included are per definition the largest in terms of traded volume (turnover) on the OMX Stockholm exchange. Since empirical research supports the theory that traded volume has a positive

[14] Henceforth referred to as EMSR

[15] Due to the lack of consensus about categorization of e.g. lit, hidden, off-exchange and auction trades.

[16] With the exception of Atlas Copco B. OMXS30 includes both A- and B-class stocks, and we chose to only extract data for A-stocks, which are the most liquid.

impact on liquidity, and low-cost MTFs largely focus on liquid stocks, choosing this sample ought to provide us with well-fragmented. This is good since it increases the likelihood of sample variation in fragmentation over time, which is required in order to accurately define the regression's slope and intercept estimates.

All stocks are listed on Stockholm, but ABB, Nokia and Astra Zeneca have dual listings.

Trading venues

Trading venues that appear in our data set and our regressions are Nasdaq OMX Stockholm, Burgundy, Chi-X, BATS and Turquoise. In May 2011 the five venues accounted for over 99%[17] of turnover in Stockholm OMX, which is why we have chosen to limit our analysis to them. In Appendix: Trading venues we provide an overview of them and their different characteristics, and in Figure 1 we display the market share development for the five venues in the Swedish OMX Index.

When looking at total traded volume both on- and off-exchange, BOAT[18] accounts for a significant share of trading across OMXS30. BOAT is a project owned by nine major investment banks, which use it to report their over-the-counter or off-exchange share trades. As it is not an exchange we do not include it as one of our competing venues.

[17] Same calculation method as that described in note 10

[18] ABN AMRO, Citigroup, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, Merrill Lynch, Morgan Stanley and UBS are the owners of project BOAT

8. Methodology

In order to test our first hypothesis, we have constructed multivariate regression models in order to analyze how the degree of fragmentation on OMXS30 stocks affects their bid-offer spreads. Our dataset is a panel consisting of N=29 stocks[19] and T=125 days (November 2010-April 2010).

For testing our second hypothesis we have as a first step constructed two regression models to study the causal relationship between a venue's share of volume at consolidated BBO and its share of total traded volume. The first regression is based on the first three trading months in 2011, and the second regression is based on the same three months, but in 2010. As a second step, we compare the extracted coefficients from the two regressions, in order to see if the impact of relative BBO performance on trade volume has increased over time. We expect the correlation to have increased over time as investment in SORT has become more widespread across investment firms, and as more experienced SORT users enable it to be used more efficiently.

In the regressions specified in the next section we have included a number of control variables, so that we do not end up with a biased coefficient on our fragmentation variable. The first criterion for including a factor in our regression is that it has a causal relationship with VWAS. The second criterion for adding it is that the factor and fragmentation are correlated with each other.

8.1 Fragmentation's impact on consolidated quoted spreads

Our regression specification uses CVWAS as the dependent variable and HHI and other liquidity affecting factors as independent. Complete explanations for all variables used in the regressions are provided in Appendix: Explanation of variables. For extra clarity we however cover the most important variables in this section too.

Variables

CVWAS

The spreads displayed in EMSR are *Volume Weighted Average Spread bps* and *Equally Weighted Average Spreads bps*[20]. They are both calculated on the price quotes placed during the trading day. The different steps applied by EMSR for deriving them are presented in Appendix: Explanation of variables, in which our choice to only focus on VWAS is covered in more detail as well.

EMSR uses the pre-trade quoted volumes for consolidating VWAS when more than one trading days or stocks are chosen, whereas it uses pre-trade number of quotes for consolidating EAS. We follow that

[19] OMXS30 includes both Atlas Copco A- and B-class stocks. We chose to only use for the more liquid A-stocks

[20] EMSR uses the term Quoted Spread bps, we however refer to it as EWAS to make it more distinguished it from its volume-weighted equivalent

methodology and therefore also use pre trade quote data for consolidating spreads since more than one venues are chosen. To obtain the consolidated VWAS we have for each stock taken each venue's daily quoted volume divided by that stock's total quoted volume, and multiplied that ratio with the corresponding venue's VWAS bps. This provides us with venue spreads that are weighted according to how much the venue accounts for of the stock's total quoted volume. We then summarize the venue-weighted spreads, which gives us the consolidated VWAS bps.

$$CVWAS = \frac{\sum_i^n VWAS\ bps_i\ (\%)_i^2 * Quoted\ Volume_i}{\sum_i^n Quoted\ Volume_i}$$

Since VWAS bps is a measure that relates the stock's spread to its price we also investigate the absolute values of the CVWAS in order to test for robustness of the model. To do this we have constructed a Consolidated Absolute VWAS (CAVWAS) by multiplying the daily CVWAS with the volume weighted average price of the stock in question.

$$CAVWAS = CVWAS * VWAP$$

Winsorization of the CVWAS and CAVWAS

Extreme values add noise to statistical tests and increase the kurtosis of distributions. Conventional methods to extreme values are to exclude upper and lower percentiles, drop observations with extreme values altogether or to log values. These methods are easy to apply, but dropping observations or logging values is a waste since the observation's effect on the dependent variable then is lost completely. This is very unfortunate since low or high values are those that are potentially most interesting for the analysis. Winsorization reduces this problem. Therefore we have winsorized our data; a process that we explain much more in detail in Appendix: Explanation of variables.

HHI

To measure the degree of market fragmentation we have used the Herfindahl-Hirschman Index. It is based on the market shares of the venues and its mathematical expression is as follows:

$$HHI = \sum_i^n Market\ Share\ (\%)_i\text{^}2 \quad \text{where i} = 1,2,3\ldots,\text{n (N} = \text{Total number of firms)}$$

The HHI variable can assume values between 0 and 1.The value is an indicator for the level of industry concentration, and is commonly used in academic work. Further description of HHI is provided in Appendix: Explanation of variables. In Section 9: Descriptive and inferential statistics, we also describe how different values of HHI are generally interpreted as an indicator for industry concentration, and how the interpretations of the HHI-values may differ in the stock exchange industry compared to those of other industries.

Panel data regressions

Our main regression is a panel data regression which absorbs firm specific effects by the inclusion of firm dummies. It is specified as:

$$\mathrm{CVWAS} = \alpha_{it} + \beta_1 * \mathrm{Fragmentation}_{it} + \beta_2 * \mathrm{Fragmentation}_{it}{}^2 + \beta_3 \,\mathrm{Log\,Volume}_{it} + \beta_4 * \mathrm{Algo}_{it} + \beta_5 * \mathrm{OTC}_{it} + \beta_6 * \mathrm{Log\,Price}_{it} + \mathrm{Firm}_i + \varepsilon_{it}$$

In order to weed out time specific effects we also test to include dummies for each of our 6 months. To take into account heterogeneity of variance issues we run the regression using robust of standard errors[21], and also try slightly different regression specifications in order to verify the results of our regression model.

As a second approach we use instrumental variable analysis. There might be factors out there that indirectly affect our liquidity measure. We believe that our fragmentation variable may be biased in the sense that it is correlated with the error term on the explanatory side of the equation. Except for having to be correlated with the endogenous term, an instrument cannot suffer from the same endogeneity problem as the endogenous term does, nor be correlated with the error term itself. We think that lagged fragmentation variables and the average order size of venues are good instruments for our fragmentation variables in the sense that they may explain variance in our fragmentation variables given the other covariates.

The regression specification is similar to our main regression except for that we run a number of first stage regressions in order to capture the effects of our instrumental variables in accordance to the 2-Stage Least Squares method.

Stage 1: Regress the endogenous variables on instruments and save the predicted values.

$$X_i = \pi_0 + \pi_1 Z_i + v_i$$

Where Z_i, the instruments, are uncorrelated with ε_{it}. Saving the estimates from this stage hopefully gives us non-biased endogenous variables.

Stage 2: Regress the CVWAS on the predicted endogenous variables from stage 1

$$Y_i = \beta_0 + \beta_1 \hat{X} + \varepsilon_{it}$$

Regressing the estimates from stage 1 on our dependent variable gives us results free from the variance that the instruments have taken away from the endogenous variables.

8.2 BBO volume and its causal relationship with trade volume

One dimension of the MiFID "Best Execution" protocol is for brokers to provide their clients with the best price. Although it is less restrictive than its US equivalent and allows other factors than BBO to be taken into account, it does oblige firms to communicate their order allocation strategies to their clients.

[21] i.e. take into account heteroscedasticity

The increased focus on routing decisions is expected to lead to more orders being allocated to the venues being at consolidated BBOs, as achieving the best price is normally considered to be in the client's best interest. At any given time, the venue that displays the best available price, either on bid or offer side, across all trading venues, is reported to be on consolidated BBO. As EMSR provides us with data on the number of shares for each venue that reach the consolidated BBO position, we possess all data that we need to investigate the relationship between BBO volume and actual trade. We test if this relationship has become stronger over the course of a year, which is expected as a result of investment in SORT and better compliance of the MiFID. To do this we will compare the first three trading months of 2010 with their equivalents 2011. We have extracted market share data for BBO volume and traded volume, both measured in number of shares, for January, February and Mars 2010 and 2011 for each venue in order to test our hypothesis. We do this in two steps that complement each other and add robustness to our results.

Test 1: Panel Regression

For each venue of interest e employ a single variable regression model approach with firm dummies included. The specification will be run on all five venues and both time periods in order to compare how the correlation between BBO volume and trade volume has increased over time across our five venues.

$$Market\ Share\ Traded\ Volume_i = Market\ Share\ BBO_i + Firm_j + \varepsilon$$

The rationale behind the regression is that the market share of traded volume should follow the market share of BBO volume to a certain degree. Investors are expected to increase their trading on marketplaces on which they get the best deal regardless of whether they want to purchase or sell stocks.

Test 2: T-test/signed rank test

By running the above stated regression in our first step on individual stocks we are able to extract the coefficients for the BBO variable. By using the coefficients as data points in our second step we test if there is a difference in the causal relationship between BBO volume and trade volume between the two periods. More specifically, we test the null hypothesis that the coefficient mean is unchanged against the alternative hypotheses that the 2011 mean is higher.

$$H_0: \mu\beta_{Period2} = \mu\beta_{Period1}$$

$$H_1: \mu\beta_{Period2} > \mu\beta_{Period1}$$

We employ two separate tests when testing our hypotheses; a normal t-test and a signed rank test. The reason for using all three is to add robustness to the hypothesis test and overcome problems arising with assumptions of distributions. We do not volume weight the firm level coefficients but treat them with equal importance in our test. This is because we want to see if a potential increase has occurred across all stocks, not only in the largest stocks.

9. Descriptive and inferential statistics

In this section we present our descriptive findings on the variables we have constructed in order to know if we safely can reject our two null-hypotheses. The variables and their implications for liquidity are explained in Appendix: Explanation of variables. In the appendix we include variables that we would have liked to control for but are unable to construct properly due to data limitations.

In this section we present following descriptive statistics:

- Liquidity measures on stock level
- Fragmentation measures on stock level
- Price competiveness measures
- Control variables on an aggregated level

Consolidated Volume Weighted Average Spreads

All spreads are measured in basis points and are presented in table 1 after having been winsorized. As seen in the table, the mean CVWAS across most of the stocks are not far from the aggregated mean of 12.85 bps. AstraZeneca, H&M, ABB and Ericsson report spreads well below the aggregated mean, whereas Lundin Petroleum and MTG report spreads well above that. The table's fifth column displays the coefficients of variance which have been constructed by dividing the stock's standard deviation with its mean.[22] The stocks with the lowest coefficients of variance are Nokia, ABB, SEB and Ericsson with values around 0.10. On the other end of the spectrum are Getinge, Lundin Petroleum and Securitas with values ranging between 0.25 and 0.30. Overall the values range from 0.081 to 0.295. One likely explanation to the seemingly large differences in variance is that the companies with low CVWAS means tend to be large and stable. ABB and AstraZeneca are very large companies with dual listings at LSE and SIX Swiss, providing them a diversified investor base which limits the risk of large daily deviations. The kurtosis indicator varies widely across the stocks. It is interesting that many of the stocks' spreads exhibit excess kurtosis of 0 or close to 0, implying mesokurtic distributions. The majority of the stocks demonstrate absolute skewness characteristics lower than 1, meaning that spread distributions are somewhat symmetric. Since most of the stocks with symmetric distributions also demonstrate excess kurtosis close to 0, they are considered as approximately normally distributed.

Fragmentation

Table 2 presents descriptive statistics for our fragmentation variable[23]. The aggregated mean HHI is 0.483. In general, a market with HHI taking on values below 0.15 is deemed as fragmented, while values

[22] Using coefficients of variance is a well recognized method to compare differently sized variances

[23] For an explanation of our fragmentation variable, see Appendix: Explanation of variables

in the range between 0.15 and 0.25 classify the market as a moderately concentrated market[24]. An industry HHI above 0.25 is considered concentrated. However, in the context of exchanges and their turnover there are no official classification limits of fragmentation. The limits should be adjusted to take into consideration the nature of the industry. The entry barriers to the stock exchange industry are high, due to considerable economies of scale and positive network externalities. Furthermore, compared to other industries, stock exchanges are quite heterogenous and cannot charge premium prices compensating for low volumes.

Compared to the HHI in Degryse (2011) of 0.725 for 2009, fragmentation in our sample is quite high. European fragmentation has been rapid and recent however, therefore data within our time frame is not perfectly comparable to data from 2009[25].

The most fragmented stock is ABB with a mean HHI of 0.310, followed by Nokia with a HHI of 0.383. On the other end of the spectrum are Sandvik, Atlas Copco and Investor with values of 0.557, 0.546 and 0.542. This is not surprising since ABB and Nokia are large firms with dual listings, indicating that pan-European MTFs have relatively large volumes in comparison to Stockholm. However, we are careful when interpreting the values for dually listed firms, as we do not know what HHI we would observe if including their other main venue.

The majority of the stocks do not deviate much from the mean, indicating that the fragmentation trend has progressed about the same across firms. The stock specific HHI variables are in overall close to being normally distributed except those for Nokia, Nordea, ABB, H&M and Ericsson.

The coefficients of variance range between 0.064 and 0.143. ABB, AstraZeneca and Boliden display the lowest values whereas Getinge, Securitas and Alfa Laval display the highest.

Comparison of descriptive statistics

Comparing the CVWAS and HHI tables indicate that there are some interesting relationships between the CVWAS and HHI variables. Dually listed firms such as ABB and AstraZeneca have the lowest CVWAS means and the lowest HHI means, which indicates that there is a positive relationship between the two.

The range of coefficients of variance values is very narrow for HHI compared to the equivalent range for CVWAS. It thus appears that fragmentation over time at firm level is far more stable than consolidated spreads over time, also that on firm level.

[24] U.S. Department of Justice and the Federal Trade Commission's classification http://www.justice.gov/atr/public/guidelines/hmg-2010.html

[25] Degryse's HHI includes venues with a combined 99% of lit volume, whereas our venues also represent 99%

10. Results

In this section we present and analyze the results obtained in our empirical tests. The first sub-section covers our primary research question and includes results from the panel data regression as well as the separate time series regressions. The second sub-section is devoted to our instrumental variable approach. The third and final sub-section details our findings from the hypothesis tests we run. All our test results are presented in tables found in the appendix.

In addition to results quoted in CVWAS bps, we have also included regression outputs where we replace it with its absolute value counterpart. All absolute value results are presented in columns to the right of the basis point regressions. Everything else is held constant except for the exclusion of the MTG stock.[26]

10.1 Regression results

Before moving on we would like to explain how our fragmentation variables work. In order to get an intuitive feel of fragmentation's effect we have inverted our HHI variable by subtracting it from 1. Doing this means that fragmentation increases with a higher value instead of the opposite. The results of our panel data base specification regression are found in table 4. It is interesting that the coefficients on the variables of interest, Fragmentation and Fragmentation^2, are both significant but with opposite signs. The linear term is negative whereas the squared is positive. This indicates a non-linear relationship between CVWAS and fragmentation. The main implication of the non-linearity is that incremental fragmentation is positive for certain levels of initial fragmentation up until a certain point where the quadratic effect eclipses the linear one. This potentially implies an optimal level of fragmentation.

The coefficient on the squared term has a smaller absolute value than the linear, which means that our fragmentation variable needs to be larger than 1 for the squared term to outweigh the negative effect of the linear. Since our fragmentation variable can never take on a value above 1, additional fragmentation always reduce predicted quoted spreads.

The coefficients of the control variables are also presented in table 4. The volume coefficient is strongly significant and leads to a reduction in predicted quoted spreads, which is what we initially expected.[27] The coefficient on our OTC/Dark trade variable indicates that additional dark trade enlarges spread sizes. Our price variable and our proxy for algorithmic trade also contribute to larger spread sizes. The coefficients on OTC trading and algorithmic trade are not as we had expected but can be explained[28]. Our findings do not contradict those of Degryse's as he obtained the same signs on the coefficients.

We have also tried to improve our base regression through the usage of monthly dummies. Including these barely affects our results. All coefficients remain of the same sign but lose some statistical

[26] MTG's spread values are noisy and therefore disturb our results

[27] See Appendix: Explanation of variables for more details on volume's expected impact on spreads

[28] See Appendix: Explanation of variables for more details on OTC and HFT's expected impact on spreads

significance which is not surprising as more explaining factors have been added. In particular the important coefficients on the two fragmentation terms remain largely unchanged.

If we exclude our squared fragmentation variable altogether we still obtain a negative coefficient on the linear fragmentation term which is about as big as the difference between the coefficients on the linear and squared terms in our base specification. The statistical significance improves substantially if we only use fragmentation as a single linear variable. Doing this however means that we do not detect the declining marginal effect of fragmentation if do not split fragmentation into two separate terms.

10.2 Robustness tests

To test the robustness of our results we have constructed a number of alternative regression specifications. In the first one we have replaced our fragmentation variables with the market share of Stockholm and its squared counterpart. The results are presented in table 5 and tell us that there exists a non-linear relationship here too. The linear term is negative whereas the quadratic is positive. Since the latter factor has a larger absolute value it implies a breaking point located somewhere within the possible fragmentation range where the net effect of a larger market share for OMX Stockholm switches signs and hurts pre-trade liquidity.

Our base specification tells us that the breaking point is located at approximately 0.79, meaning that the spreads shrink in size until OMX Stockholm reaches a market share of approximately 80%. Running this test across all venues however give us different optimal level for all five venues, which are impossible to combine since market shares can only sum to 1. Nevertheless, having verified that the effect on spreads only increases up to a certain breaking point supports the notion that there while there are gains from having a concentrated market, a fragmented one takes it a step further.

We have also run the regressions on market share for OMX Stockholm without using time dummies and with absolute spread values as dependent variables and obtain similar results. If we remove the quadratic term we get a positive spread size coefficient on the market share of OMX Stockholm which translates into worse pre-trade liquidity the more market share that is captured by the main exchange. In essence, this supports the arguments made by supporters of fragmentation and is well in line with the main regression results.

Another robustness test we have run takes into account the first differences, or daily changes, of our fragmentation variables. By doing this we aim to remove long term effects of fragmentation that might affect the spread size. Doing this however did not change our base regression results much. The first difference coefficients do not reach statistical significance. Adding monthly time dummies and removing the squared term does not significantly alter any results. The results are presented in table 6.

10.3 Instrumental Variables

As our final approach to the matter we have employed two instrumental variable approaches in accordance to that of Degryse (2011) in order to alleviate eventual endogeneity and omitted variable problems. Since there might exist variables that are correlated with our independent variables it is in our interest to control for indirect causal impact. First we have a specification where we instrument our fragmentation variables with their one day lagged counterparts. Degryse argues that the fragmentation coefficients could be biased because daily shocks might affect liquidity and fragmentation simultaneously. In that case there might not only be a causal relationship between fragmentation and liquidity, but the source of the daily shock is causally related with both. The second approach is also inspired by Degryse's paper, instrumenting our fragmentation variables with the daily average order size of each of our five main venues. This is done in order to avoid an eventual self-selection bias if fragmentation of a firm's stock is a result of the average order sizes of different venues. We have employed a 2 step least-squared methodology with firm dummies for both of our tests. Monthly dummies are used to isolate time-specific effects.

Instrumenting our variables of interest with their lagged counterparts does not change our main results from the base regression. The magnitude of our coefficients differs somewhat but all the signs remain intact. This regression setup pushes our variables of interest just outside of significance in the base setup. The linear term however retains its significance when month dummies and when the quadratic term are excluded. The coefficient of the quadratic fragmentation term is still smaller than the linear which means that fragmentation's positive effect on quoted spreads is still present. . This particular result differs from that of Degryse but their coefficients lose significance which ours do not always do. The results are displayed in table 7. We do not present our first stage regression results for the sake of simplicity but the output shows that there is next to no correlation between our instrumented and instrumental variables. In other words, daily shocks do not have any significant effect on either the quoted spreads or the daily fragmentation variables that they instrument.

Our second instrumental regression takes into account the possibility that average trade size of marketplaces and their effect on the degree of fragmentation under the logic that order allocation migrates to venues with already high activity. The results of this specification can be found in table 8. The quality of the venues themselves might therefore affect quoted spreads by increasing fragmentation, leading to a self-selection bias. Our five first pass regressions, which we will not present, show that there indeed exists a causal relationship between the average order size of a venue and fragmentation. The results are mixed and are only significant when we choose to run the specification without time dummies. Since the number of instruments exceed the number of our regressors we have employed an over identifying test in order to test our instruments. Doing this however rejects the null hypothesis that our instruments jointly are valid instruments, meaning that they seem to affect liquidity both through fragmentation and directly. We will therefore not make any attempt to interpret the results.

10.4 The causal relationship between price competitiveness and order allocation

Panel regressions for 2010

The results from our panel regressions, with market share of trade volume as dependent and market share of BBO volume as independent variable, are reported in table 9 for each of our venues. In the table we clearly see that there is a positive relationship between the total BBO market share and the traded volume market share. The results for OMX Stockholm are particularly interesting. Whereas the other venues have constants close to zero in period 1, OMX Stockholm's is as high as 0.418. We conclude that during the first quarter of 2010, OMX Stockholm was able to capture a large volume market share despite not offering the BBOs. Other trading venues had much lower market shares before the effect of their competitive performance is included. This trend can also be seen on stock level[29] with many shares having constants higher than 0.50. Possible reasons for the high constants are that OMX Stockholm either fulfills other "Best Execution" criteria such as execution speed or depth, or because brokers lack the SORT required to gain access to the consolidated BBOs. Without multi-market access brokers or investment managers execute their orders on OMX Stockholm because they are used to doing so. In time period 1 Stockholm also has a much larger coefficient than the other venues, which indicates that when Stockholm is at BBO it attracts order flow to a much higher extent than the other venues. This could also be due to lack of SORT among investors which constrain them from allocating orders to the other venues despite them being at BBO.

Chi-X, the MTF in our sample with the highest market share among the MTFs, has across the MTFs the highest constant but the weakest coefficient on BBO in both time periods. Reasons behind this might be that Chi-X has many market participants guaranteeing a certain degree of volume, and that it does not rely as much on its price performance since the market participants trade there regardless of order flow. For those that are not members of Chi-X however it is difficult to allocate orders there than on OMX Stockholm. This might be a reason why the two exchanges differ so in betas despite having the highest alphas in the sample. The other three MTFs have higher betas than Chi-X despite not providing easier market access than Chi-X does, which might possibly be because they have a lower guaranteed order flow than Chi-X which existence brings down the relative importance of price competition for an exchange.

Panel regressions for 2011

The columns with panel regression output for the first quarter of 2011 show that coefficients are higher for all venues compared to 2010. The differences, with the sole exception of OMX Stockholm, are considerable in magnitude. CHI-X has gone from a coefficient of a mere 0.023 to 0.223. Burgundy and

[29] For the sake of simplicity we do not report the results on individual stock bases.

Turquoise's coefficients have more than doubled themselves, going from 0.080 and 0.065 in period 1 to 0.185 and 0.173 in period 2 respectively. The biggest change is attributed to BATS for which the BBO coefficient has gone up from 0.019 to 0.314. OMX Stockholm on the other hand enjoys a slight increase from 0.184 to 0.223. It thus seems like the effects of price competition is more equal across the venues in period 2. As all aggregated coefficients are coupled with significant t-values we can conclude that the relationship between BBO market share and traded volume market share has become stronger over the year that separates the two time periods.

The only constant that has changed significantly in magnitude is OMX Stockholm's which has gone down from 0.418 to 0.327. The high BBO coefficient combined with a smaller constant indicates that OMX Stockholm has migrated to relying less on guaranteed volume and more on the ability to provide BBO. It is thus more affected by the competition from MTFs in the second period. The actors on OMX Stockholm seem to have become more rational when it comes to price. It is however evident that there are still many other factors affecting order allocation since the coefficients are far from 1.0 which would be the case if price is the only parameter that matters and perfect SORT is available to all investors. It is also clear that the MTFs are fighting an uphill battle; even though they price compete on the same conditions as OMX Stockholm they do not have the automatically granted volume that Stockholm appears to have as a result of its history as a national regulated exchange.

Testing the difference between regression results from 2010 and 2011

We employ three different tests to see if the difference between the firm level means of coefficients on BBOs between the two time periods is significant. In the tests we use the betas discussed in the section above and we have done them for each of the 5 venues we have studied so far. The results are presented in table 9. As the Student's t-test requires the two samples to follow normal distributions and have the same variances we have run normality and variance ratio tests on all 10 samples. The results from these tests enable us to run the paired t-test on only the OMX Stockholm and CHI-X samples since at least one of the two samples for each of the remaining three pairs are distributed significantly differently than if following a normal distribution. We present the results for the t-tests and sign tests in tables 10 to 11. Table 10 shows that the average firm BBO coefficient on OMX Stockholm is not significant larger in the second time period even when applying a significance level of 10%. This is a disappointingly weak result but at least confirms the sign of our panel regression comparison where Stockholm displayed a slight improvement. CHI-X on the other hand demonstrates an improvement of the average coefficient between the two periods, which is significant at all reasonable significance levels.

The sign tests for OMX Stockholm and CHI-X support the results from the t-tests although the test for OMX Stockholm does not reach significance. We see that BATS has a significantly improved coefficient whereas the results for Burgundy and Turquoise are too noisy for us to be able to draw any conclusions. The output is shown in table 11.

The overall significant and consistent results from the different types of hypothesis tests seem to support the fact that price discovery is significantly higher in the first quarter of 2011 than it was in 2010. The hypothesis test results should however be carefully interpreted for generalization purposes as we have not weighted the coefficients on basis of volume or any other important metric. Nevertheless, the results from the significance tests suffice for the purpose of testing whether the results from our panel regressions are reasonably reliable.

11. Conclusions

The financial landscape has been significantly altered since the implementation of the MiFID. The intention of the directive is to increase competition and enhance investor protection. This paper aims to analyze the impact of the MiFID in two ways. The first is to analyze a more fragmented financial landscape's effects on liquidity, and the second is to analyze whether investors' ability to allocate their orders to venues exhibiting the best quotes has become better over time.

In order to answer whether fragmentation reduces liquidity costs or not we have constructed a number of regressions that have been run on our sample of stocks which consists of the 29 most traded stocks on the OMX Stockholm exchange. Our main result is that fragmentation is good for liquidity in the sense that quoted spreads tend to decrease when fragmentation increases. We also observe a quadratic effect of fragmentation on the quoted spreads of our sample. This effect is however dominated by the linear which means that additional fragmentation is always good across all plausible levels of initial fragmentation. We can therefore not observe an optimal level of fragmentation. By construction the stocks in our sample has high traded volume. The high volume can be split over separate venues without completely eroding liquidity from the individual venues' LBOs. Therefore the negative effects of fragmentation may not be as strong in our sample as if we had also included stocks with volumes not sufficiently large to support fragmentation. In our sample the marginal effect of fragmentation may therefore never reach the breaking point after which it starts harming liquidity, since the general negative effects are underestimated. We therefore do not state that fragmentation is good for all stocks, but think it is very likely to observe breaking points in other samples. To add robustness to our results we have employed numerous regression variations including two instrumental variable setups. These do not contradict the results from our main regression. For example, substituting our linear and squared fragmentation terms with the linear and squared market shares of OMX Stockholm support our findings.

The MiFID's "Best Execution" protocol states that brokers acting on behalf on their clients are obliged to execute their trades on the venue with the best quotes, assuming that all other execution criteria are held constant.[30] Our results show that number of traded shares follows number of shares at BBO to a much higher extent the first quarter of 2011 than it did the corresponding time period 2010. In particular this is the case for the MTFs. This indicates that MiFID compliance has become better which could be the result of market actors becoming more aware of MiFID, better SORT or a combination of the two. The various hypothesis tests which we have employed, in order to verify that the causal relationship between BBO volume and traded volume is in deed higher in the second time period than in the first, all support that the improvement is statistically significant.

Overall, for the aspects of market quality we have studied, we assess that the added competitive dimensions of trade that the MiFID has introduced have been beneficial for liquidity. Brokers have also become better at routing their trades to BBOs which is welfare enhancing for the investors acting indirectly through them.

[30] E.g.execution speed and LBO depth

Suggestions for further research

A natural extension to our study would be to include a larger sample of stocks exhibiting larger variation in characteristics. Since the stocks in our sample all exhibit high trade activity it might have affected our results. The inclusion of low trade activity stocks is particularly interesting in the Nordic region. This follows because of Burgundy and its strategy of capturing volume not only on large stocks but also on micro, small and midcaps. This stands in stark contrast to the high liquidity strategies of the pan-European MTFs. This has led to the Nordic stock market becoming unique in the sense that fragmentation has occurred across all stocks. Therefore the Nordic region is very interesting for future research on the impact of fragmentation on liquidity.

As the implications of MiFID are currently being revised in order to form the basis for further changes to financial regulations in Europe, the competition between exchanges and its consequences undoubtedly deserves more academic attention.

The rapid development of SORT and algorithmic software makes the new phenomenon extremely interesting for deeper investigation as the development might have large implications on stock exchange liquidity. As the large increase in fill/cancel ratios has lead to exchanges proposing to introduce minimum times for orders to remain at the market before cancelled, their implications for market quality aspects need to be verified.

Appendix I: Explanation of variables

Pre-trade data

EMSR provides analysis of liquidity and price performance across European trading venues. The performance analysis is separated into the Best Bid Offer (BBO) view and the spread analytics view. In this section we will first derive the spread calculations, how and why we use them for our empirical tests. Then we will explain how cross-market BBOs are computed and what their competitive implications are for our tests.

Bid-offer spreads

Since EMSR's performance data is pre-trade data, all spreads are quoted spreads. Spreads are displayed as *Volume Weighted Average Spread bps*[31] and *Equally Weighted Average Spreads bps*. Daily average spreads are calculated on the price quotes placed during the trading day. The VWAS bps is calculated in 4 steps:

1. $VWAS = \frac{(\sum(Offer\ Price - Bid\ Price) * (Bid\ Size + Offer\ Price))}{\sum(Bid\ Size + Offer\ Price)}$
2. Volume Weighted Average Bid price
   $$VWAB = \frac{\sum(Bid\ Price * Bid\ Size)}{\sum Bid\ Size}$$
3. Volume Weighted Average Offer price:
   $$VWAO = \frac{\sum(Offer\ Price * Offer\ Size)}{\sum Offer\ Size}$$
4. $VWAS\ bps = \frac{VWAS}{Avg(VWAB, VWAO)} * 10000$

Similarly, the EWAS bps is calculated as:

1. $EWAS = \frac{\sum(Offer\ Price - Bid\ Price)}{Number\ of\ quotes}$
2. $EWAS\ bps = \frac{EWAS}{Avg(VWAB, VWAO)} * 10000$

We initially regarded both VWAS and EWAS as potentially interesting and therefore extracted both measures. In order to properly consolidate the spreads at a later stage we also needed data on the quoted volumes and number of quotes. We ensured ourselves of the accuracy of this approach by verifying what method EMSR applied to consolidate spreads when more than one stock or trading day was selected.

However, it soon became apparent that EWAS was an extremely volatile measure, as low-volume-quotes were treated equally as high-volume-quotes. The EWAS were for most days in line with VWAS but could also take on extremely high values, presumably due to low-volume-quotes far away from local

[31] Henceforth referred to as EWAS bps

BBO. We did not want these quotes to distort the liquidity measure, and therefore stopped extracting EWAS and the number of quotes.

Extracting data for 29 stocks and 5 venues within our chosen time period has resulted in 3617 consolidated daily spread observations built from 36378 underlying observations.

Consolidated Volume Weighted Average Spread

As mentioned above, EMSR uses the quoted volumes when it consolidates VWAS, which is why we also use quoted volumes for consolidation purposes.

For us to obtain the consolidated VWAS we have for each stock taken each venue's daily quoted volume divided by that stock's total quoted volume, and multiplied that ratio with the venue's VWAS bps. This provides us venue spreads that are weighted according to how much the venue accounts for of the stock's total quoted volume. We then summarize the weighted spreads, which gives us the consolidated VWAS bps[32].

$$CVWAS = \frac{\sum_i^n VWAS\ bps_i\ (\%)_i^2 * Quoted\ Volume_i}{\sum_i^n Quoted\ Volume_i}$$

Consolidated Absolute Volume Weighted Average Spread

VWAS bps is a relative measure, relating the spread to the corresponding stock price. In order to test for robustness of the model we also investigate the absolute values of the CVWAS. Therefore we have constructed a Consolidated Absolute VWAS (CAVWAS) by multiplying the daily CVWAS with the volume weighted average price[33] of the stock in question.

$$CAVWAS = CVWAS * VWAP$$

Winsorization of the CVWAS and CAVWAS

Extreme values add noise to statistical tests and increase the kurtosis of distributions. Conventional methods to extreme values are to exclude upper and lower percentiles, drop observations with extreme values altogether or to log values.

These methods are quite easy to apply. But dropping observations or logging values is a waste since the observation's effect on the dependent variable then is lost completely, which is very unfortunate since low or high values are those that are potentially most interesting for the analysis. Winsorization is a method reducing this problem. The method means that values outside predetermined percentile ranges are transformed into the value located closest to, but inside, the percentile limit. An additional advantage

[32] Henceforth referred to as CVWAS
[33] VWAP are based on the main venue's prices for each stock, but we have verified that they do not differ much between venues

of using this method is that we do not have to reduce our dataset, which would have limited its ability to provide us with statistically significant results.

CAVWAS have not been explicitly winsorized. The variables are based on the already winsorized CVWAS, and prices proved to be much more stable than quoted spreads with no observations suddenly taking on extreme values , we did not see the need for additional winsorization of CAVWAS..

The BBO Measure

The second performance analytics view provides various statistics on the market venues' BBO performance. At any given time, the venue that displays the best available price, either on bid or offer side, across all trading venues, is reported to be on consolidated BBO. In the event that two venues share the same best price the venue with the greatest order volume at that price is reported as BBO. If volume also would happen to be the same, then the venue with the earliest quote wins. If the same venue displays the best price both on bid and offer side, it is given double credit in the consolidated MP statistics. Hence, BBO is a measure of price aggressiveness, with priority given as follows to price, volume and submission time. A venue can therefore reach BBO either by posting a more aggressive quote, or by expanding the order's volume if it's local BBO is the same as that of the venue at consolidated BBO.

It is very important for a venue to be at global BBO in order to attract order flow, since investors are seeking the best prices. EMSR uses three different BBO-related benchmarks:

- Duration at BBO – seconds during the trading day that the venue is on global BBO.
- Frequency at BBO – number of times that the venue goes up to the BBO position
- Volume at BBO – total number of shares bid or offered when the venue is at BBO during the day

For the empirical test concerning BBO and its impact on traded number of shares, we only consider Volume at BBO as a relevant measure.

Post-trade data

EMSR stores post-trade data from January 2008, which includes data on daily turnover in Euro, number of traded shares and number of transactions, all on stock level. For our main test we have used post-trade data to control for traded volume, but have also used it to construct a variable which measures the degree of the market fragmentation.

The market fragmentation measure

Following the methodology of Degryse, De Jong and Van Kervel, we use traded visible volume defined as *turnover in Euro* in order to construct our fragmentation measure. The amounts of traded stocks or transactions do not include the full extent and magnitude of the transactions and therefore do not convey the entire truth about trade volume evolution. We have therefore extracted turnover on stock and venue level.

To measure the degree of market fragmentation we have used the Herfindahl-Hirschman Index, an industry concentration measure named after economists Orris Herfindahl and Albert Hirschman. It is based on the market shares of the venues and its mathematical expression is as follows:

$$HHI = \sum_{i}^{n} Market\ Share\ (\%)_i\text{^}2 \quad \text{where i} = 1,2,3\ldots,\text{n (N = Total number of firms)}$$

HHI tells us the relation between independent venues' volumes and the total volume of the market. The measure has a range from 0 to 1. A value near 0 indicated that there are many small actors on the market, whereas a value near 1 implies that the market is dominated by one actor.

We have calculated the market share for each venue during that trading day, using the daily turnover. To simplify the analysis we have defined our market as the aggregated trade volume of BATS, Burgundy, Chi-X, OMX Stockholm and Turquoise. This restriction has saved as considerable time and will not distort our results, as these five venues capture over 99% of total turnover. To include other market venues would have been time-consuming but not likely to alter neither our consolidated spreads nor our fragmentation measure since their values are extremely low. The market share for an individual venue is therefore its turnover divided with total turnover for all five. The turnover that we have used is based only on visible orders. Since EMSR only calculates the spreads on visible quotes, we do not want to include hidden orders in our fragmentation measure.

Other factors

In this section we discuss variables for which there is strong theoretical and empirical support they need to be controlled for in order not to risk a biased estimator for the coefficient on fragmentation. To illustrate why omitting variables from the regression might lead to biased coefficients, we provide the following example using volume as a potential factor:

Since there is positive correlation between HHI and volume, a high value of HHI indicates that volume is high as well for that observation. Volume is proven to have a positive impact on the VWAS. If volume is wrongly left out of the model it would thus seem as if it is the high value of HHI that causes VWAS to improve, even though volume is the actual source to the improvement. Hence, given positive correlation between HHI and volume, and between volume and VWAS, the coefficient on HHI becomes overestimated; i.e. a positive bias occurs. (Wooldridge, 2009)

In order to know whether we risk having a biased coefficient of fragmentation if omitting a variable, we need to investigate its potential for correlation with HHI and VWAS. For each variable in the regression we provide possible reasons to correlation in Appendix: Explanation of variables.

Size

When the matched sample approach is used in market microstructure studies, and matching is based on a single characteristic, then standard practice is to match firms according to market capitalization. Across all research articles we have studied, market capitalization is used as a control variable. Its effect on liquidity appears to be taken so for granted that researchers never provide any explanations for why they use it. It is obviously easier to find counterparties for immediate execution when transacting with securities in a large firm than a small firm.

The correlation between HHI and firm size is rather clear-cut. We have earlier described the MTFs large-stock-strategies, indicating that fragmentation mostly occurs for high-volume stocks. We have also described theories suggesting that larger stocks attract more dispersed investors with heterogeneous preferences[34], consequently seeking different trading venues.

Traded volume

Although volume is highly correlated with the size variable, many empirical tests employ both trade volume and size as their implications are slightly different.[35]

Pagano has constructed a theoretical model that when the number of traders increases, the mean fraction held by an investor decreases. The further away that the size of a transaction is from the mean fraction, the larger is the adverse price impact. Hence, a high number of traders implies a lower elasticity of the market price to net demand. For any given transaction size, the need to climb down or up the order book decreases, which keeps the spread tight. (Pagano, 1989) Note that in order to use this model to explain correlation between volume and VWAS, we assume that a larger turnover is consistent with a larger number of traders on the market.We expect positive correlation between HHI and volume which is largely due to the strong correlation between Volume and Size.

As with HHI, volume is defined as total turnover of lit trades, because only lit orders appear in the bid-offer spreads.

$$Total\ Traded\ Volume_{All\ Venues} = \sum Total\ Lit\ Volume_i$$

Stock Price

Price is often controlled for in empirical studies on factors potentially affecting liquidity. Institutional investors tend to avoid low-priced stocks as they are considered more risky. A low-priced firm could be a firm with poor recent performance with a corresponding drop in share price, making it questionable whether the firm will eventually break the downward trend, or it might be that the share price is low because it is a young firm that has only been on the stock market for short time. The price hence

[34] Different types of traders are e.g. institutional-, retail- and HFT investors

[35] E.g. Degryse et al (2011), Aitken, Cook, Harris and McInish (2006), Jain and Kim (2006)

contains some risk dimensions, increasing the risk that limit order investors not having their orders executed or being "picked-off".

A high stock price could also increase execution risk, if the stock price is so large that investors refrain from entering a position, since even a single stock would make it overrepresented in the investor's portfolio. The price then does not include the riskiness of a firm, but reduces the number of potential transaction parties. Hence, the correlation between price and liquidity is not clear-cut but its sign could differ between ranges.

Correlation between price and HHI is also likely. Firms with high fragmentation tend to be old firms, whose stock prices have often increased over the years. Although we do not expect prices to have a strong, straight-forward impact, it fulfills the criterion for why we it may include it in the regression.

High Frequency Trading/Algorithmic Trading

A trend that has gained immense momentum during recent times is the increased prevalence of high frequency trading, HFT for short. AT/HFT traders today account for a large portion of volume. There are no clear cut definitions of what exactly is classified as HFT, but it is estimated that over 70 % of the US stock trading is HFT. (Hendershott, Jones, & Menkveld, 2011)

HFT allows traders to rapidly cancel and submit new quotes, which reduces both execution risk, the option effect and adverse selection risk. If the market price moves away from a limit order quote and execution risk increases, the HFT investor can track the market price with a more aggressive order. Analogously, if the price moves in the other direction and the risk of being picked-off increases, the quote can be changed to a more defensive level. Often HFT orders are designed to be cancelled if not filled within a certain time, limiting the option provided to the market. Since limit order investors experience lower risk through the use of algorithms, they ought to require a smaller premium for providing liquidity. Theoretically spreads are therefore predicted to narrow as algorithmic trading increases. Industry experts are concerned that HFT and the consequently high cancel/fill ratios improve pre-trade liquidity measures, but not post-trade measures.[36]

The implications of increased algorithmic trading have been studied empirically, but the results are mixed. Hendershott et al. (2011) find that the impact on liquidity costs is positive, whereas Degryse et al. (2011) obtain a statistically significant coefficient of the opposite sign, although of small economical magnitude. This contradiction implies that the relation between HFT and liquidity might not be as theory and general beliefs suggest. It might be that the orders changed to more defensive levels widen the spread more than the orders changed to more aggressive levels narrow the spread. Our proxy for

[36] The concern was shared between panel debate participants at DI Trading Conference

HFT resembles that used by Degryse, which is the number of electronic messages[37] divided by traded volume, whereas our proxy uses the quoted volume divided by traded volume.

$$HFT = \frac{Quoted\ Volume}{Traded\ Volume}$$

Correlation between HFT and HHI is more straight forward to derive since HFT investors by definition possess advanced tracking technology, which most likely grants them multimarket access too.

OTC Trading

OTC means that investors abandon the exchanges to seek off-exchange transaction opportunities. It therefore reduces exchange volume which is unarguably bad for liquidity. However, as the number of traders is largely controlled for through the volume variable, we need to investigate the nature of the transactions that are executed OTC. Actors prefer OTC as their transactions might adversely impact the market price. A transaction with adverse price impact is in general a large transaction which needs to climb several layers in the LBO for complete execution, thus removing much of the liquidity. Since OTC's impact on exchange volume is already controlled for through Volume one could expect OTC to have a positive impact on liquidity, since it is the liquidity removing orders that tend to go OTC. However, since investors choose between limit or market orders conditional on the probability that there will be matching market orders, the number of liquidity suppliers is to be reduced as well. The true relationship between OTC and liquidity is therefore difficult to predict. Degryse (2011) obtains a statistically significantly negative impact on liquidity. OTC therefore seems to capture liquidity at the expense of exchanges in a way that is not entirely incorporated in the volume variable. A possible reason for this apparently strange relationship is that informed traders quickly want to exploit price inefficiencies and consequently have a large demand for immediacy. Therefore they turn to exchanges, which means that exchanges have a larger proportion of informed traders than OTC venues do. The adverse selection risk is therefore larger on exchanges and liquidity premiums hence increase as disproportionately many uninformed traders seek OTC opportunities.(Riordan, Storkenmaier, & Wagener, 2010)

There are reasons to expect correlation between OTC and HHI, depending on what type of traders turning to OTC venues. One possibility is that investors seeking OTC largely are investors with low search costs relative to the costs of adverse price impact. These investors are often large in size and have the capacity to invest in SORT, implying a negative relationship since a disproportionately large share of traders that abandon exchanges in favor of OTC, are those that would have had their order flows fragmented between trading venues.

[37] Electronic messages are either *submit-*, *cancel-* or *change an order*

Relevant factors not included in the regression

Volatility

In previous research we showed the frequent usage of volatility in academic research as a characteristic in grouping stocks projected to have similar liquidity costs. Empirical research indicates that an increase in volatility affects liquidity partially through its effect on turnover but also has a direct impact on liquidity costs. (O'Hara, 1995) An example of its impact on liquidity costs is through its impact on the option effect. Option value functions include volatility as a key component. As the term option effect implies, its value depends on the same factors as option values do.

Riordan (2010obtained results indicating that more volatile firms have remained less fragmented after the introduction of MiFID. This is possibly an effect of its correlation with volume, which correlation with HHI is easier to derive. Most economic theories point towards negative correlation between volatility and volume. Higher volatility induces risk-averse traders to reduce their trading in the security, which limits the number of traders.

The volatility measure used in academic research is however intraday realized volatility. We are unable to construct this variable due to limited intraday data. We can therefore not construct the variable but at least capture much of its effect due to its correlation with volume and price.38

Macroeconomic events

Theoretical models predict that these events should increase the adverse selection component of the spread, since different investors have varying capabilities to interpret news announcements. Increased risk for limit order investors to meet better informed traders increases their required compensation for liquidity provision. (Kim & Verrecchia, 1994). There are empirical studies supporting the theoretical argument, providing evidence for an increase of bid-offer spreads around macroeconomic announcements. (Green, 2004)

However,the data collection needed to construct the control variable is most likely too time-consuming relative the variable's potential to improve the regression model. We therefore do not make an attempt to control for it. To some extent we include it by controlling for volume, since trading volume tends to increase when there is new information about a security given dispersed interpretations of the news.

[38] See Appendix: Explanation of variables

Appendix II: Trading venues

Stockholm

In 1993 the Swedish Stock Exchange was the first RE ever to become a for-profit limited company. It merged with Helsinki, Tallinn, Riga, Vilnius, Copenhagen and Iceland stock exchanges before it was acquired by the US stock exchange group Nasdaq in 2007, currently owning 24 financial markets worldwide. (Nasdaq OMX acquisitions)

MiFID has had large implications for Stockholm, which pre-MiFID charged the highest direct trading fees of all major REs globally, despite the inability to offer competitive indirect transaction costs. (Cherbonnier & Vandelanoite, 2008) As a response to competition Stockholm has lowered transaction fees with over 40% between 2008 and 2010, and has invested in technology projected to enable further reductions. (Liedholm, 2010) Fees however remain high comparison to those charged by MTFs.

As an RE Stockholm has the important first mover advantage. Investors without SORT allocate their orders to Stockholm. It is seen as the natural place for liquidity suppliers and seekers. The enviable position as the traditional main venue almost automatically asssures it high levels of natural liqudity. Stockholm does not contract any market makers but applies assymetric maker-taker pricing; both transaction counterparties are charged but fees are higher for the second counterparty. (NASDAQ OMX Nordic Cash Market Pricelist) Stockholm also uses call auctions to open and close trading days.

In September 2008 OMX Stockholm launched a London-based MTF, Nasdaq OMX Europe, but had to close down its operations in May 2010 as competition was too intense (The NASDAQ OMX Group).

Burgundy

14 Nordic investment firms and banks initiated Burgundy in May 2009, as a response to the high fees charged by Stockholm and concerns that power was to be transitioned away to USA following Nasdaq's acquisition of Stockholm. Today Burgundy has around 25 trading participants, although trading is concentrated with four banks accounting for 60% of total turnover. (Burgundy)

As opposed to a narrow focus on large, liquid stocks which is usually the strategy of low-cost MTFs, Burgundy has chosen to focus on Nordic stocks regardless of their size. Shares traded at Burgundy are listed at Stockholm, First North Sweden and Denmark, AktieTorget, Oslo Börs and Oslo Axess, Nasdaq OMX Helsinki, Nasdaq OMX Copenhagen, NGM Equity. It is possible also for retail investors to trade on Burgundy through e.g. online brokers. Burgundy applies market making through agreements with investment firms, to have them offer pre-specified order volumes. Currently Burgundy only offers market making in selected large cap stocks, but more specific details are confidential.

Chi-X

Instinet, an agency broker owned by Japanese Nomura Holdings, initiated the London-based Chi-X Europe trading platform in March 2007, as soon as MiFID's regulatory changes were known. Initially it offered trading in selected German and Dutch stocks, but has expanded its geographic scope so that it today offers stocks trading in 15 European countries. It entered the Swedish market in March 2008. (Chi-X Europe)

It has rapidly increased turnover and was in May 2011 the market leader of Europe with 17% of turnover, despite the strategy to only offer trading in the most liquid European stocks.[39] Across our 29 stocks it only trails Stockholm with 20% of turnover. Graham Dick, Chi-X, expects further growth as technology adoption becomes more widespread across investment firms. (Bursell, 2010)

No positive earnings indicators have ever been released by Chi-X. The aggressive business model is often criticized for not generating profit, but is only used as a mean for the financially strong owners to scare off competitors from the industry. Jens Henriksson, CEO at Stockholm, believes that the strategy will prove unsustainable in the long run. (Herin, 2011)

BATS

BATS Europe is the European division of US BATS Global Markets. In Europe it operates an MTF with both visible and non-displayed liquidity, as well as a Dark Pool with only non-displayed liquidity. It offers trading on selected high-liquidity stocks in 15 European countries, ETFs, exchange traded commodities and exchange traded currencies.

BATS applies both market making and an aggressive rebate/charge schedule. Across our sample of stocks, it reported a market share of 6.5 % in May.

Turquoise

Turquoise was initially founded by a consortium of nine investment banks, and is now owned by twelve leading investment banks. It operates a MTF with one trading platform for equities and one for derivatives. The equity platform covers over 2000 securities over 19 countries across Europe and United States.

Customers are global banks and brokers to institutions with local, regional and sector focus, and specialist trading and market-making firms. Hence retail investors do not have access.

[39] Currently approximately 1300 stocks

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Appendix III: Tables and graphs

Table 1 – Cross Sectional Consolidated Volume Weighted Average Spreads Descriptives

The mean is calculated arithmetically by dividing the sum of all daily observations with the number of days. SD is the standard deviation of the quoted spreads. SD/Mean is a ratio that gives us a comparable descriptive of the magnitude of standard deviations. Skewness is a measure of asymmetry while kurtosis gives us an idea on the peakedness of the distribution. All measures are on daily levels.

Firm	N	Mean	SD	SD/Mean	Skewness	Kurtosis	Median	Min	Max
ABB	125	9.001	0.768	0.085	0.773	3.409	8.870	7.750	10.920
Alfa	125	15.047	1.783	0.119	0.510	2.390	14.760	12.300	18.810
Assa	124	13.228	1.941	0.147	0.431	2.184	12.975	10.270	17.100
Astra	125	6.030	0.868	0.144	2.418	9.423	5.800	5.160	9.240
Atlas	125	10.341	1.807	0.175	1.215	4.315	9.960	8.010	15.470
Boliden	125	14.758	3.017	0.204	1.451	4.657	13.930	11.220	23.250
Electrolux	125	12.336	2.001	0.162	0.800	3.001	12.130	9.710	17.200
Ericsson	125	9.003	0.954	0.106	1.055	4.176	8.990	7.650	11.650
Getinge	125	16.477	3.602	0.219	0.768	2.897	15.890	11.700	25.310
Svenska Handelsbanken	124	10.103	1.357	0.134	0.940	3.418	9.840	8.310	13.650
HM	125	7.657	1.159	0.151	1.321	4.391	7.430	6.220	10.840
Investor	125	14.243	2.874	0.202	1.424	4.673	13.610	10.700	22.370
Lundin Petroleum	125	20.359	4.934	0.242	1.143	4.035	19.280	13.140	33.850
MTG	125	19.706	3.260	0.165	0.643	2.793	18.890	14.740	27.260
Nokia	125	12.126	0.987	0.081	0.378	3.014	12.050	10.320	14.450
Nordea	124	12.130	1.701	0.140	0.654	2.976	11.950	9.430	16.120
Sandvik	125	13.130	1.685	0.128	0.630	2.619	12.890	10.670	16.850
SCA	125	13.906	2.418	0.174	-0.322	3.396	13.940	8.350	18.780
Scania	124	13.968	1.762	0.126	0.320	2.427	13.930	11.120	17.690
SEB A	125	11.952	1.207	0.101	0.636	2.507	11.690	10.250	14.570
Securitas	125	15.926	4.036	0.253	1.211	3.996	14.960	11.020	27.140
Skanska	125	14.087	1.930	0.137	0.321	2.802	14.150	10.600	18.440
SKF B	125	10.738	1.519	0.141	0.695	2.874	10.560	8.460	14.270
SSAB	124	13.701	1.684	0.123	-0.002	2.510	13.659	10.540	16.920
Swedbank A	124	12.372	1.939	0.157	0.162	2.020	12.295	15.790	15.960
Swedish Match	124	13.636	2.823	0.207	0.852	3.197	13.005	19.920	20.720
Tele2	125	12.607	2.391	0.190	0.288	2.162	12.520	8.670	17.300
Telia	124	12.445	2.157	0.173	0.034	3.061	11.980	7.620	16.720
Volvo	125	11.909	1.733	0.145	-0.692	3.248	12.140	7.780	14.750
Total	3617	12.860	3.799	0.295	1.072	5.937	12.490	5.160	33.850

Table 2 – Cross Sectional HHI Descriptives

The mean is calculated arithmetically by dividing the sum of all daily observations with the number of days. SD is the standard deviation of the quoted spreads. SD/Mean is a ratio that gives us a comparable descriptive of the magnitude of standard deviations. Skewness is a measure of asymmetry while kurtosis gives us an idea on the peakedness of the distribution. All measures are on daily levels. Do note that this is the raw form of our fragmentation variable where 0 signifies a perfectly fragmented market and 1 a concentrated market.

Firm	Observations	Mean	SD	SD/Mean	Skewness	Kurtosis	Median	Min	Max
ABB	125	0.310	0.020	0.064	0.732	5.395	0.308	0.266	0.394
Alfa	125	0.471	0.055	0.117	0.304	3.481	0.462	0.328	0.657
Assa	124	0.474	0.053	0.111	0.429	2.566	0.466	0.351	0.602
Astra	125	0.478	0.039	0.083	0.123	3.171	0.482	0.372	0.589
Atlas	125	0.546	0.050	0.091	0.354	3.155	0.541	0.435	0.693
Boliden	125	0.520	0.044	0.085	0.166	2.682	0.519	0.430	0.650
Electrolux	125	0.495	0.043	0.086	0.666	3.698	0.488	0.411	0.655
Ericsson	125	0.469	0.041	0.087	0.664	4.234	0.466	0.379	0.620
Getinge	125	0.525	0.073	0.139	0.117	3.897	0.526	0.321	0.742
Svenska Handelsbanken	124	0.474	0.048	0.101	0.664	3.247	0.470	0.384	0.626
HM	125	0.477	0.046	0.097	0.423	4.343	0.479	0.357	0.658
Investor	125	0.542	0.058	0.106	-0.166	3.089	0.539	0.387	0.681
Lundin Petroleum	125	0.506	0.057	0.112	-0.197	3.277	0.511	0.353	0.664
MTG	125	0.482	0.052	0.109	0.307	2.745	0.481	0.378	0.624
Nordea	124	0.438	0.051	0.115	1.631	9.209	0.434	0.335	0.691
Sandvik	125	0.526	0.054	0.103	0.127	3.223	0.529	0.378	0.648
SCA	125	0.496	0.056	0.113	0.393	3.256	0.492	0.380	0.680
Scania	124	0.461	0.049	0.106	-0.066	2.515	0.467	0.348	0.575
Securitas	125	0.487	0.059	0.122	0.380	3.497	0.484	0.343	0.657
Skanska	125	0.525	0.049	0.094	0.298	2.937	0.518	0.408	0.658
SKF B	125	0.519	0.052	0.101	-0.005	2.609	0.515	0.398	0.654
SSAB	124	0.515	0.052	0.101	0.222	3.072	0.515	0.395	0.646
Swedbank A	124	0.486	0.045	0.092	0.189	2.887	0.485	0.366	0.607
Swedish Match	124	0.487	0.057	0.116	-0.257	2.689	0.494	0.341	0.626
Tele2	125	0.460	0.047	0.102	0.520	3.417	0.456	0.344	0.610
Telia	124	0.437	0.048	0.110	0.351	2.617	0.434	0.341	0.564
Volvo	125	0.474	0.054	0.113	0.212	2.433	0.472	0.369	0.612
SEB A	125	0.496	0.045	0.090	0.184	3.563	0.497	0.378	0.636
Nokia	125	0.383	0.044	0.115	1.916	12.443	0.376	0.299	0.650
Total	3617	0.483	0.069	0.143	-0.244	3.487	0.486	0.266	0.742

Table 3 – Cross Sectional Variable Descriptives

Below are the means of the rest of our variables we include in our regression specifications. HHI^2 is simply our HHI from above squared. Price is the volume weighted average price of each of the stocks. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. Algo is our proxy for algorithmic trade and is obtained by dividing quoted volume with traded volume. LN OTC is the natural logarithm for OTC trade conducted through BOAT in €1000s. We have excluded the absolute values of CVWAS since they are dependent on stock prices and therefore not always comparable between stocks.

Firm	Observations	HHI^2	Price	LN Volume	Algo	LN OTC
ABB	125	0.097	149.264	18.561	23.983	17.135
Alfa	125	0.225	131.997	17.047	10.709	15.217
Assa	124	0.227	182.332	17.272	7.561	15.876
Astra	125	0.230	314.178	18.545	7.281	16.801
Atlas	125	0.301	159.843	18.207	7.110	14.001
Boliden	125	0.273	131.767	17.597	6.853	15.161
Electrolux	125	0.247	169.213	17.755	4.644	15.893
Ericsson	125	0.222	77.663	18.526	15.021	17.247
Getinge	125	0.281	150.618	16.510	4.870	13.975
Svenska Handelsbanken	124	0.227	213.934	17.574	7.056	15.805
HM	125	0.229	220.697	18.548	3.749	16.801
Investor	125	0.297	145.356	17.122	8.653	15.436
Lundin Petroleum	125	0.259	79.824	16.607	9.215	14.039
MTG	125	0.235	468.797	16.605	1.983	14.172
Nokia	125	0.149	63.463	18.367	91.969	17.802
Nordea	124	0.194	72.280	18.352	32.436	16.610
Sandvik	125	0.280	121.420	18.056	10.591	16.235
SCA	125	0.249	104.900	17.056	10.835	15.511
Scania	124	0.215	145.686	17.055	6.053	15.305
SEB A	125	0.248	56.049	17.812	26.863	15.764
Securitas	125	0.241	75.684	16.369	10.541	14.258
Skanska	125	0.278	129.041	17.000	8.586	15.021
SKF B	125	0.271	181.429	17.835	4.936	16.097
SSAB	124	0.267	101.820	17.128	8.709	15.042
Swedbank A	124	0.238	101.860	17.935	13.406	16.220
Swedish Match	124	0.240	197.720	16.718	5.020	15.298
Tele2	125	0.214	144.096	17.271	6.232	15.646
Telia	124	0.193	53.472	17.943	46.245	16.300
Volvo	125	0.227	108.306	18.644	6.906	17.094
Total	3617	0.236	146.511	17.587	14.066	15.716

Table 4 – Main Regression

The dependent variables (1) and (2) are given by consolidating and averaging the VWAS of all venues. (1) is the relative basis point term while (2) is the calculated absolute counterpart. The fragmentation variable is given by subtracting 1 with our HHI concentration index, resulting in a variable that becomes bigger as the degree of fragmentation increases. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. OTC is a relative term calculated by summing Dark and Off Exchange volume and then dividing it by total volume. Algo proxies algorithmic trade by dividing quoted volume with traded volume. LN price is the natural logarithmic version of the VWAP.

	CVWAS bps (1)			**CVWAS Absolute (2)**		
Coefficients	**Base Spec. (a)**	**Without time dummies (b)**	**Without Frag^2 (c)**	**Base Spec. (a)**	**Without time dummies (b)**	**Without Frag^2 (c)**
Frag	-25.052**	-25.581**	-4.787***	-0.325**	-0.326**	-0.049***
	(-2.850)	*(-2.860)*	(-5.180)	*(-2.760)*	*(-2.750)*	(-4.230)
Frag^2	20.122**	20.265**	**N/A**	0.2740**	0.2714**	**N/A**
	(2.340)	*(2.310)*	**N/A**	*(2.370)*	*(2.340)*	**N/A**
LN Volume	-0.981***	-0.866***	-0.971	-0.013***	-0.011***	-0.013***
	(-9.190)	*(-8.390)*	*(-9.120)*	*(-9.000)*	*(-8.190)*	*(-8.910)*
OTC	0.165**	0.095	0.172*	0.004	0.002	0.004
	(1.590)	*(0.930)*	*(1.640)*	*(2.210)*	*(1.520)*	*(2.240)*
Algo	0.012**	0.011**	0.012**	0.000	0.000	0.000
	(2.770)	*(2.670)*	*(2.740)*	*(-0.580)*	*(-0.420)*	*(-0.590)*
LN Price	1.270*	0.076	1.174*	0.141***	0.135***	0.139***
	(1.510)	*(0.100)*	*(1.400)*	*(14.070)*	*(15.140)*	*(14.000)*
Constant	30.521***	35.266***	25.823***	-0.205***	-0.191***	-0.269***
	(6.320)	*(7.780)*	*(5.620)*	*(-3.490)*	*(-3.510)*	*(-4.870)*
Number of observations	3611	3611	3611	3486	3486	3486
R^2	0.6629	0.6549	0.6622	0.7964	0.7920	0.7959
Monthly Time dummies	Yes	No	Yes	Yes	No	Yes

**p<0.1, **p<0.05, ***p<0.001*

Table 5 - OMX Stockholm Market Share

The dependent variables (1) and (2) are given by consolidating and averaging the VWAS of all venues. (1) is the relative basis point term while (2) is the calculated absolute counterpart. The fragmentation variables are replaced by OMX Stockholm's market linear and squared market shares. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. OTC is a relative term calculated by summing Dark and Off Exchange volume and then dividing it by total volume. Algo proxies algorithmic trade by dividing quoted volume with traded volume. LN price is the natural logarithmic version of the VWAP.

	CVWAS bps (1)			**CVWAS Absolute (2)**		
Coefficients	**Base Spec. (a)**	**Without time dummies (b)**	**Without OMXShare^2 (c)**	**Base Spec. (a)**	**Without time dummies (b)**	**Without OMXShare^2 (c)**
OMX Market share	-7.195*	-8.324**	3.837***	-0.109**	-0.119**	0.035***
	(-2.620)	*(-3.100)*	*(4.500)*	*(-2.610)*	*(-3.000)*	*(3.300)*
OMX Market share^2	9.069***	10.139***	**N/A**	0.120***	0.130**	**N/A**
	(3.730)	*(4.230)*	**N/A**	*(3.430)*	*(3.860)*	**N/A**
LN Volume	-0.963***	-0.847***	-0.835***	-0.013***	-0.011***	-0.013***
	(-9.020)	*(-8.210)*	*(-8.080)*	*(-8.820)*	*(-8.020)*	*(-8.740)*
OTC	0.175**	0.104	0.110	0.004**	0.003**	0.004**
	(1.680)	*(1.020)*	*(1.070)*	*(2.270)*	*(1.590)*	*(2.290)*
Algo	0.013**	0.012**	0.010**	0.000	0.000	0.000
	(2.910)	*(2.880)*	*(2.560)*	*(-0.380)*	*(-0.140)*	*(-0.580)*
LN Price	1.432**	0.210***	-0.189	0.004**	0.137***	0.138***
	(1.670)	*(0.270)*	*(-0.250)*	*(2.270)*	*(15.070)*	*(13.880)*
Constant	22.667***	27.569***	25.866***	-0.297***	-0.280***	-0.316***
	(4.870)	*(6.590)*	*(6.060)*	*(-5.470)*	*(-5.690)*	*(-5.790)*
Number of observations	3611	3611	3611	3486	3486	3486
R^2	0.6618	0.6537	0.6523	0.7959	0.7915	0.7952
Monthly Time dummies	Yes	No	Yes	Yes	No	Yes

*$p<0.1$, **$p<0.05$, ***$p<0.001$

Table 6 - First Differences

The dependent variables (1) and (2) are given by consolidating and averaging the VWAS of all venues. (1) is the relative basis point term while (2) is the calculated absolute counterpart. The fragmentation variable is given by subtracting 1 with our HHI concentration index, resulting in a variable that becomes bigger as the degree of fragmentation increases. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. OTC is a relative term calculated by summing Dark and Off Exchange volume and then dividing it by total volume. Algo proxies algorithmic trade by dividing quoted volume with traded volume. LN price is the natural logarithmic version of the VWAP.

	CVWAS bps (1)			**CVWAS Absolute (2)**		
Coefficients	**Base Spec. (a)**	**Without time dummies (b)**	**Without Frag² (c)**	**Base Spec. (a)**	**Without time dummies (b)**	**Without Frag² (c)**
Frag	-36.770***	-38.352***	-4.896***	-0.520***	-0.530***	-0.048***
	(-3.230)	*(-3.320)*	*(-4.51)*	*(-3.420)*	*(-3.460)*	*(-3.390)*
Frag²	31.600**	32.350**	**N/A**	0.468***	0.470***	**N/A**
	(2.850)	*(2.870)*	**N/A**	*(3.150)*	*(3.150)*	**N/A**
First Difference Frag	14.373	15.599	0.096	0.248**	0.258**	-0.003
	(1.490)	*(1.610)*	*(0.110)*	*(1.960)*	*(2.030)*	*(-0.230)*
First Difference Frag²	-14.137	-14.735	**N/A**	-0.249**	-0.252**	**N/A**
	(-1.520)	*(-1.570)*	**N/A**	*(-2.030)*	*(-2.050)*	**N/A**
LN Volume	-0.986***	-0.869***	-0.972***	-0.0130***	-0.011***	-0.130***
	(-9.210)	*(-8.390)*	*(-9.090)*	*(-9.040)*	*(-8.210)*	*(-8.880)*
OTC	0.168	0.098	0.174	0.004**	0.002	0.004**
	(1.600)	*(0.950)*	*(1.660)*	*(2.210)*	*(1.540)*	*(2.270)*
Algo	0.012**	0.011**	0.012**	0.000	0.000	0.000
	(2.800)	*(2.730)*	*(2.670)*	*(-0.450)*	*(-0.300)*	*(-0.610)*
LN Price	1.214	0.051	1.074	0.140***	0.135***	0.138***
	(1.430)	*(0.070)*	*(1.270)*	*(13.830)*	*(14.950)*	*(13.680)*
Constant	33.825***	38.757***	26.380***	-0.152	-0.138**	-0.262***
	(6.510)	*(7.890)*	*(5.650)*	*(0.017)*	*(-2.310)*	*(-4.670)*
Number of observations	3582	3582	3582	3458	3458	3458
R²	0.6634	0.6556	0.6623	0.7964	0.792	0.7956
Monthly Time	Yes	No	Yes	Yes	No	Yes

dummies		

*p<0.1, **p<0.05, ***p<0.001

Table 7 – Instrumental Variables Approach 1: Lagged Frag and Frag²

The dependent variables (1) and (2) are given by consolidating and averaging the VWAS of all venues. (1) is the relative basis point term while (2) is the calculated absolute counterpart. The fragmentation variable is given by subtracting 1 with our HHI concentration index, resulting in a variable that becomes bigger as the degree of fragmentation increases. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. OTC is a relative term calculated by summing Dark and Off Exchange volume and then dividing it by total volume. Algo proxies algorithmic trade by dividing quoted volume with traded volume. LN price is the natural logarithmic version of the VWAP. Frag and $Frag^2$ are instrumented with their lagged counterparts $Frag_{t-1}$ and $Frag^2_{t-1}$ in order to control for daily shocks.

	CVWAS bps (1)			CVWAS Absolute (2)		
Coefficients	**Base Spec (a)**	**Without time dummies (b)**	**Without Frag² (c)**	**Base Spec (a)**	**Without time dummies (b)**	**Without Frag² (c)**
Frag	-88.076*	-93.849**	-7.632**	-1.381**	-1.419**	-.041
	(-1.950)	*(-2.070)*	*(-2.470)*	*(-2.310)*	*(-2.390)*	*(-0.980)*
Frag²	81.810*	85.135*	**N/A**	1.322**	1.337**	**N/A**
	(1.880)	*(1.940)*	**N/A**	*(2.300)*	*(2.330)*	**N/A**
LN Volume	-1.021***	-0.929***	-0.888***	-.013***	-.012***	-.013***
	(-8.350)	*(-7.890)*	*(-8.030)*	*(-8.180)*	*(-7.670)*	*(-8.300)*
OTC	0.147	0.072	0.102	0.003**	0.002	0.004**
	(1.390)	*(0.680)*	*(0.980)*	*(1.990)*	*(1.270)*	*(2.290)*
Algo	0.012**	0.012**	0.011**	0.000	0.000	0.000
	(2.730)	*(2.890)*	*(2.670)*	*(-0.450)*	*(-0.040)*	*(-0.660)*
LN Price	1.463*	0.376	-0.017	0.145***	0.139***	0.138***
	(1.670)	*(0.460)*	*(-0.020)*	*(13.610)*	*(14.370)*	*(13.790)*
Constant	45.921***	51.815***	32.160***	-0.041	-0.017	-0.353***
	(3.850)	*(4.440)*	*(7.100)*	*(-0.260)*	*(-0.110)*	*(-4.870)*
Number of observations	3582	3582	3582	3458	3458	3458
R2	0.6564	0.6464	0.6534	0.7888	0.7838	0.7955

Time dummies	Yes	No		Yes	No	Yes

**p<0.1, **p<0.05, ***p<0.001*

Table 8 – Instrumental Variables Approach 2: Venue Average Order Size

The dependent variables (1) and (2) are given by consolidating and averaging the VWAS of all venues. (1) is the relative basis point term while (2) is the calculated absolute counterpart. The fragmentation variable is given by subtracting 1 with our HHI concentration index, resulting in a variable that becomes bigger as the degree of fragmentation increases. LN volume is the natural logarithm of total turnover in €1000s. We only include lit orders since quoted spreads only exists for lit trade. OTC is a relative term calculated by summing Dark and Off Exchange volume and then dividing it by total volume. Algo proxies algorithmic trade by dividing quoted volume with traded volume. LN price is the natural logarithmic version of the VWAP. Frag and $Frag^2$ are instrumented with the logarithms of each venue's average order size in order to control for self-selection bias.

	CVWAS bps (1)			**CVWAS Absolute (2)**		
Coefficients	**Base Spec. (a)**	**Without time dummies (b)**	**Without $Frag^2$ (c)**	**Base Spec. (a)**	**Without time dummies (b)**	**Without $Frag^2$ (c)**
Frag	142.892	209.185**	-2.527*	1.557	2.851	-0.017
	(1.600)	*(2.050)*	*(-1.650)*	*(1.560)*	*(0.017)*	*(-0.890)*
$Frag^2$	-143.441	-208.354**	**N/A**	-1.554	-2.823	**N/A**
	(-1.630)	*(-2.080)*	**N/A**	*(-1.580)*	*(0.016)*	**N/A**
LN Volume	-0.848***	-0.692***	-0.826***	-0.011***	-0.009***	-0.011***
	(-6.830)	*(-5.460)*	*(-7.860)*	*(-7.020)*	*(-5.340)*	*(-7.710)*
OTC	0.226*	0.181	0.106	0.004	0.004	0.003
	(1.800)	*(1.310)*	*(1.040)*	*(2.380)*	*(1.790)*	*(1.630)*
Algo	0.010"	0.007	0.010	0.000	-0.000	0.000
	(2.110)	*(1.370)*	*(2.470)*	*(-0.840)*	*(-1.130)*	*(-0.710)*
LN Price	0.443	-1.113	-0.075	0.130***	0.117***	0.132***
	(0.440)	*(-1.090)*	*(-0.100)*	*(10.720)*	*(9.280)*	*(14.840)*
Constant	-4.821	-13.890	35.155***	-0.749	-0.1036	-0.363
	(0.821)	*(-0.580)*	*(6.830)*	*(-3.120)*	*(-3.710)*	*(-6.260)*
Number of observations	3593	3593	3593	3468	3468	3468
R2	0.6154	0.5635	0.6511	0.7753	0.731	0.791
Time dummies	Yes	No	Yes	Yes	No	Yes

**p<0.1, **p<0.05, ***p<0.001*

Table 9 – BBOs and Price Discovery

The dependent variable Traded Volume Market Share is given by the aggregated market share of traded stocks minus those sold in auctions a venue has. The BBO Volume coefficient is the aggregated market share a venue has on the consolidated BBO.

Traded Volume Market Share

Coefficients	**Stockholm Period 1**	**CHI-X Period 1**	**Burgundy Period 1**	**BATS Period 1**	**Turquoise Period 1**
BBO Volume	0.184***	0.023***	0.080***	0.019***	0.065***
	(8.300)	*(14.950)*	*(16.630)*	*(6.240)*	*(6.230)*
Constant	0.418***	0.093***	0.022***	0.030***	0.029***
	(26.110)	*(73.370)*	*(25.880)*	*(63.740)*	*(58.330)*
N	1710	1710	1710	1710	1710
R^2	0.815	0.335	0.292	0.285	0.272
Coefficients	**Stockholm Period 2**	**CHI-X Period 2**	**Burgundy Period 2**	**BATS Period 2**	**Turquoise Period 2**
BBO Volume	0.223***	0.189***	0.185***	0.314***	0.173***
	(7.000)	*(13.040)*	*(8.070)*	*(14.180)*	*(4.980)*
Constant	0.327***	0.108***	0.041***	0.039***	0.024***
	(15.020)	*(46.040)*	*(29.540)*	*(67.230)*	*(50.370)*
N	1736	1736	1736	1736	1736
R^2	0.746	0.465	0.409	0.365	0.448

$*p<0.1$, $**p<0.05$, $***p<0.001$

Table 10 – Student's t-tests on coefficient mean differences for OMX Stockholm and Chi-X

The t-tests are constructed by subtracting period 2 (Q1 2011) with period 1 (Q1 2010) values. The test-statistics are therefore negative when coefficients on average are larger in the second period and vice versa.

Paired t test Stockholm		**Observations**	**Mean**	**Std. Dev.**
Period 1		29	16.41 %	21.49 %
Period 2		29	24.52 %	17.24 %
Diff		29	-7.78 %	32.27 %
Degrees of freedom	28			
t-value: -1.2979	**P-Value:** 0.1024			
Ha: mean(diff) < 0				

Paired t test CHI-X		**Observations**	**Mean**	**Std. Dev.**
Period 1		29	6.64 %	8.01 %
Period 2		29	21.60 %	12.20 %
Diff		29	-14.97 %	11.78 %
Degrees of freedom	28			
t-value: -6.8403	**P-Value:** 0***			
Ha: mean(diff) < 0				

Table 11 – Sign Tests on coefficient mean differences

The sign tests are constructed by subtracting period 2 (Q1 2011) with period 1 (Q1 2010) values. The following tests are all one-tailed towards the left-tail.

Sign test Stockholm OMX	**Observed**	**Expected**
Negative	18	14.5
One Sided Test	Pr(Number of negative>=11)=Binomial(n=29,x>=18, p=0.5)	
Ho: median of period1 - period2 = 0 **Ha: median of period1 - period2 < 0**	P-value = 0.1325	
Sign test CHI-X	**Observed**	**Expected**
Negative	27	14.5
One Sided Test	Pr(Number of negative >=28)=Binomial(n=29,x>=27, p=0.5)	
Ho: median of period1 - period2 = 0 **Ha: median of period1 - period2 < 0**	P-value = 0***	
Sign test Burgundy	**Observed**	**Expected**
Negative	13	14.5
One Sided Test	Pr(Number of negative >=14)=Binomial(n=29,x>=13, p=0.5)	
Ho: median of period1 - period2 = 0 **Ha: median of period1 - period2 < 0**	P-value = 0.7709	
Sign test BATS	**Observed**	**Expected**
Negative	24	14.5
One Sided Test	Pr(Number of negative >=25)=Binomial(n=29,x>=24, p=0.5)	
Ho: median of period1 - period2 = 0 **Ha: median of period1 - period2 < 0**	P-value = 0.0003***	
Sign test Turquoise	**Observed**	**Expected**
Negative	17	14.5
One Sided Test	Pr(Number of negative >=18)=Binomial(n=29,x>=17, p=0.5)	
Ho: median of period1 - period2 = 0 **Ha: median of period1 - period2 < 0**	P-value = 0.2291	

Graphs and illustrations

Figure 1 – Market share development for OMX Stockholm constituents

The graph displays market shares for the different venues on stocks listed at Stockholm OMX. Other REs except Stockholm OMX have been removed so that the breakdown only includes Stockholm OMX in relation to MTFs. This is done due to stocks having dual listings. Other Res are not considered to compete with Stockholm since they do employ the strategy of offering trading on stocks that are not listed on their exchanges, which is what the MTFs do.

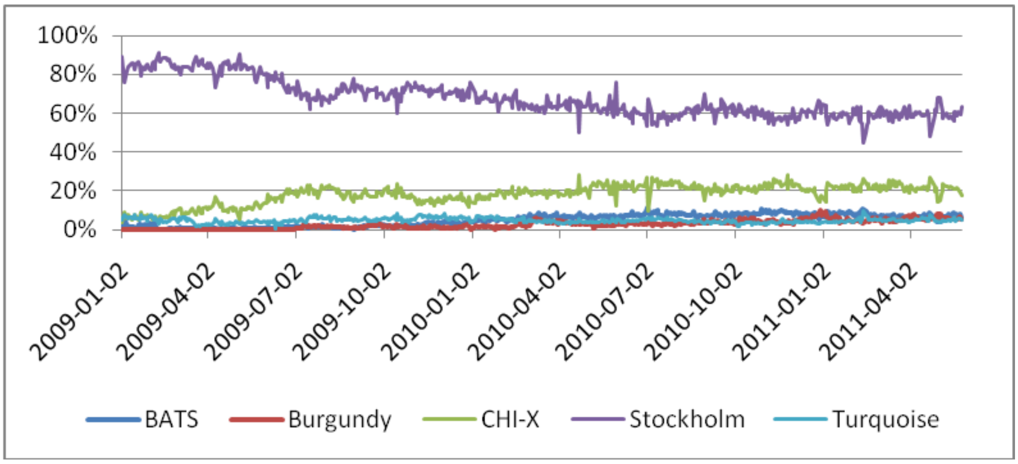

Figure 2 - Market share development of regulated exchanges

The graph displays market shares for the main venues on four European indices. As in figure 1 we removed other REs except the traditional RE for every index when we calculated the market share, in order to display the market shares that are lost due to competition from MTFs.

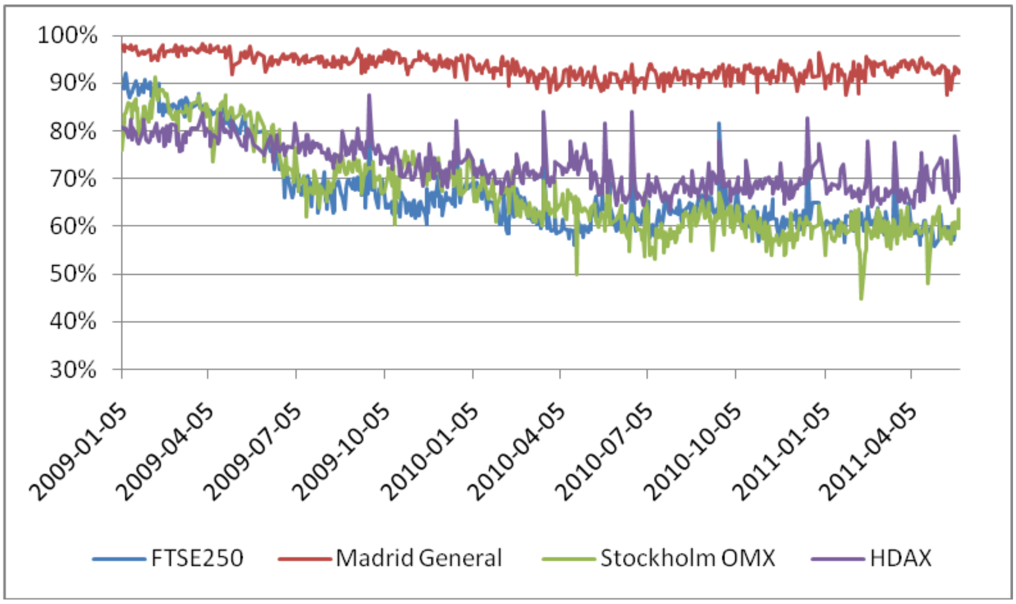

Figure 3 - The relationship between CVWAS and Fragmentation

Below is a scatter plot diagram showing us the aggregate relationship between the degree of fragmentation and quoted spreads. Our inverted fragmentation variable is on the x-axis and quoted spreads on the y-axis. The trend-line tells us that the degree of fragmentation has a negative size impact on quoted spreads.

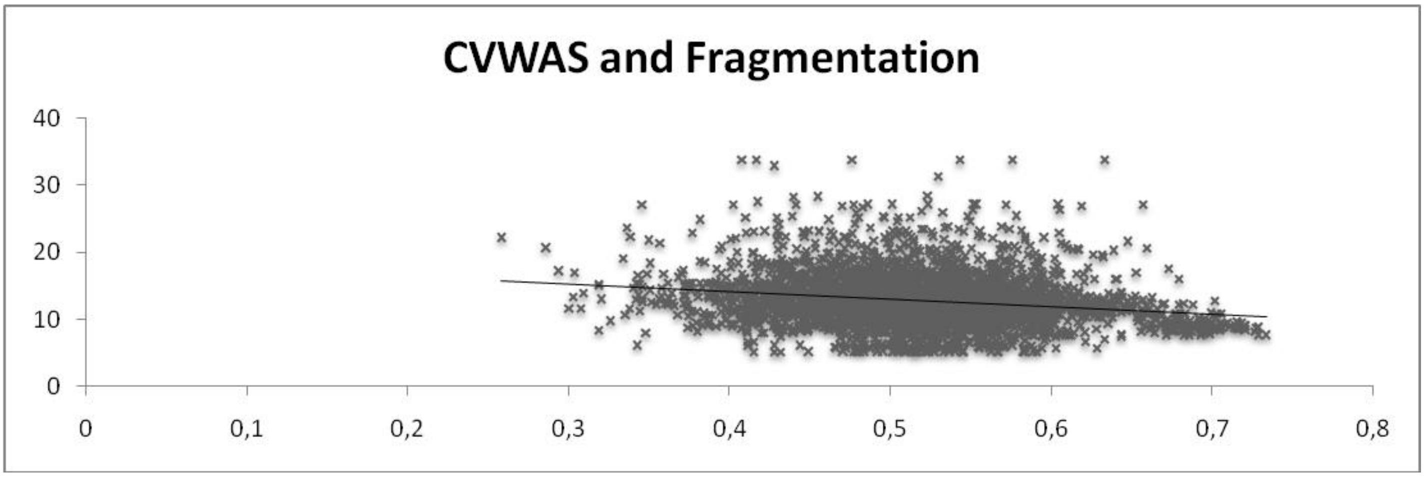

Figure 4 - The relationship between CVWAS and Turnover

Below is a scatter plot diagram showing us the aggregate relationship between the logged trade turnover in €1000 and quoted spreads. Our volume variable is on the x-axis and quoted spreads on the y-axis. The trend-line clearly shows us that trade activity has a negative size impact on quoted spreads.

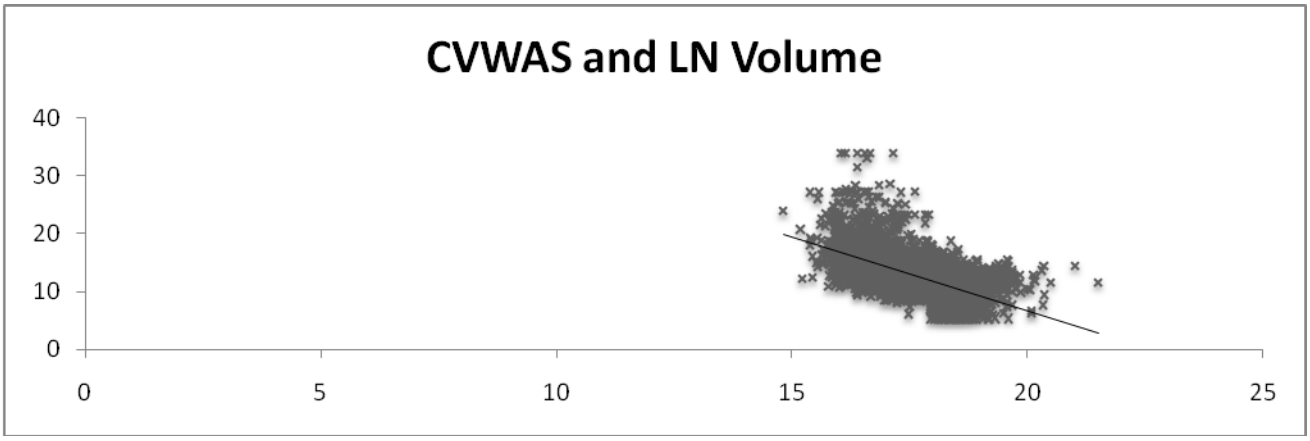

Figure 5 - Histogram of the CVWAS

The graph shows us the distribution of our consolidated quoted spreads in basis points.

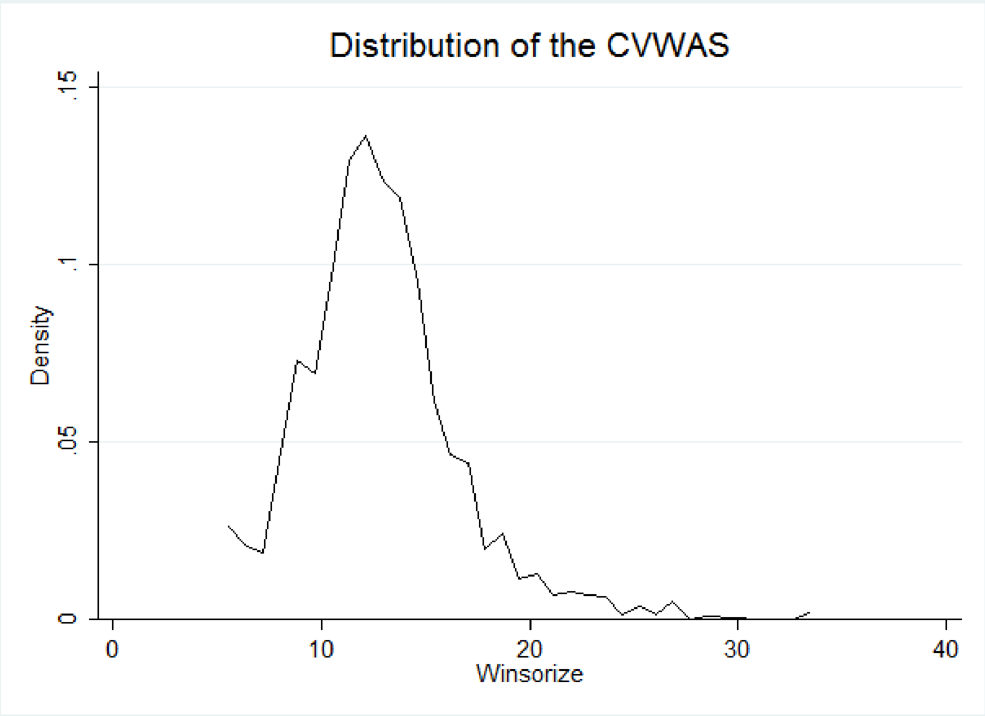

Figure 6 - Histogram of the Inverted HHI

The histogram shows us the distribution of our Inverted HHI variable.